MEASURING INTERNATIONAL HEALTH INEQUALITIES

MEASURING INTERNATIONAL HEALTH INEQUALITIES AND SOCIOECONOMIC STATUS USING HOUSEHOLD SURVEY DATA

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Lay Abstract

This thesis investigates social inequalities in health and how to measure socioeconomic status (SES) using household surveys in a way that is robust across jurisdictions. It examines how wealth indices compare to income and consumption, and develops a new method to calculate transnational health inequalities. Chapter two conducts a comprehensive evaluation of evidence surrounding the use of wealth indices in urban and rural areas, robustness to changes in assets, future applications, and the advantages and disadvantages of the primary competing methods for quantifying household SES. The third chapter systematically evaluates how health inequality magnitudes evolve over time and across country-incomes according to SES measure. Finally, a transnational measurement of health inequalities was calculated for the island of Hispaniola in chapter four, uncovering the distribution of disease between nations, subnational regions, and urban-rural areas. Detailed instructions for all methodological aspects of the new transnational method are presented.

Abstract

The methods underlying the quantification of health inequalities have profound consequences for measuring progress in achieving health for all. In Chapter two, associations between household wealth indices, income, and consumption were systematically compiled and different methods of wealth index calculation were evaluated for appropriateness of use in a variety of settings. Researchers are presented with a synthesis of existing evidence about the appropriateness of use of wealth indices in urban and rural areas, their robustness to changes in the asset mix, future applications, and advantages and disadvantages of primary competing methods of quantifying SES using household survey data. In Chapter three, international microdata were analyzed to evaluate how magnitudes of health inequality are affected by different methods of quantifying household socioeconomic status (SES), including income, consumption, and asset wealth. In Chapter four, the need for a transnational approach to measuring health inequalities was justified and the new method was developed using an empirical example. Substantively, these chapters develop the most complete evaluation of the association between the asset wealth, consumption, and income using both critical interpretive synthesis and microdata analysis, as well as the first meta-analysis evaluating changes in health inequality magnitudes according to the SES measure used over time and across country-income levels. The transnational analysis of health inequalities uncovered previously hidden health disparities in the island of Hispaniola, and detailed instructions for all methodological aspects of the new method were presented. The distribution of disease between nations, subnational regions, and urban-rural areas in Hispaniola were

analyzed from 1994 to 2013, and the first relative geospatial wealth ranking between Haiti and the Dominican Republic was presented. Global health researchers should strive to measure the equity of health between people, and this sometimes requires analyzing populations that are not neatly contained by national boundaries.

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List of all Abbreviations and Symbols

CHEPA - Centre for health economics and policy analysis

CIS - Critical interpretive synthesis

DHS - Demographic and health survey

GPS - Global positioning system

GNI - Gross national income

HAZ - Height-for-age z-score

HIV - Human immunodeficiency virus

IRT - Item response theory

LTM - Latent trait modeling

LAC - Latin American and Caribbean

LSMS - Living standards measurement study

LMIC - Low- and middle-income country

MSA - Mokken scale analysis

MCA - Multiple correspondence analysis

MICS - Multiple indicator cluster surveys

PCA - Principal components analysis

PPP - Purchasing power parity

RII - Relative index of inequality

SII - Slope index of inequality

SES - Socioeconomic status

SDG - Sustainable development goals

UNICEF - United Nations children's fund

USAID - United States agency for international development

WAZ - Weight-for-age z-score

WHZ - Weight-for-height z-score

Declaration of Academic Achievement

This thesis contains an introduction (Chapter 1), three original research studies (Chapters 2-4), and a concluding chapter (Chapter 5). I, Mathieu Poirier, am the lead author of every chapter that follows, am responsible for the conceptualization and design of every research chapter, and conducted all analyses of quantitative and qualitative data. My supervisor, Dr. Michel Grignon, contributed to the design of Chapter 4, interpretation of results for all research chapters, and provided revisions for every chapter. Committee member Dr. Karen Grépin contributed to the design of Chapter 3, interpretation of results for all research chapters, and provided revisions for every chapter. Committee member Dr. Michelle Dion contributed to the interpretation of results for all research chapters and provided revisions for every chapter. Dr. Emmanuel Guindon also contributed to the interpretation of results and provided revisions to Chapter 2.

Chapter 1. Introduction

This chapter introduces the rationale for writing, the research process, and the contributions of three thesis chapters to the measurement of international health inequalities. I first describe why the methods underlying the measurement of health inequalities have profound consequences for achieving more equitable achievement of health around the world. The questions that motivated my research into this topic are then discussed, and the research agenda I created to address these questions is laid out. Finally, the substantive, methodological and theoretical contributions of each chapter are outlined before concluding with the impact I hope my research can have on breaking down entrenched norms within the global health research community that are preventing more rigorous and meaningful knowledge creation.

International health inequalities

Inequalities in health that are unjust and preventable are known as inequities in health. The political determinants of these inequities have been recognized for centuries, with the likes of Rudolf Virchow declaring politics to be “nothing else but medicine on a large scale” and Friedrich Engels explicitly linking ill health to class status in 19th century England (Basu et al., 2017; Engels, 1845). Following Michael Marmot’s (1991) publication of the Whitehall II study firmly establishing large class-based inequalities among British civil servants, an explosion of research measuring health inequalities occurred, with the number of published articles growing from a couple hundred in 1990 to more than 5,000 in 2014 (Bouchard et al., 2015). This tremendous increase in research output led global health researchers to the question of whether findings consistently linking socioeconomic status (SES) to health in high-income countries would be replicated in low- and middle-income countries (LMICs). Although anecdotal evidence and intuition supported the hypothesis, those wanting to quantify the magnitude of health inequalities in these countries had to overcome many challenges.

The challenges of extending the study of inequalities in health to LMICs underscored the many social constructs and assumptions that underpin methodologies commonly used in high-income countries. Not only was data sparse and often of poor quality, even the norm of using income to measure a household's SES could no longer be taken for granted. With the availability of a regularly collected household income becoming the exception rather than the assumed norm for survey data collected in LMICs, new strategies of measuring household SES had to be developed. The primary alternative method employed to measure household SES was to ask a household how much they spent on various common expense categories, but even this proved to be time consuming, expensive to conduct on large scales, and often plagued by recall error (Bollen et al., 2002; Howe et al., 2012). In addition, any utility-improving goods that are produced directly by the household, inherited, or shared within the community are not captured by either income or consumption. In response to these difficulties, several economists and health researchers independently worked to devise a method to quantify the assets owned by a household into a meaningful measure of household SES. By far the most influential method to come out of this process was developed by Filmer and

Pritchett (2001), and their principal components analysis- (PCA-) based wealth index would rapidly be established as the norm in the field of global health (Rutstein, 2008; Sahn and Stifel, 2003).

Since the establishment of this norm, institutional inertia has effectively led to lock-in effects since the time invested learning the methodology and the importance of coordinating activities of many researchers around the world has tended to maintain the *status quo* (Kuhn, 1970; Pierson, 2000, 1993). Global health researchers now default to using the household wealth index as the primary method of quantifying SES in LMICs – especially now that the method is easily available as a pre-calculated variable in the most widely used health surveys in the field (Rutstein and Johnson, 2004). Standardized household surveys such as Demographic and Health Surveys (DHS) supported by the United States Agency for International Development, Multiple Indicator Cluster Surveys (MICS) supported by the United Nations Children's Fund, and World Health Surveys supported by the World Health Organization collect information on household asset possession rather than household income or consumption. Survey variables summarizing asset wealth are most often made available in the form of quintiles (fifths of households ordered by raw wealth index) and are used to compare high and low SES households in one country regardless of the context or health outcome. These are the methods that I was taught in my global health education and that I employed in the field in my time working in Latin America and the Caribbean, where, as I describe below, I was motivated to question the assumptions underlying these methods and decided to pursue a new line of research.

Rationale for undertaking research

The many complexities of measuring household wealth and the peculiarity of limiting analysis only to the extent of national borders began to impress themselves on me while conducting public health research in Bolivia, the Dominican Republic, and Haiti. The importance of the informal economy, which supports a majority of residents of many LMICs, was not accurately captured by household income measures due to the extreme volatility of money that would be made in any given week. Accurately measuring household consumption was extremely time consuming and required expertise and resources that only the most well-financed survey groups could implement on a large scale. While the appeal of household asset indices quickly became clear, I was bothered by lingering questions about how the methods used to calculate the index would affect my results. Would the inclusion of owning a bed net in the calculation of a household asset index affect the integrity of results linking lower SES households to mosquito-borne disease outcomes? How would the inclusion of piped water provision (available only to city dwellers) affect wealth-related inequalities of water-borne disease, and especially if I was interested in whether there was an urban-rural disparity? I was never taught whether I should be concerned about these possible biases, and I could not find the answer to my questions in a scan of published literature. Even more fundamentally, I couldn’t even find out whether household SES I was quantifying using household asset indices would affect the magnitude of health inequalities in a different way than income or consumption measures would.

While these questions about the methods underlying how SES is measured remained unanswered, I also began to question the routine of splitting up populations into neat national groups and analyzing them as separate and distinct entities. National boundaries marked as sharp lines on a map were often crossed several times daily over unmarked land by transnational communities, to say nothing about mosquitoes or contaminated water. Different regions within national borders were often far more foreign to each other in terms of living standards, language, culture, and health outcomes than regions that happened to be on the other side of an often arbitrary border. Beyond the mismatch between lived experiences of the populations I was conducting research with and the methods I was using to measure health inequalities, a deeper examination of published literature revealed problematic assumptions and implications that were once again based on misunderstandings of asset indices. Studies would use relative wealth distributions within one country to compare health inequalities with several other countries, all without accounting for extreme disparities in absolute wealth between the countries. This absolute disparity, nowhere clearer than where I was working on the island of Hispaniola, motivated my decision to develop methods with which researchers could measure health inequality on a transnational scale.

Approaches for the three studies

The three chapters that comprise this thesis are linked conceptually and each build on the knowledge gained from the last. The methods employed by each are suited to the goals of the study and span the qualitative-quantitative spectrum. Specifically, the objectives of each study are to:

1) systematically compile all known associations between household asset indices, income, and consumption and evaluate the appropriateness of different methods of calculation of household asset wealth (Chapter 2)
2) analyze how the magnitude of health inequalities is affected by the use of household asset indices, income, consumption, and predicted income using international microdata (Chapter 3)
3) justify the need for a transnational approach of measuring health inequalities and begin developing the new method with an empirical example (Chapter 4).

Methods were tailored to meet the objectives of each chapter. Due to the complex and dispersed literature informing the construction of household asset indices, the method of critical interpretive synthesis (CIS) was chosen for Chapter 2. In addition to being well suited to the development of theory from a complex body of evidence, CIS is ideal for fields which lack comparable outcomes and have yet to achieve universal definitions of key concepts (Ako-Arrey et al., 2016; Boyko et al., 2012; Dixon-Woods et al., 2006, 2005). Chapter 3 used the knowledge gained from Chapter 2 to select polychoric PCA as the method to quantify household assets into a measure of household wealth (Kolenikov and Angeles, 2009) as well as the decision to include predicted income as a fourth household SES comparator (Fink et al., 2017; Harttgen and Vollmer, 2013). Health inequalities were quantified using the concentration index, slope index of inequality, and relative index of inequality, and meta-analysis was used to answer the overall research question of whether the method used to quantify household SES affects the magnitude of health inequalities (Ernstsen et al., 2012; Higgins et al., 2009; O'Donnell et al., 2008). Finally, Chapter 4 used both PCA and polychoric PCA (Filmer and Pritchett, 2001; Kolenikov and Angeles, 2009) to rank several waves of Demographic and Health Surveys over a transnational sample of Haiti and the Dominican Republic. Inequalities in child anthropometrics and child deaths were calculated using the concentration index (O'Donnell et al., 2008; Wagstaff, 2005), georeferenced data was interpolated onto a map of Hispaniola (Auchincloss et al., 2007), and the concentration index was decomposed into national, subnational, and urban-rural components (Jimenez-Rubio et al., 2008; O'Donnell et al., 2008).

The general approach to the order of these studies followed the logic of a fully mixed sequential equal status mixed methods design (Collins et al., 2007; Leech and Onwuegbuzie, 2009). The qualitative-dominant study in Chapter 2 (which also includes quantitative information) was used to synthesize information and generate theory which was used to inform the two subsequent chapters. A quantitative analysis of microdata in Chapter 3 addressed the unanswered empirical question identified in Chapter 2 regarding how different methods of measuring household SES affected the magnitude of health inequalities. Finally, Chapter 4 leverages both qualitative and quantitative descriptions of the methods needed to implement a transnational index of health inequality. Together, these three studies form a cohesive body of work that address three substantive questions within the field of international health inequality measurement.

Substantive, methodological and theoretical contributions

Substantive contributions of this thesis can be found in all three chapters, although Chapters 3 and 4 provide a greater number of more easily abstracted quantitative results. An exhaustive compilation of published associations between asset indices, income, and consumption is first established in Chapter 2 and empirically calculated using the same microdata over more than one country using all three measures for the first time in Chapter 3. Chapter 3 also presents the first meta-analysis evaluating how health inequality magnitudes evolve over time and across country-income levels depending on the measure of household SES selected. Chapter 4 represents the first transnational measurement of health inequalities and evaluates how the distribution of disease has evolved between nations, subnational regions, and urban-rural areas for the island of Hispaniola from 1994 to 2013. The chapter also establishes the first relative geospatial wealth ranking between the two countries ever conducted and identifies hidden transnational health inequalities that had previously gone unnoticed. Moving past these substantive contributions, the methodological contributions are ultimately how this thesis will make a lasting impact.

While Chapter 3 has methodological implications, Chapters 2 and 4 are entirely centered around breaking down unjustified methodological norms in the global health community and proposing more rigorous and innovative ways forward. Chapter 2 presents global health researchers with a detailed synthesis of existing evidence about the appropriateness of use of asset indices in urban and rural areas, its robustness to changes in the asset mix, future possible applications, and details the advantages and disadvantages of the primary competing methods for quantifying SES using household survey data. The findings from Chapter 3 imply that the choice of household SES measure used by global health researchers may affect the magnitude of resulting health inequalities they observe, and that Harttgen and Vollmer's (2013) predicted income method may resemble the asset index results they are based on more closely than the household income it is supposed to be predicting. Chapter 4 is entirely centered on introducing a new method of measuring transnational health inequalities. Detailed instructions on case selection, the use of appropriate data, which SES and health inequality measures to use, and possible applications for the method are all presented in the hopes that it will inspire other researchers to build on the method and apply it in new contexts around the world.

Lastly, the theoretical contributions of this thesis are what bind the three chapters together. The fact that SES is a fluid and multidimensional concept is at the core of every chapter. Whether the implications are that asset indices can be used to measure SES in a number of effective ways (Chapter 2), that income, consumption, and asset indices measure different but equally valid dimensions of SES (Chapter 3), or that asset indices can be used to rank the relative SES of households across national boundaries (Chapter 4), the latent and ultimately immeasurable nature of SES is both frustrating and fascinating. Finally, the idea that global health researchers should be interested in measuring the equity of health outcomes between people, and that this sometimes requires analyzing populations that are not neatly contained by national boundaries is the theoretical contribution that underlies the transnational method. The next chapter begins the process of presenting these substantive, methodological, and theoretical contributions with a CIS of the approaches and alternatives to the PCA-derived wealth index.

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Chapter 2. Approaches and Alternatives to the Wealth Index to Measure Socioeconomic Status using Survey Data: A Critical Interpretive Synthesis

Preface

This chapter begins the work of establishing how closely asset wealth is associated with household income and consumption before evaluating under which conditions asset indices can be appropriately employed in the field. Alternative methods of calculating a wealth index are compared, and opportunities for future research are laid out. The method of critical interpretive synthesis was used to evaluate diverse qualitative and quantitative results published throughout many academic fields, ultimately allowing for the creation of a theory regarding which latent concept of SES each measure is addressing and generating research questions that inspired work in the following chapters.

I conceived, extracted data for, and wrote a preliminary version of the study in September 2015, after which I received significant input from Dr. Emmanuel Guindon and the Centre for Health Economics and Policy Analysis (CHEPA). The study was then refined and received significant input on data interpretation and manuscript organization from my committee members Dr. Karen Grépin and Dr. Michel Grignon. I then refreshed the literature search in September 2018 and received final revisions from all committee members which were incorporated into this final version.

Approaches and Alternatives to the Wealth Index to Measure Socioeconomic Status Using Survey Data: A Critical Interpretive Synthesis

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Abstract

The most commonly used method to measure socioeconomic status (SES) in contexts where income and consumption data is not available is the wealth index, which has been incorporated into many international household health surveys due to the ease by which it can be collected. Monitoring progress towards the Sustainable Development Goals by 2030 requires the global community to disaggregate targets along socio-economic lines, but little has been published critically analyzing the appropriateness of wealth indices to measure social health inequalities in low- and middle-income countries around the world. The following chapter conducts a critical interpretive synthesis (CIS) of the complex body of literature that has evaluated the appropriateness of use of the wealth index to measure SES and provides an overview of alternative methods to calculate SES using data also captured in standardized household surveys. Our aggregation of all published associations of wealth indices with both income and consumption indicates a mean Spearman rank correlation coefficient of 0.42 and 0.55 for each measure, respectively. Health and educational outcomes are similarly distributed using all SES measures, but magnitudes in inequalities may be larger using wealth indices and context-specific factors such as country development level may affect the concordance of consumption and wealth index measures. Urban-rural disparities can be more pronounced using wealth indices relative to alternative measures but examining these areas separately or lessening the disparity using one of several approaches is possible. Similarly, assets causally associated with health outcomes can be removed from wealth indices with minor changes in rankings. Research into future uses of wealth indices suggest that it is possible to quantify SES inequality using assets,

that the index can be used to study SES across national boundaries and identifies promising new technological developments. A review of alternative approaches to constructing household wealth indices suggests lack of evidence of superiority for count measures, item response theory, and Mokken scale analysis; equivalent performance of multiple correspondence analysis; and evidence-based advantages to the use of polychoric PCA and predicted income. In sum, asset indices are an equally valid, but distinct measure of household SES from income and consumption measures, and more research is needed into its relationship with income and consumption and its potential applications for international health inequality measurement.

Introduction

To evaluate global progress in achieving the Sustainable Development Goals (SDG) by 2030, there is a need to disaggregate key outcomes according to socioeconomic status (SES) of households. Goals of ending poverty in all its forms everywhere and of reducing income inequality within and among countries take aim at SES directly, while several goals targeting health and education outcomes now aim to reduce socioeconomic inequalities (United Nations, 2015). In many countries, and especially among neglected populations and low- and middle-income countries (LMICs), reliable and timely data on income and consumption are not always available. In global health, the wealth index has become the variable of choice to measure SES, in large part because of the inclusion of questions to measure it in key surveys such as the Demographic and Health Survey (DHS) and Multiple Indicator Cluster Surveys (MICS).

The need for an alternative to income and consumption measures of SES is not an artifact of the past. Standardized household surveys such as DHS supported by the United States Agency for International Development, MICS supported by the United Nations Children's Fund, World Health Surveys supported by the World Health Organization, and many others collect information on household asset possession rather than household income or consumption[1]. This is because in many LMICs, income can be highly variable or difficult to accurately measure (Bollen et al., 2002). Alternatively, consumption data, such as that measured by the Living Standards and Measurement Studies, can be extremely

[1] Also referred to as household expenditure or consumption expenditure

time consuming and expensive to collect (Sahn and Stifel, 2003). Given the richness of data, and especially data relevant to health and social welfare, in standardized household surveys which now span decades and cover nearly all LMICs of the world, there was great demand in finding a way of measuring household SES using only the information contained in these survey instruments. The consensus solution to this challenge has involved the use of information about household durable assets, such as housing materials, toilet or latrine access, phone ownership, or agricultural land and livestock, which are regularly collected in most household surveys to create an index of household wealth.

Moving beyond the use of wealth index quintiles[2] can be challenging for many researchers due to the technicality of the literature informing the construction, interpretation, and theoretical underpinnings of the index, and a paucity of studies that have used alternative approaches. This critical interpretive synthesis (CIS) systematically collected and synthesized information from the diverse bodies of literature examining wealth indices using two compass questions. First, under what conditions is the use of wealth indices appropriate when measuring health inequalities using household surveys? Second, what alternative methods of calculating wealth indices are available and how do they compare to the most commonly used wealth index calculation methods? This CIS does not aim to rank the various methods used to measure SES or select a method that dominates the others under all circumstances, but does aim to map these tools to normative choices and values. The findings of this study should be of interest to global health

[2] All sampled households divided into fifths in order of the raw wealth index score. Wealth index quintiles are included in all DHS survey datasets and are commonly used as the primary measure of household SES.

researchers, survey design teams, and policymakers; all of whom should be aware that there is no gold standard for measuring household SES and that the choices they make regarding how to measure this latent and disputed concept have significant implications for the research they conduct, the policies they inform, and ultimately, the SDGs we aim to achieve.

For fifteen years, the overwhelming majority of research creating wealth indices from household survey data uncovered in this CIS have followed the method developed by Filmer & Pritchett (2001) that summarizes multi-dimensional information on ownership of various household assets using principal components analysis (PCA) (Filmer and Scott, 2012). Hundreds of manuscripts have used the method to examine topics ranging from malnutrition (Mohsena et al., 2010; Sahn and Stifel, 2003), educational attainment (Booysen et al., 2008; Nwaru et al., 2012), malaria transmission (Chuma and Molyneux, 2009; Rohner et al., 2012), and poverty (Harttgen and Vollmer, 2013; Zeller et al., 2006). The advent of the application of PCA to the measurement of household wealth using DHS surveys can be traced to the challenge of developing a method for converting a series of ownership variables, many of which were binary (yes/no) or categorical (roof material, e.g.), into a continuous SES gradient. Initial approaches mostly relied on simple sums of asset ownership such as housing quality, durable asset ownership, or public utility access. However, this implicitly gave equal weight to all assets, whether it was a relatively rare major expense such as a car, or a nearly ubiquitous commodity such as a radio (Howe et al., 2012).

The PCA approach provided a way to systematically reduce reliance on the judgment of analysts by orthogonally layering linear combinations of the variables with maximum variation. The covariance matrix underlying the structure of the data is used to solve for coefficient vectors for each independent variable such that each layer (or principal component) produces the direction of greatest variance. Other applications of PCA make use of several of these layered combinations ordered by the degree of underlying data variance (i.e. eigenvalues), sometimes visually inspecting a scree plot for changes in slope to decide how many components to keep. In calculating asset wealth, however, only the first principal component (which extracts the largest amount of information from the underlying asset data) is typically used as a measure of the "size" of the underlying structure of SES and ordinal data is often recoded as several binary dummy variables (Kolenikov and Angeles, 2009). Filmer and Pritchett first justified the use of this method by presenting a high Spearman rank correlation of "asset poverty" in Indian states with national poverty statistics of 0.794 ($p<0.001$, $N=16$) and results comparable to household consumption with data from Nepal, Indonesia, and Pakistan; leading to the conclusion that "Principal-components analysis provides plausible and defensible weights for an index of assets to serve as a proxy for wealth" (2001, p. 128).

Since the publication of this study, many researchers have focused on proving the utility and improving the process of the original DHS wealth index method, while others have proposed alternative methods of asset index construction. Despite this progress, there has been no comprehensive synthesis of the evidence and debates surrounding the method which continues to be the standard for constructing a proxy for household SES in lieu of consumption or income data.

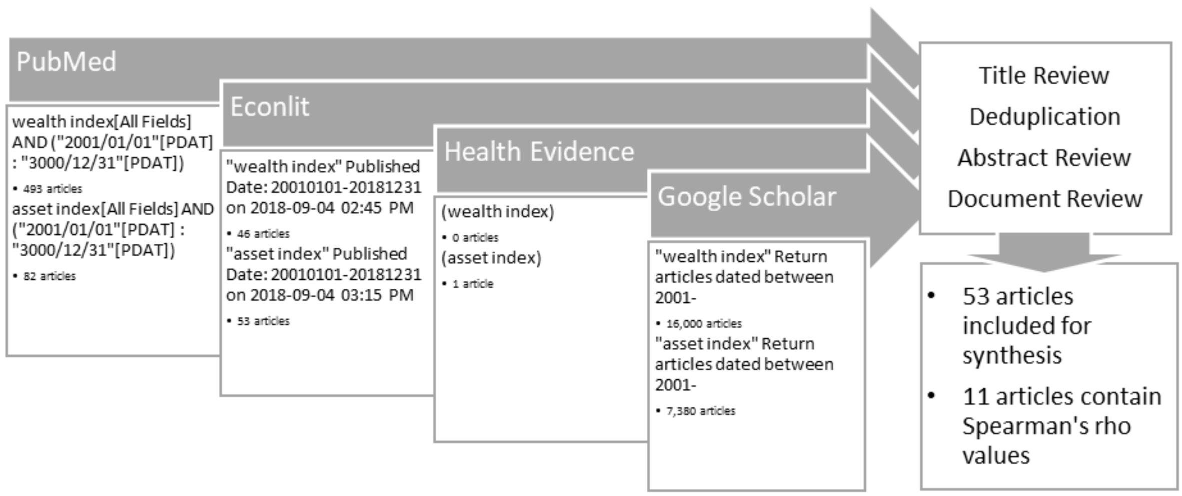
Methods

This CIS of the diverse bodies of literature informing the construction of wealth indices synthesizes comparisons of the index with both long-established and emerging alternatives, as well as how the theoretical foundations and practical considerations of the index affect the appropriateness of its use in the field. Since many of the constructs underpinning this research have yet to achieve universal definitions and the relevant literature is dispersed throughout field-specific journals of economics, demography, epidemiology, global health, and sociology, a systematic review is neither ideal or appropriate. Asset wealth is defined and calculated in different ways, the "gold standard" it is evaluated against is highly field-dependent, and even when the same method and comparator are used, methods used to evaluate performance can be incomparable from study to study. Because of these challenges, CIS - a method created to assemble findings from a complex body of evidence to inform policy in a theoretically grounded manner (Dixon-Woods et al., 2006, 2005) – was used following established norms within the health policy literature (Ako-Arrey et al., 2016; Boyko et al., 2012; Ellen et al., 2018; Moat et al., 2013). The compass questions guiding initial search and article evaluation was whether the standard DHS wealth index should retain its status as the primary method for estimating asset wealth and under what conditions it was appropriate to use. Constant reflexivity in the search and evaluation process resulted in the incorporation of several emerging themes, including delving into the ways in which wealth indices differ from income and consumption measures, a specific focus on how the urban-rural divide affects the choice of SES measure, and the possibilities, challenges, and advances in the effort to extend the use of wealth indices to the study of international health inequalities.

The merits of alternative asset indices were evaluated for their statistical validity, ease of calculation, and validity of results; all of which had to be supported by empirical research in a diversity of settings. Statistical validity examined issues such as the statistical assumptions underlying each method and issues that categorical, ordinal, and interval variables could have on the calculation of the index. Ease of calculation evaluated how much training was necessary to begin using the method, how dependent the method was on human judgement, and whether the method was supported by statistical packages. Validity of results do not rely on any one gold standard, but rather synthesize information from alternative SES measures, health outcomes, and contextual social factors using methods detailed below.

An initial search strategy broadly targeted articles comparing different methodologies for constructing wealth indices – especially as they related to the DHS wealth index. Specifically, initial searches of EconLit, Database of Abstracts of Reviews of Effects, PubMed, and Google Scholar in September 2015 focused on terms of "wealth index" "asset index" “principal components analysis”, “survey”, and “wealth” restricting searches to years following the publication of Filmer and Pritchett’s foundational article in 2001. Articles focused on the use of PCA in clinical research, imaging research, and any other unrelated applications were excluded from the review. In addition, applied studies that use wealth indices without comparing results with at least one other measure of SES were excluded. After evaluating titles and abstracts for relevance, bibliographies were combed for any studies that were not identified through database searches. This stage of literature search was followed by a first stage of synthesis, workshopping of initial findings at the McMaster University Centre for Health Economics and Policy Analysis (CHEPA), and consulting with content experts. Following this stage of article evaluation, a second systematic search was conducted in September 2018 following the search strategy outlined in Figure 1 and the same inclusion and exclusion criteria as the first search. A comprehensive screen of titles and abstracts was possible for each database except for Google Scholar, which was screened until saturation was reached and article titles were no longer relevant. This resulted in a total of 53 articles included for synthesis, of which 11 articles were used for the quantitative comparison of wealth indices, income, and consumption. Key information from each article, including SES measures investigated, countries of study, academic discipline, key themes, and evidenced used for synthesis were extracted into a table presented in Appendix Table 1.

Figure 1. Flow chart of article inclusion process



The extracted information is presented in a format adapted from meta-ethnographic review (Dixon-Woods et al., 2006). Specifically, measures of SES, discipline, study design, countries of study, key ideas, and specific contributions to CIS were first extracted into Appendix Table 1, and then organized and synthesized according to emergent themes. Key themes and concepts for each subsection are presented (reciprocal translational analysis), then contradictions between studies are examined (refutational synthesis), and finally, a general interpretation of findings grounded in the literature is proposed (lines-of-argument synthesis). The complex relation of wealth indices with income and consumption measures is discussed first, including the most complete compilation of quantitative comparisons of these three SES measures yet assembled. Once wealth indices' relation to these traditionally dominant measures of household SES is established, their appropriateness of use is discussed with a special focus on urban-rural issues (i.e. are wealth indices applicable across the urban-rural divide?), alterations to the standard approach, extension to the study of multiple countries, and emerging trends and opportunities for future research. The final section then evaluates all major alternatives to the DHS wealth index, with a critical interpretation of the merits and weaknesses of each method.

Results

Income, Consumption, and Wealth Indices

Wealth indices are generally viewed as a measure of long-term wealth or SES, but not of short-term poverty, income, or consumption (Filmer and Pritchett, 2001; Howe et al., 2012). This is because the household assets on which they are based are accumulated gradually over time and are unlikely to change rapidly even in periods of shifting income or consumption patterns. This confers the advantage of an index which is far more stable than income and consumption, but may also obscure real improvements (or declines) in household living standards over the short and medium term (Booysen et al., 2008). The inclusion of spending on household durables in the calculation of consumption measures means that there is overlap what is being measured, but there is a notable difference between the amount a household is willing to pay for an asset, and the implicit utility derived from the ownership of that asset.

Despite these distinctions, wealth indices are frequently compared to consumption data based on the argument that it is the most accessible and closely related comparator with which to measure their performance (Aryeetey et al., 2010; Howe et al., 2012). Even though many authors default to household consumption as a gold standard measure of SES, reporting errors are known to affect even the most carefully planned and executed surveys due to recall error, exclusion of some expenses, choice of deflator, and currency exchange fluctuations (Bollen et al., 2002; Kolenikov and Angeles, 2009; Moser and Felton, 2007; Sahn and Stifel, 2003). In addition to being compared to income and consumption, wealth index data has even been used as a counterpoint to national accounts data. A heated debate over whether an African growth "miracle" occurred in the 1990s was sparked due to comparisons of well-being based on asset indices, which had grown considerably, with well-being based on national accounts, which had not. Further analysis of this mystery revealed that factors such as new cheap imports of household durables from Asia and the tendency of household asset prices to drop over time were driving this discrepancy, but to this day there are many dissenting opinions and uncertainty over whether welfare has truly improved (Johnston and Abreu, 2016).

A major difference between the wealth index and other measures of SES is that the former is based on *household* assets and cannot be expressed in per-capita units. This is not to say that other measures of SES are superior in this regard, since intrafamilial distribution of income is often highly unequal and consumption is usually inexactly divided into household equivalents using one of several methods (Aaberge and Melby, 1998). This means that the wealth index is more closely related to household economies of scale models than per-capita consumption models, reinforcing the idea that it is tracking a separate, but equally valid construction of SES (Filmer and Scott, 2012). Nevertheless, there is evidence that some conditions improve the concordance of the two measures. There is evidence, for example, that consumption data tracks wealth indices more closely in middle income countries, and especially if a greater variety of assets are included (Howe et al., 2009). Similar findings suggest that asset indices and consumption expenditure are more closely related when a higher percentage of consumption is captured by assets included in DHS surveys and that they are more highly correlated in countries where the average share of non-food expenditures is high (Filmer and Scott, 2012). Despite the paucity of knowledge about the degree of concordance between income, consumption, and wealth indices, few studies have quantified this relationship in a systematic manner.

The only systematic review yet published on the topic found only weak to moderate association between asset indices and consumption data (Howe et al., 2009). These findings may be disputed due to the inclusion of all asset index construction methods, and arbitrary cut-offs for strength-of-agreement (as acknowledged by the authors themselves). In general, there are two general approaches to comparing income and consumption rakings with wealth index rankings – comparison of ordered subgroups such as quintiles or terciles, or comparison of entire distributions. Studies opting for the first approach may use consumption or income as a "gold standard" and quantify the percentage of households missing from the poorest subdivision as errors of exclusion (Aryeetey et al., 2010). As one example, this was done in Turkey, finding that a wealth index was moderately associated with consumption and income, with 54.1% being in the lowest quintile for both wealth index and consumption, and 47.1% in the lowest quintile for both wealth index and income (Ucar, 2015). For the second approach, the most common method of measuring distributional associations in this literature is Spearman rank correlation, which is a nonparametric measure of association varying between -1 and +1 for two variables across a ranked distribution (Spearman, 1904). The second distributional approach was chosen as the measure of interest for this CIS because rank correlations take the entire distribution into account rather than losing granularity of data through grouping. Additionally, direct comparison of population groupings would not have been possible because the construction of subgroups varied too much for systematic comparison. Therefore, only the studies explicitly reporting Spearman correlation coefficients were included in the meta-analytic tables (Tables 1 & 2).

Table 1. Spearman rank correlation coefficients for wealth indices with household consumption and income

Authors	Country	Comparator	Data Source	Sample Size	Spearman's rho
Ferguson et al, 2003	Peru	Consumption	LSMS (2000)	4,000	0.73
	Pakistan	Consumption	PIHS (1991)	4,752	0.34
Filmer & Pritchett 2001	Nepal	Consumption	NLSS (1996)	3,372	0.64
	Indonesia	Consumption	DHS (1994)	16,242	0.56
	Pakistan	Consumption	PIHS (1991)	1,192	0.43
Filmer & Scott, 2012	Albania	Consumption	ALSMS (2002)	3,598	0.47
	Brazil	Consumption	BPPV (1997)	4,940	0.72
	Ghana	Consumption	GLSS (1992)	4,522	0.43
	Nepal	Consumption	NLSS (1996)	3,373	0.48
	Nicaragua	Consumption	EMNV (2001)	4,191	0.71
	Panama	Consumption	PENV (1997)	4,945	0.70
	Papua New Guinea	Consumption	PNGHS (1996)	1,144	0.47
	South Africa	Consumption	SAIHS (1993)	8,791	0.67
	Uganda	Consumption	UNHS (2000)	10,696	0.55
	Vietnam	Consumption	VLSS (1993)	4,800	0.61
	Zambia	Consumption	LCMS (2004)	19,247	0.39
Lindelow, 2006	Mozambique	Consumption	DHS (1997)	8,250	0.37
McKenzie, 2005	Mexico	Consumption	ENIGH (1998)	10,777	0.84
Opuni et al, 2011	Tanzania (men)	Consumption	KHDS (2004)	691	0.61
	Tanzania (women)	Consumption	KHDS (2004)	833	0.59
Sahn & Stifel, 2003	Ivory Coast	Consumption	CILSS (1988)	2,169	0.51
	Ghana	Consumption	GLSS2 (1988)	3,192	0.43
	Ghana	Consumption	GLSS3 (1992)	4,552	0.42
	Jamaica	Consumption	JSLC (1998)	7,375	0.39
	Madagascar	Consumption	EPM (1994)	4,800	0.50
	Nepal	Consumption	NILSS (1995)	3,388	0.55
	Pakistan	Consumption	PIHS (1991)	4,794	0.42
	Papua New Guinea	Consumption	PNGHS (1996)	1,396	0.47
	Peru	Consumption	ENNIV (1994)	3,623	0.71
	South Africa	Consumption	SAIHS (1994)	8,848	0.71
	Vietnam	Consumption	VNLSS (1993)	4,800	0.55
	Vietnam	Consumption	VNLSS (1998)	5,999	0.67
SIMPLE MEAN				**5,461**	**0.55**
WEIGHTED MEAN					**0.55**

Authors	Country	Comparator	Data Source	Sample Size	Spearman's rho
Ferguson et al, 2003	Peru	Income	LSMS (2000)	4,000	0.72
	Pakistan	Income	PIHS (1991)	4,752	0.16
Nkonki, 2011	South Africa	Income	Good Start (2008)	133	0.42
Balen et al, 2010	China	Income	Wuyi (2006)	258	0.27
	China	Income	Laogang (2006)	246	0.27
SIMPLE MEAN				**1,878**	**0.37**
WEIGHTED MEAN					**0.42**

The results of the pooled Spearman rank correlation coefficients (Table 1) indicate wide variability and overall moderate agreement of wealth indices with consumption or income. Spearman's rho values ranged from 0.34 to 0.84, with a sample-size weighted average of 0.55 for consumption data and 0.42 for income data. Since wealth index constructions can differ even when the same data source and method are used because of decisions such as asset inclusion, and income and consumption comparators can also vary according to the calculation methods used, a range of correlation coefficient magnitudes is not unexpected. It is notable that besides Ferguson et al.'s (2003) two country comparison, no one has yet examined the relationship between all three SES measures in more than one country. There appears to be a moderate association between wealth indices and both income and consumption, allowing us to move on to understanding more about how the index relates to health and social welfare outcomes, when it is appropriate to use, and the alterations to the index that are possible for researchers.

The Wealth Index and Social Welfare

Rather than using consumption or income comparators, many researchers appraise the performance of wealth indices by examining their relationship with health or educational outcomes. Decades of research spanning nearly every country of the world have documented inequalities in health and educational outcomes associated with SES. Some have claimed that wealth indices may be more directly associated with these outcomes than household consumption or income because health and education outcomes are more significantly affected by long-run household SES than by monetary highs or lows (Mohanty, 2009). This is especially the case for outcomes like childhood stunting which take many years to develop, but also applies to other social welfare outcomes (Filmer and Pritchett, 2001; Sahn and Stifel, 2003).

One of the first multi-country comparative studies suggested that the use of wealth indices resulted in smoother declines in stunting by wealth quintiles when compared to household consumption in 10 LMICs (Sahn and Stifel, 2003). This is supported by the correlation of wealth index quintiles with low birthweight, education level, and occupation in the Vietnamese context, indicating that the index was capturing both a measure of social class and health outcomes (Vu et al., 2011). Another evaluation used Bayesian information criterion to predict fertility rates with several SES proxies, finding that a wealth index performed better than all other measures, including consumption measures (which predicted almost no variation in fertility) (Bollen et al., 2002). There is weaker evidence from a wealth index of a Chinese community, finding only low to moderate correlation with maternal and child health indicators; although both an occupational index and educational index found equally weak associations (Nwaru et al., 2012).

In general, there is some evidence that asset measures may increase the magnitude of social health inequalities. Pro-rich inequalities in immunizations, maternity care, institutional deliveries, and hospital visits were greater when measured with a wealth index than consumption data in Mozambique (Lindelow, 2006). In Tanzania, the use of a wealth index instead of household expenditure resulted in a statistically significant change in concentration index for AIDS mortality in men, but the effect was small and made no difference for women (Opuni et al., 2011). A focused review of SES ranking specifically for tuberculosis surveys concluded that wealth indices more consistently identified inequities in health than income or consumption surveys (Van Leth et al., 2011). Another team investigating insecticide-treated net ownership in Kenya found a mixed picture of larger inequalities in urban areas using a wealth index compared to consumption, but smaller inequalities in rural areas (possibly due to free net distributions in rural areas), concluding that neither the wealth index or consumption index approach is superior for health research in LMICs (Chuma and Molyneux, 2009).

This trend did not translate to the outcome of seeking medical care, with wealth indices and consumption levels generating almost identical results in a large cross-sectional country comparison (Filmer and Scott, 2012). There was greater health-seeking behavior found among the relatively poor in these countries, although this is hypothesized to be a product of the poorest quintile's disproportionate share of illness. This theory is supported by the finding that the highest levels of child mortality are not uniformly found in the poorest quintiles of the consumption model, but are always found in the poorest quintiles of wealth index models – a statistically significant difference-in-difference (Filmer and

Scott, 2012). In general, the tendency of publicly-provided services tending to be of more importance in the lower end of the SES gradient and private goods tending to be more important for the upper end (Booysen et al., 2008) may have some impact on inequalities in health and healthcare seeking behaviour.

The outcome of educational attainment has similarly mixed results. One study using wealth index and consumption data to rank households in a multi-country data exercise found a statistically significant educational inequality in 7 of 11 countries included, with the DHS wealth index most often resulting in larger inequalities (Filmer and Scott, 2012). In Ghana, however, the wealth index was modestly correlated to parental education levels (maternal r=0.32, paternal r=0.36), explaining only 14% of parental education and occupation variance (Doku et al., 2010). Using education as a ranking variable rather than an outcome yields similarly mixed results. A multi-country study found that wealth indices are not statistically different than maternal education as a ranking variable for quantifying inequalities in vaccination coverage, although wealth index inequalities were slightly smaller,[3] and some countries had much larger inequalities using one or the other[4] (Arsenault et al., 2017).

Considering these results as a whole, we can conclude that the widespread practice of comparing wealth indices to income or consumption in studies of social inequalities of health and educational outcomes produces some contradictory outcomes, but generally

[3] Haiti had larger inequalities using education ([SII = 0.34 95% CI = 0.20, 0.48] than the wealth index [SII = 0.10 95% CI = 0.04, 0.24].
[4] Mozambique had larger inequalities using wealth index [SII = 0.30 95% CI = 0.22, 0.37] than maternal education [SII = 0.16, 95% CI = 0.09, 0.24].

points in the same direction as income and consumption research. That is, poor health and educational attainment is found among lower SES populations regardless of how SES is measured. However, there is an undeniably tautological reasoning underlying many comparisons. Even if wealth indices are an equally valid, but separate measure of household SES than income and consumption; then verifying both the validity of wealth indices through the presence of health and educational inequalities *and* confirming the presence of health and educational inequalities using wealth indices risks being dismissed as circular and baseless evidence. Larger inequalities in health outcomes such as child mortality clearly lend face validity to a measure of SES, but the many causal pathways that may lead one context to have larger inequalities using wealth indices, consumption, or income should be explored in all their complexity rather than relying on the unidimensional logic of a "true" effect size being the largest.

Challenges and Opportunities

Urban-Rural Considerations

Since the DHS wealth index was first developed, there have been concerns over comparability of results between urban and rural areas (Filmer and Pritchett, 2001). Many have expressed concerns that since urban households are more likely to own many assets and are more likely to benefit from publicly provided assets such as piped water, they will be inappropriately classified as wealthier than comparable rural households (Booysen et al., 2008). Others counter that this is not misclassification, but an accurate representation of the relative affluence of urban households (Vyas and Kumaranayake, 2006). Adding to this complexity, there are indications that unmet healthcare need can be underestimated in rural areas and overestimated in urban areas (Mohanty, 2009). Beyond misclassification errors, the issue is complicated by the fact that assets like chickens or bicycles are an indicator of relative wealth in rural areas, while also being an indicator of relative poverty in urban areas (Chuma and Molyneux, 2009). Regardless of whether it is an accurate representation of household SES or not, urban-rural disparities appear to be larger when SES is measured using a wealth index than income or consumption measures. The difference in urbanization between the poorest and richest quintiles can be as large as 75% in a wealth index compared to 22% in an expenditure model in Albania, with several other countries also having large discrepancies in SES ranking due to urban status (Filmer and Scott, 2012). Perhaps the most dramatic example of these vast differences was demonstrated in Kenya, where a wealth index placed no rural households in the richest quintile and only one rural household in the second richest (Chuma and Molyneux, 2009).

The mechanism for this urban divide can largely be attributed to a combination of rural households having fewer assets, more commonly owned assets, and agricultural assets often being assigned negative factor loadings. As one illustrative example, there is a village in Guinea-Bissau where (unlike the rest of the country) portable gas stoves are highly desired, and therefore behave as a normal good,[5] but because that village is relatively poor compared to other villages, the wealth index scoring of gas stoves is negative (Johnston

[5] i.e. a good for which demand increases as when SES increases.

and Abreu, 2016). Similarly, owning a common asset will usually imply a negative scoring, which could perversely rank a household as poorer than one lacking the asset at all (Wittenberg and Leibbrandt, 2017). Even obtaining reliable information on rural assets is complicated by survey respondents often having difficulty answering questions about the number of hectares of agricultural land owned or even whether they live in an urban or rural area (Chakraborty et al., 2016).[6] In response to these concerns, a variety of strategies to identify and address urban-rural issues with wealth indices have been proposed.

One common strategy to identify relative affluence in both urban and rural areas is simply to split the sample into two groups and calculate a rural wealth index and an urban wealth index. In fact, the standard DHS approach to dealing with urban-rural issues is to regress both an urban-only sample and a rural-only sample against the complete sample to obtain a modified index influenced by all three factor loadings (Rutstein, 2008).This strategy can lead to agricultural assets having positive weights for rural households and negative weights for urban households (Ward, 2014), but the magnitude of effect appears to depend heavily on the setting. One study comparing a rural-only sample wealth index to one calculated for the full sample in Zimbabwe found a Spearman rank correlation coefficient of 0.862 (95% CI 0.854–0.869) between the two indices, indicating a fairly high association (Chasekwa et al., 2018). A Ghanaian study using consumption as a comparator found a weaker concordance: the wealth index "misclassified" 63% of consumption-poor households in urban settings compared to 46% in semi-urban settings, and 53% in rural

[6] This can be resolved by having survey teams classify urban and rural areas rather than eliciting the information from survey respondents.

settings (Aryeetey et al., 2010). Another Chinese study using income as a comparator found the same relatively weak association to household income (Spearman's rho 0.27) in both a rural and peri-urban village, and a similar proportion of variation captured by the wealth index (27.8% vs. 24.3%) for both villages (Balen et al., 2010).

The different strategies used to address urban-rural biases also appear to have a moderate effect. One small Zambian study found that dropping all assets which are more likely to be found in an urban household did not significantly affect the overall variance explained by the wealth index (Boccia et al., 2013). Another large multiyear pooled analysis in China that found negative factor weights for all agricultural assets suggested that secondary principal components weights (which were positive) could be used in these cases, although dropping all agricultural assets appeared to make little difference, with 90% of households being classified in the same quintile (Ward, 2014). A study designed to evaluate this approach in India found 39% of households to be classified in the same quintile, 50% to have moved to an adjacent quintile, and 10% to have moved to the farthest quintile (Mohanty, 2009). Alternatively Ngo and Christiaensen (2018) have proposed adding a small number of binary consumption variables such as food and clothing purchases, finding that it increased identification of consumption-poor households in rural settings by 9%, but made no difference in urban settings. In sum, urban-rural differences should always be monitored and can be addressed through a number of approaches, but do not present an insurmountable obstacle to the use of wealth indices.

Robustness to changes in the asset mix

Another common criticism of wealth indices relates to their reliance on assets which have direct impact on health, such as water and sanitation quality or food availability in research on the associations of SES and health (Homenauth et al., 2017). There is some evidence for this effect, with one study finding that dropping household construction variables from a wealth index in Uganda resulted in a significant association with mosquito human biting rate becoming insignificant, even though the two indices are highly correlated[7] (Tusting et al., 2016). Another set of researchers in Zambia built an alternative index without food-related variables (which may have affected tuberculosis outcomes of interest directly) and found no significant difference with the wealth index using all variables (Boccia et al., 2013). A low-to-moderate effect is supported by a 10-country World Bank comparison of three alternative indices that exclude direct determinants of health and factors provided at the community-level, in which only 18% of households were categorized in a different wealth quintile with most of these shifting to an adjacent quintile (Houweling et al., 2003); as well as the use of a simplified asset list dropping various country-specific, urban-rural specific, and agricultural questions with 16 surveys finding inter-quintile agreement ranging from 75% to 83% (Chakraborty et al., 2016).

Despite relatively strong concordance of indices based on difference assets, some measures of social health inequality may be sensitive to these changes. One study found up to a 60% change in the relative index of inequality for five health outcomes with alternative wealth indices, although the direction of change appeared to be random and was

[7] Spearman's rho = 0.93

not significant in some countries (Houweling et al., 2003). Dropping assets can also be motivated by time and resource savings for survey collection teams. In one example comparing two simplified asset indices to the full index, there was almost perfect agreement (kappa value greater than 0.61) after reducing the number of variables from 111 to 24 variables in Honduras and from 111 to 21 variables in Senegal using an iterative ranking of factor loadings (Ergo et al., 2016). This limited effect of dropping variables is mirrored by an expanded set of assets collected to measure progress in the Millennium Villages Project failing to predict income poverty more effectively than the standard DHS asset mix (Michelson, 2013). Nevertheless, the variables that matter most vary according to the country context and reducing the number of accepted answers might not reduce the amount of time needed to survey a household because each variable may still require a separate question. In sum, changing the asset mix included in surveys may have a smaller effect than many anticipate, meaning that avoiding appearance of endogeneity with health-related variables or simplifying a survey instrument can be done with appropriate care.

Future Applications

Research on the use of wealth indices is not limited to refining existing applications. One emerging area of research concerns extending the wealth index to the study of economic inequality research. Care must be taken before applying inequality measures to asset indices, however, because Gini coefficients can only be applied to the absence or presence of real assets, due to the inherent lack of scale for categorical variables

(Wittenberg and Leibbrandt, 2017). One of the earliest investigations into whether wealth index inequality[8] was correlated to expenditure-based inequality in 31 Mexican states found a Spearman's rho of 0.566 (about the same strength of association as food expenditure), and slightly stronger association than either a housing-based wealth index or a utility-based wealth index (McKenzie, 2005). This method was recreated in China and evaluated ecologically against known consumption inequality, appearing to track the same pattern of rising inequality through the 1990s until a peak was reached around 2000, suggesting broadly shared growth and an eventual decline in urban and rural wealth inequality (Ward, 2014). A more recent application in South Africa found wealth index inequality fell from a Gini coefficient of 0.47 to 0.29 from 1993 to 2008, but cautions that the use of a negatively loaded first eigenvalue in the calculation of wealth index inequality could lead to this method performing poorly (Wittenberg and Leibbrandt, 2017). Although there is clearly more research to be done on the limitations of wealth index inequality, this is an area of research which could grow rapidly given the increasing public interest on this topic.

Another commonly cited limitation of the wealth index is the perceived inability to make comparisons in wealth across countries. Since the wealth index in any given country is a relative measure, comparisons across countries may neglect important differences in cultural and social values associated with household assets. Much of the reasoning behind this skepticism lies on claims that the assets contained in standardized household surveys

[8] Wealth index inequality is calculated as the proportion of variation of wealth explained by the first eigenvalue.

cannot be relied upon in countries that traditionally value assets differently than others. Despite this assertion, a “traditional wealth index” constructed to represent Kenyan cultural constructions of wealth was nearly identical to standard PCA of household assets (Opuni et al., 2011). Further support comes from a finding that a wealth index is more strongly correlated with locally identified factors indicating poverty (female-headedness of household, dependency ratios, and household food insecurity) than household income (Michelson, 2013). Another effort to construct a wealth index applicable to 21 Latin American and Caribbean countries using telephone survey data found generally encouraging results. Pooling wealth indices resulted in broadly applicable SES rankings from poorer countries like Peru to richer countries like Costa Rica, and the resulting relative wealth quintiles were strongly correlated with years of schooling and self-reported income (Córdova, 2008).

The largest effort to construct an asset index of worldwide comparability with wealth indices, however, comes from a Dutch team that overcame the difficulty of incomparability of many survey items by grouping accessories into cheap and expensive utensil categories (Smits and Steendijk, 2013).[9] This approach results in a wealth index applicable to 165 household surveys across 97 LMIC and is robust to removal of any region from analysis (Pearson correlation coefficient ≥ 0.996), removal of any time period (Pearson correlation coefficient ≥ 0.997), and removal of any one asset (Pearson correlation

[9] Incidentally, this approach has also been used to compare assets over time for variables like landlines and cell phones, which can be combined into one "phone" asset in response to criticisms that the social significance of certain assets such as landlines, radios, and bicycles changes significantly over time (Wittenberg and Leibbrandt, 2017; Harttgen and Vollmer, 2013).

coefficient ≥ 0.986).[10] Furthermore, there is good agreement between the international wealth index and country-specific wealth indices, country-specific poverty levels, life expectancy, and most strong agreement with the Human Development Index. Finally, the authors assert that reasonable estimates of purchasing power parity (PPP) poverty levels can be placed at 30^{th} percentile of the index equivalent to PPP$1.25 a day and 50^{th} percentile at PPP$2.00 a day (Smits and Steendijk, 2013). This international poverty line can be coupled with the finding that transitions out of poverty occur at the same rate using asset indices and household income, with approximately 12-20% of the lowest quartile households transitioning to the highest quartile households after two years (Michelson, 2013). These studies are breaking new ground, but it appears that international poverty studies using wealth indices are becoming increasingly possible.

Lastly, there are several research teams attempting to proxy wealth indices using new technologies. One team has developed a machine learning algorithm that can be used to roughly approximate wealth indices using phone usage characteristics in Rwanda and Afghanistan, although the models must be developed separately for each country and cannot be applied naively across borders (Blumenstock, 2018). Another team has created a convolutional neural network trained on ground imagery that is able to predict 37-55% of variation in consumption and 55-75% of variation in asset wealth if trained separately for each country, although this drops to 19-52% and 24-71% if applied to other countries (Jean et al., 2016). This is slightly more predictive than phone-use estimation models, and

[10] Although these results were obtained with ordinary PCA, sensitivity checks with MCA, factor analysis, and categorical PCA did not change the results.

the difference in estimation is likely due to the area's wealth itself rather than directly identifying household features such as roofing materials directly. The fact that ground imagery is more highly correlated with a wealth index than with consumption also provides further evidence that a separate, but equally valid construct of SES is being captured by the method. In sum, ground-breaking research is being conducted into new ways to apply wealth indices to measuring SES inequality, to constructing high-quality cross-country pooled sample analysis, and to using new technologies to measure household SES.

Alternative Approaches

The standard wealth index constructed using PCA is not the only method used to measure SES using information of assets collected by household survey data. What follows is a short summary of the intersection of alternative approaches and a DHS-style wealth index, evaluating statistical validity, ease of calculation, and consistency of results supported by empirical research in a diversity of settings.

Count measures

The most basic asset indices used for household survey data are simple asset counts. One Albanian team found that a wealth index was more highly correlated with consumption than a count measure consisting of water and sanitation provision, adequate housing provision, less crowded dwellings, and minimum education of household head (Azzarri et al., 2005). Similarly, an early comparison of the DHS wealth index, consumption measures, and count measures as predictors of fertility rate found the simple count measures to have the second-best fit (after the wealth index) using Bayesian Information Criterion (Bollen et al., 2002). This is contradicted by a team in Bangladesh, asserting that using a basic count measure outperforms the DHS wealth index in discriminating households more at risk for stunting, wasting, and underweight (Mohsena et al., 2010). Their use of a simple count of radio, television, bicycle, motorcycle, telephone, and electricity to construct wealth quintiles resulted in 49.1% of households in the lowest SES quintile and only 4.2% of the highest SES quintile having all three outcomes of interest, while the wealth index produced equivalent percentages of 28.6% and 11.4%, respectively. However, this study was strongly disputed by another team using the same indices in Cote d'Ivoire with rigorous biometric measures of nutritional status while accounting for the effect of malarial infection, age, and residency; where the wealth index resulted in larger socioeconomic inequalities in anemia, stunting, and wasting in children and women of reproductive age than the count score (Rohner et al., 2012). In sum, count measures may present an easily constructed and persuasive SES measure, but results are highly dependent on the judgement of the analyst of which household assets to include and may not be transferable to other contexts.

Multiple correspondence analysis

Many researchers have pointed out a fundamental flaw in the application of PCA to the types of variables needed to construct a wealth index; namely, that the technique is not meant to be applied to binary and categorical variables (Howe et al., 2012; Kolenikov and Angeles, 2009). Since an average of 60% of household survey questions used to construct asset indices are binary, this is no minor limitation (Kolenikov and Angeles, 2009). This is commonly skirted by applying a qualitative judgement of superiority by an analyst recoding variables, possibly introducing bias and most likely affecting the fidelity of the final data. A long-standing alternative to PCA which does not have these inherent weaknesses is Multiple Correspondence Analysis (MCA), which has a similar approach of using a correlation matrix to determine "principal inertias" of the assets included for analysis and can be calculated using modules for most statistical packages (Booysen et al., 2008).

A large seven-country analysis of DHS data opted to use MCA rather than PCA because of these limitations, but found that despite some differences in variable weight orders, there was no significant difference between both indices ($r=0.953$, $p<0.01$) and the few households that were classified into different quintiles were restricted to one level higher or lower (Booysen et al., 2008). Another application of MCA in Kenya found it to be highly correlated to the DHS wealth index ($r=0.997$, $p<0.01$) with 93% of households placed in the same quintiles, although it explained the highest total variation of variables (47.3%) (Amek et al., 2015). Yet another comparison of MCA and the DHS wealth index found that they were not significantly different in year over year change and were both more strongly autocorrelated to themselves than to household income in several sub-Saharan countries (Michelson, 2013). In this case we conclude that although MCA has yet to significantly differentiate itself empirically from the DHS wealth index when applied in the field, its theoretical superiority in handling a diverse set of variables makes MCA a valid alternative measure of household SES.

Item response theory/ latent trait modeling

Seizing on the controversial application of PCA to non-continuous data, other researchers have advocated the adoption of Item Response Theory (IRT), which is also referred to as Latent Trait Modeling (LTM). At a basic level, observed assets (whether they are dichotomous, polytomous, nominal, or ordinal) which demonstrate the most discrimination according to a latent trait (SES) are given larger weights, and are then assessed for reliability with a non-parametric bootstrap (Vandemoortele, 2014). Despite claims of differentiation, an independent 11 country comparison found rank correlations for the DHS wealth index and IRT between 0.95 and 1.00 – the most highly correlated alternative measure in the study (Filmer and Scott, 2012). Another empirical evaluation of this technique by a strong advocate of IRT on Malawian DHS data also found high correlation with a PCA index (Spearman rank correlation = 0.88) (Vandemoortele, 2014). Furthermore, the two key assumptions of normal distribution of data and independence of variables offer no improvement to the existing PCA approach, and its calculation is acknowledged to be more time consuming (Vandemoortele, 2014). Given these disadvantages and the lack of significant difference in the field, the DHS wealth index remains the more viable option until evidence of superiority can be presented.

Mokken scale analysis

Mokken Scale Analysis (MSA) is a nonparametric technique which relies on Guttman scales of items which are statistically determined to be increasingly “harder” to answer. Using a combination of positive ownership of assets with the difficulty of eliciting a positive response, MSA is able to rank households along a latent SES gradient (Reidpath and Ahmadi, 2014). Key assumptions include unidimensionality of SES, local independence of variables, monotonicity of responses, and invariant item ordering. An empirical application of the technique found very high Pearson product moment correlation with a polychoric PCA index (r=0.96) and a lower correlation to household expenditure (r=0.59) (Reidpath and Ahmadi, 2014), a result which the authors concluded was similar to the pattern observed for the DHS wealth index. The real or perceived downside of complexity of the technique with only marginal statistical effect may limit the widespread adoption of MSA, so the DHS wealth index also remains the more viable option of the two options at this time.

Polychoric PCA

As a response to the primary statistical vulnerability levelled against the DHS wealth index – its inappropriate application to non-continuous variables – an improved polychoric PCA was proposed by Kolenikov and Angeles (2009). Criticizing Filmer and Pritchett’s technique for creating spurious correlation through the introduction of dummy variables and for losing directionality of ordinal data, Kolenikov and Angeles propose the use of a slightly amended multivariate technique, originally derived by the same statistician as ordinary PCA. Not only is there greater statistical fidelity, but the status of *not* owning an asset is also taken into account. This can be important in cases like indoor plumbing, which may only be missing from a small percentage of the poorest households of a population (Moser and Felton, 2007). The key findings of the proof-of-concept study were that polychoric PCA demonstrated lower misclassification rates compared to consumption, explained a higher proportion of variance in asset ownership, was more robust to the number of categories used, and was more robust to changes in variable coding scheme than the Filmer and Pritchett PCA procedure (Kolenikov and Angeles, 2009).

Interestingly, the standard PCA and polychoric PCA methods demonstrate divergent classifications at the lower end of the SES spectrum with increasing agreement of classification on the upper end of the SES spectrum (Kolenikov and Angeles, 2009). An independent comparison of the DHS wealth index with polychoric PCA using Bangladeshi DHS data also concluded that the DHS index lacks the ability to discriminate at the lower end of the spectrum due to its under-emphasis of common assets (Benini, 2007). Despite this lower-end discrepancy, agreement remains very high. A Kenyan study found polychoric PCA to be closely correlated with standard PCA ($r=0.991$, $p<0.01$) and to even more closely mirror MCA ($r=0.991$, $p<0.01$), while placing 87% of households in the same quintiles as standard PCA and 91% in the same quintiles as MCA (Amek et al., 2015). Another comparison conducted using Zimbabwean data found a Spearman rank coefficient of 0.910 (95% CI: 0.904–0.915) and 94% agreement between wealth quintiles between the DHS wealth index and polychoric PCA (Chasekwa et al., 2018). Similarly, Filmer and

Scott's 11 country comparison found both indices to be generally comparable (2012). There may be evidence of lack of robustness to variable loss, however, with an attempt to reduce a 17 item asset index to 11 items using polychoric PCA in Vietnam resulting in much lower concordance with both expenditure (r=0.57 v r=0.41) and an MSA-derived asset index (r=0.98 v r=0.68) (Reidpath and Ahmadi, 2014).

Table 2. Spearman rank correlation coefficients for polychoric PCA with household consumption and income

Authors	**Country**	**Comparator**	**Data Source**	**Sample Size**	**Spearman's rho**
Reidpath, 2014	Vietnam	Consumption	WHS (2003)	4,154	0.57
SIMPLE MEAN				**4,154**	**0.57**
WEIGHTED MEAN					**0.57**
Ward, 2014	China	Income	CHNS (1989)	4,400	0.35
	China	Income	CHNS (1991)	4,400	0.40
	China	Income	CHNS (1993)	4,400	0.41
	China	Income	CHNS (1997)	4,400	0.33
	China	Income	CHNS (2000)	4,400	0.42
	China	Income	CHNS (2004)	4,400	0.43
	China	Income	CHNS (2006)	4,400	0.44
SIMPLE MEAN				**4,400**	**0.40**
WEIGHTED MEAN					**0.40**

As the only other method systematically compared to income and consumption by several studies, all available Spearman correlation coefficients between polychoric PCA wealth indices and either household consumption or income encountered in the literature search are presented in Table 2. The results are not as robust as those presented in Table 1 due to both income and consumption comparisons being based on one study,[11] but polychoric PCA appears to have an almost identical association as the DHS wealth index for both consumption (0.57) and income (0.40). Given that polychoric PCA overcomes the challenges relating to variable types, overcomes issues of "clumping" through greater discriminatory power at the lower end of the SES spectrum, and is integrated into several statistical packages, there is a strong case to be made for the superiority of this approach.

[11] Even so, the income comparisons include seven separate survey comparisons.

Predicted Income

A newly emerging technique overcomes the limits imposed by the ordinal nature of wealth indices by linking a country and year-specific predicted income to households according to their relative standing, as determined by a wealth index. An early application of a similar method using regressed prediction of consumption based on household assets found that it resulted in inequality levels in between those predicted by a wealth index approach and actual consumption, and that rankings of Mexican states by inequality were more similar to consumption than using a wealth index (McKenzie, 2005). Since this early application, Harttgen and Vollmer (2013) have proposed a streamlined method, in which any wealth index is used to rank households into centiles or quintiles, and the resulting ordering is linked to an open access dataset estimating household income for 88 LMICs from 1993-2014.

The strength of this method is supported by studies finding more variation in stunting prevalence using the predicted income approach (38%) compared to wealth quintiles (20%) (Fink, 2016), and predicted income better predicting skilled birth delivery in a large 100-country study, with log-normalized predicted income explaining 51.6% of variation, wealth quintiles predicting 22.0%, and the raw wealth index predicting 12.8% (Joseph et al., 2018). It is also possible to compare health outcomes taking predicted income inequality into account using tools such as equiplots with this approach, revealing countries which have similar outcomes at any given income level, and others that are performing poorly at a given income level (Fink, 2016). Furthermore, comparisons of all countries over time reveals important trends such as countries that have succeeded in increasing skilled birth attendance in spite of stalled income growth, and those that have not improved outcomes even in times of sustained economic growth (Joseph et al., 2018). More study of this emerging method is clearly needed including whether the predicted income is more closely associated to actual household income or the wealth index on which it is based, but the new avenues of research made possible by the approach warrants its inclusion in future studies.

Conclusion

The construction of a wealth index using household survey data must be conducted with an awareness that the methodology chosen to quantify SES using assets contained in the survey data has a significant effect on the results. More straightforward alternatives to constructing asset indices like count measures offer simplicity but may overly depend on context and analyst expertise. While more complex methods of MCA, IRT, MSA, polychoric PCA, and predicted income offer varying degrees of improvement of statistical validity, they may do so at the expense of simplicity with only marginal improvement in outcomes compared to the standard DHS wealth index. Taking all published alternatives and evidence into account, analysts striving for an alternative to constructing a wealth index from household survey data can consider polychoric PCA as a method which meets the standards of statistical validity, ease of calculation, and validity of results, with MCA as another valid alternative. If wealth rankings in a meaningful scale are needed, the predicted income approach based on either the DHS wealth index or any comparable alternative offers great promise but must also be investigated in a greater diversity of settings and applications.

Evidence gathered in this review lends support to the idea that wealth indices represents a related, but distinct measure of latent SES from consumption or income measures. There is robust evidence linking the wealth index to health and educational outcomes at least as strongly as household consumption and income throughout the world. However, interpreting wealth indices as having a causal effect on health and educational outcomes cannot be taken as a given; especially with the knowledge that wealth indices, income, and consumption measures take aim at entirely separate models of SES. Long-known vulnerabilities to urban-rural distortions or changes in the asset mix included in surveys should always be considered, but with proper care, these vulnerabilities can be seen as ultimately informative rather than confounding. Future applications to inequality research, large-scale international studies, and the use of new technologies are promising prospects for which the groundwork has yet to be fully laid.

The main limitations of these conclusions stem from the paucity of research designed to answer these methodological issues specifically, rather than as a secondary research question dispersed throughout many fields. We are further limited by highly variable and sometimes inconsistent definitions of key concepts, which in many cases such as asset wealth, even lack a commonly agreed-upon name. These limitations can only be overcome with greater research intensity and debate. Because of these limitations, a critical interpretive synthesis was the most appropriate choice to present the debates surrounding this methodology in all its complexity. This presentation of key concepts, exploration of contradictions in the literature, and proposal of lines-of-argument synthesis aims to promote a shared understanding of an emerging field of study across the multitude of disciplines that are involved in its development. Further strengths of the study include our inclusion and synthesis of more studies than any prior work on wealth indices, and the first systematic search and compilation of Spearman correlation coefficients between wealth indices and both consumption and income.

The implications of these findings to measuring progress in achieving the SDGs cannot be understated. Developing countries and neglected populations which lack consumption and income data will necessarily be studied using wealth indices as a proxy for SES. If we are to adequately measure progress in achieving equity-focused SDGs around the world for these populations, we must acknowledge the challenges in developing reproducible, rigorous, and easily implemented methodologies for constructing asset indices using household surveys. However, we can also look to the many strengths of the method, not the least of which is the increasingly real possibility of worldwide comparability of SES among all populations of the world. Further study of this possibility must account for the many potential pitfalls in conducting research across national boundaries. Finally, it is remarkable that with the hundreds of studies using the wealth indices to measure health and social welfare outcomes, no study has yet systematically examined whether inequalities in health or social outcomes are larger in magnitude than would be measured using income or consumption in more than one country. Wealth indices have become the dominant method to measure SES in LMICs in the field of global health. Researchers using the method to develop surveys, analyze data, or interpret data for policymakers must understand its strengths, its limitations, the normative choices associated with the tool, and the potential to improve and extend the method to new areas of research.

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Appendix Table 1. Data extraction table for critical interpretive synthesis

Article	SES Measures	Discipline	Study Design	Spearman's ρ Retrieved	Countries	Key Ideas [12]	Main Contributions to Model Development
Amek et al., 2015	PCA; Polychoric PCA; MCA	Global Health	Cross-sectional survey	No	Kenya	c	MCA is highly correlated to PCA ($r=0.997$, $p<0.01$), 93% of households placed in the same quintiles, and MCA explained the highest total variation of variables (47.3%) Polychoric PCA is closely correlated with standard PCA ($r=0.991$, $p<0.01$) and MCA ($r=0.991$, $p<0.01$). Places 87% of households in the same quintiles as standard PCA and 91% in the same quintiles as MCA
Arsenault et al., 2017	PCA; Multidimensional Poverty Index	Global Health	Cross-sectional survey	No	Armenia; Azerbaijan; Bangladesh; Benin; Bolivia; Burundi; Burkina Faso; Cambodia; Cameroon; Comoros; Congo; Côte d'Ivoire; Democratic Repulic of the Congo; Ethiopia; Gambia; Ghana; Guinea; Guyana; Haïti; Honduras; India; Indonesia; Kenya; Kyrgyzstan; Lesotho; Liberia; Madagascar; Malawi;	c,d,e, i	PCA derived wealth index is not statistically different than maternal education or multidimensional poverty index, wealth index inequalities slightly smaller, and some countries have much larger inequalities using one or the other. Haiti had larger using education (SII = 0.34 95% CI = 0.20, 0.48) than the wealth index (SII = 0.10 95% CI = 0.04, 0.24); Mozambique larger using wealth index (SII = 0.30 95% CI = 0.22, 0.37) than maternal education (SII = 0.16, 95% CI = 0.09, 0.24)

[12] a: Income vs Assets; b: Consumption vs Assets c: Asset index comparisons; d: Assets and Education; e: Assets and Health; f: Urban-Rural Dynamics; g: Robustness to Variable Loss; h: Income/Consumption Inequality; i: Worldwide Comparability

					Mali; Moldova; Mozambique; Nepal; Niger; Nigeria; Pakistan; Rwanda; São Tomé and Príncipe; Senegal; Sierra Leone; Tajikistan; Tanzania; Timor Leste; Uganda; Zambia; Zimbabwe		
Aryeetey et al., 2010	PCA; Participatory Wealth Ranking, Consumption	Global Health	Cross-sectional survey	No	Ghana	b,f	Compared to consumption, both PCA and participatory wealth ranking had high inclusion and exclusion errors in Ghana using consumption as the gold standard In the urban setting, PWR excludes fewer poor households (50%) than PMT (63%), but also includes more non- poor households (50%) than PMT (36%). In the rural setting, PWR excludes more poor households (73%) than PMT (53%), but also includes fewer non-poor households (17%) than PMT (21%). In the semi-urban setting, PWR excludes fewer poor households (3%) than PMT (46%), but also includes more non-poor households (60%) than PMT (27%)
Azzarri et al., 2005	PCA, Consumption	Economics	Cross-sectional survey	No	Albania	b,c,f	PCA-derived asset index was more highly correlated with consumption than a count measure consisting of water and sanitation provision, adequate housing provision, less crowded dwellings, and minimum education of household head
Balen et al., 2010	PCA, Income, PAF	Epidemiology	Cross-sectional survey	No	China	a,b,c, f	PCA and PAF performed very similarly in two Chinese villages with both rural and peri-urban areas having the same association relatively weak association (0.27) to household income The proxy wealth models explained a higher proportion of data in the peri-urban setting than the rural setting

							(27.8% vs. 24.3% for PCA), which may add strength to the concern that an asset-based index is a more ‘appropriate’ measure of wealth in urban areas compared with rural areas
Benini, 2007	PCA, Polychoric PCA	Economics	Cross-sectional survey	No	Bangladesh	c	Comparison of PCA and polychoric PCA using Bangladeshi DHS data concludes that ordinary PCA lacks the ability to discriminate at the lower end of the spectrum due to its under-emphasis of common assets
Blumenstock, 2018	PCA	Economics	Machine learning	No	Rwanda	c, i	A machine learning algorithm can be used to roughly approximate PCA wealth index using phone usage characteristics in Rwanda and Afghanistan, the models must be developed separately for each country and cannot be applied naively across borders
Boccia et al., 2013	PCA, Consumption	Global Health	Cross-sectional survey	No	Zambia	c,e,f, g	Dropping all variables which are more likely to be found in an urban household did not significantly affect the overall variance explained by the PCA model. In addition, a smaller Zambian study (N=318) found that a regression of consumption measures had only mild agreement with PCA-based asset index, with 46% of households classified in the same tercile An alternative PCA-derived index without any food-related variables (which may have affected tuberculosis outcomes of interest directly) was not significantly different than the PCA-derived index using all variables (32.1% v 34.5%). A regression of consumption measures had only mild agreement with PCA-based asset index, with 46% of households classified in the same tercile

Bollen et al., 2002	PCA, Simple Sum Index, Consumption	Demography	Cross-sectional survey	No	Ghana; Peru	b,c,e,g	In many low and middle income countries (LMIC), income can be highly variable or difficult to accurately measure and asset indices can rely on assets which have direct impact on health, such as water and sanitation quality or food availability. An alternative PCA-derived index without any food-related variables (which may have affected tuberculosis outcomes of interest directly) was built and found no significant difference with the PCA-derived index using all variables (32.1% v 34.5%). A PCA-derived asset index using DHS data performed better than all other measures, including consumption measures(which predicted almost no variation in fertility) based on BIC. The simple count measures to has the second-best fit (after PCA-derived asset index) according to Bayesian Information Criterion
Booysen et al., 2008	MCA, Consumption	Economics	Cross-sectional survey	No	Ghana; Kenya; Mali; Senegal; Tanzania; Zambia; Zimbabwe	b,c,f	Urban households are more likely to own many assets and are more likely to benefit from publicly provided assets such as piped water, so they will be inappropriately classified as wealthier than comparable rural households . Opted to use MCA rather than PCA because of statistical limitations, but found that despite some differences in variable weight orders, there was no significant difference between both indices (r=0.953, p<0.01) and the few households that were classified into different quintiles were restricted to one level higher or lower. The general trend of publicly-provided services tending to be of more importance in the lower end of the socioeconomic gradient and private goods tending to be more important in the upper end when using PCA may have some impact on health inequalities. Asset indices are slow to change over time - even when

							significant household improvements can be measured using consumption
Chakraborty et al., 2016	PCA	Global Health	Cross-sectional survey	No	Bangladesh; Benin; Cambodia; Cameroon; Ethiopia; Malawi; Mozambique; Nepal; Nigeria; Pakistan; Philippines; Rwanda; Senegal;Tanzania; Uganda; Zimbabwe	f,g,i	Survey respondents may have difficulty answering questions about the number of hectares of agricultural land owned, which type of toilet construction is used in their home, or even whether they live in an urban or rural area. An attempt to create a simplified asset list for PCA-derived index using data from 16 DHS survyes found inter-quintile agreement ranging from 75% to 83% by dropping various country-specific, urban-rural specific, and agricultural questions.
Chasekwa et al., 2018	PCA, Polychoric PCA	Global Health	Cross-sectional survey	No	Zimbabwe	c,f	A Zimbabwean survey finds a Spearman rank coefficient of 0.910 (95% CI: 0.904–0.915) and 94% agreement between wealth quintiles between PCA and Polychoric PCA. Separately, a rural-only sample using only PCA achieved Spearman rank correlation coefficient of 0.862 [95% CI 0.854–0.869] with the standard DHS wealth index
Chuma and Molyneux, 2009	PCA, Consumption	Global Health	Cross-sectional survey	No	Kenya	b,e,f	Investigation of insecticide-treated net ownership in Kenya found a mixed picture of larger inequalities in urban areas using a PCA-derived asset index compared to expenditure-classification, but smaller inequalities in rural areas. They speculate that this may be due to free net distributions in rural areas, and conclude that neither the asset index or consumption index approach is superior for health research in LMIC. A traditional PCA-derived index placed no rural

							households in the richest quintile and only one rural household in the second richest. Both indices bore little resemblance to the consumption data, with only 30.5% of rural expenditure-poor households also classified asset poor and 43.4% of urban expenditure-poor households also being classified as asset-poor. When constructing separate indices for urban and rural areas in the same country, assets like chickens or bicycles can be an indicator of relative wealth in rural areas, while being an indicator of relative poverty in urban areas.
Córdova, 2008	PCA, Income	Economics	Cross-sectional survey	No	Argentina; Bolivia; Brazil; Chile; Colombia; Costa Rica; Dominican Republic; Ecuador; El Salvador; Guatemala; Haiti; Honduras; Jamaica; Mexico; Nicaragua; Panama; Peru; Trinidad and Tobago; Uruguay	a,d,i	Constructed a PCA index applicable to 21 Latin American and Caribbean countries using telephone survey data found generally encouraging results. Pooled principal components were broadly applicable from poorer countries like Peru to richer countries like Costa Rica, and the resulting relative wealth quintiles were strongly correlated with years of schooling and self-reported income scale.
Doku et al., 2010	PCA	Global Health	Cross-sectional survey	No	Ghana	c,d	The association of PCA-derived “material affluence” of adolescents was only modestly correlated to parental education levels (maternal r=0.32, paternal r=0.36), explaining only 14% of parental education and occupation variance
Ergo et al., 2016	PCA	Global Health	Cross-sectional survey	No	Honduras; Senegal	c,g,i	Comparing two simplified asset indices to the gold standard of the full DHS index in Honduras, there was almost perfect agreement (kappa value greater than 0.61) after reducing the number of variables from 111 to 24 variables using an iterative ranking of factor loadings, and from 111 to 21 variables in Senegal. However, the variables that mattered most varied according to the

							country context, and single variables may still require their own questions.
Ferguson et al., 2003	PCA, Regression, Income, Consumption	Global Health	Cross-sectional survey	Yes	Greece; Peru; Pakistan	a,b,c, i	A regression-based approach used a variant of a hierarchical ordered probit model (DIHOPIT) to link household assets to both income and expenditure with varying success. In Greece and Peru, which achieved low levels of measurement error, the regressions all reached 0.60 Spearman's rho or greater with both household income and consumption; and importantly, found results nearly identical to a standard PCA index. Even in Pakistan, which found very low correlation to income and expenditure due to measurement error, the PCA and DIHOPIT models gave nearly identical results
Filmer and Pritchett, 2001	PCA, Consumption	Demography	Cross-sectional survey	Yes	India	b,c,d, f	The PCA approach provided a way to systematically reduce the variables of interest to a minimum while reducing reliance on the judgment of an analyst. There is a high Spearman rank correlation of "asset poverty" in Indian states with national poverty statistics of 0.794 ($p<0.001$, N=16) and acceptable performance with data from Nepal, Indonesia, and Pakistan; allowing the authors to conclude that "Principal-components analysis provides plausible and defensible weights for an index of assets to serve as a proxy for wealth". Asset indices are generally viewed as measures of long-term wealth or SES, but not of short-term poverty, income, or consumption. There are concerns over comparability of results between urban and rural areas

Filmer and Scott, 2012	PCA, Consumption, IRT, Count index	Demography	Cross-sectional survey	Yes	Albania; Brazil; Ghana; Nepal; Nicaragua; Panama; Papua New Guinea; South Africa; Uganda; Vietnam; Zambia	b,c,d, e,f,i	Since asset indices are based on *household* assets and cannot be divided on a per-capita basis, interpretation of results must bear this in mind. This means that asset indices are more closely related to household economies of scale models than pure per-capita consumption models, reinforcing the idea that the indices are tracking a separate, but equally valid construction of SES. Asset indices and consumption models are more closely related when a higher percentage of consumption is captured by assets included in the household surveys, and they are more highly correlated in countries where the average share of non-food expenditures is high. PCA and consumption indices generate almost identical results for inequalities in care seeking behavior. There was greater health-seeking behavior found among the relatively poor, although this is hypothesized to be a product of the poorest quintile's disproportionate share of illness. The highest levels of child mortality are not uniformly found in the poorest quintiles of the expenditure model, but are always found in the poorest quintiles of PCA models – a statistically significant difference-in-difference. Statistically significant educational inequality in 7 of 11 countries included, with the PCA approach most often resulting in larger inequalities. The difference in classification of urbanization between the poorest and richest quintiles can be as large as 75% in a PCA model and 22% in an expenditure model in Albania, with several other countries also having large discrepancies in SES ranking due to urban status. Rank correlations for PCA and IRT between 0.95 and 1.00 – the most highly correlated alternative measure to PCA.

Fink et al., 2017	PCA; Predicted Income	Global Health	Cross-sectional survey	No	88 Low and Middle Income countries	a,e,h, i	More variation in stunting prevalence was captured using the Harttgen & Volmer predicted income approach (38%) compared to wealth quintiles (20%). It is possible to compare health outcomes taking income (or wealth) inequality into account using tools such as equiplots with this approach, revealing countries which have similar outcomes at any given income level, and others that are performing poorly at a given income level.
Harttgen and Vollmer, 2013	PCA; Predicted Income	Economic s	Cross-sectional survey	No	Bolivia; Indonesia, Zambia	a,f,h, i	It should be possible to use a PCA-derived asset index to simulate household income distribution where national income is log-normally distributed and household ranks are the same for both the asset index and income. Pooling assets over time would theoretically allow absolute differences in wealth to be compared over time, but this is complicated by the fact that the social significance of certain assets such as landlines, radios, and bicicles changes significantly over time.
Homenauth et al., 2017	PCA	Global Health	Cross-sectional survey	No	Tanzania	c,f,g	Three alternative wealth indices were compared to a standard DHS wealth index in their ability to predict vector-borne disease risk. Authors suggest that indices that contain durable assets best predict SES-related risk, but there are clearly errors in constructing the reference DHS-style wealth index
Houweling et al., 2003	PCA	Global Health	Cross-sectional survey	No	Bolivia; Brazil; Indonesia; Cameroon; Chad; Kenya; Malawi; Pakistan; Tanzania; Uganda	c,e,g	Comparison of a World Bank PCA-derived wealth index using DHS data to three alternative indices that exclude direct determinants of health and factors provided at the community-level, in which 18% of households were categorized in a different wealth quintile, with most of these shifting to an adjacent quintile. 60% change in the relative index of inequality for five health outcomes with alternative PCA-derived wealth indices, although the direction of change appeared to be random and was not significant in some countries.

Howe et al., 2009	PCA, Consumption	Global Health	Cross-sectional survey	No	Albania; Brazil; Côte d'Ivoire; Ghana; Guatemala; Indonesia; Jamaica; Madagascar; Malawi; Mexico; Mozambique; Nepal; Nicaragua; Pakistan; Panama; Papua New Guinea; Peru; South Africa; Tanzania; Uganda; Vietnam; Zambia	b,i	SES is at least partially dependent upon long-term earnings, shared assets, consumption, and consumption smoothing. There is evidence that consumption data tracks asset indices more closely in middle income countries, and especially if a greater variety of assets are included. Weak to moderate association between asset indices and expenditure data, although these findings may be disputed due to the relatively small sample size (17 studies), inclusion of all index construction methods, and arbitrary cut offs of effectiveness (as acknowledged by the authors themselves).
Howe et al., 2012	PCA; Consumption, Income; Participatory wealth ranking	Global Health	Methods	No	N/A	a,b,c, d,e,f, g	The advent of PCA can be traced to the challenge of developing a method of converting a series of ownership variables, many of which were binary (yes/no) or categorical (roof material, e.g.), into a continuous SES gradient. Initial approaches mostly relied on simple sums of asset ownership such as housing quality, durable asset ownership, or public utility access. However, this implicitly gave equal weight to all assets, whether it was a relatively rare major expense such as a car, or a nearly ubiquitous commodity such as a radio. Asset indices are generally viewed as measures of long-term wealth or SES, but not of short-term poverty, income, or consumption. Asset indices are frequently compared to consumption data by researchers that argue that it is the most accessible and closely related comparator with which to measure the performance of PCA. There is a fundamental flaw in the application of ordinary PCA to the types of variables needed to construct an asset index - the technique is not meant to be applied to binary and categorical variables.

Jean et al., 2016	PCA, Consumption	Economics	Machine learning	No	Malawi; Nigeria; Rwanda;Tanzania; Uganda	b,f,i	A convolutional neural network trained on ground imagery is able to predict 37-55% of variation in consumption and 55-75% of variation in asset wealth if trained separately for each country, although this drops to 19-52% and 24-71% if applied to other countries. This is slightly more predictive than phone use estimation models, and the difference in estimation is likely due to the area's wealth itself rather than directly identifying household features directly.
Johnston and Abreu, 2016	PCA	Economics	Methods	No	All African countries	a,b,d, e,f,i	There is a village in Guinea-Bissau where portable gas stoves are a normal good, but because that village is relatively poor compared to other villages, the factor loading is negative. A heated debate over whether an African growth "miracle" occurred was sparked due to comparisons of asset wealth with national accounts. Factors such as new cheap imports of household durables from Asia and the tendency of houshold asset prices to drop over time were not fully accounted for, leading to many dissenting opinions and uncertainty over whether welfare had truly improved.
Joseph et al., 2018	PCA, Predicted Income	Global Health	Cross-sectional survey	No	100 low- and middle-income countries	a,e,h, i	Predicted absolute income better predicted skilled birth delivery in a large 100-country study, with log-normalized predicted income explaining 51.6% of variation, DHS wealth quintiles predicting 22.0%, and mean wealth quintile PCA score predicting 12.8%. Comparisons of all countries over time reveals important trends such as countries that have succeeded in increasing skilled birth attendance in spite of stalled income growth, and those that have not improved outcomes even in times of sustained economic growth.

Kolenikov and Angeles, 2009	PCA, Polychori c PCA	Economic s	Cross-sectional survey; Simulatio n	No	Bangladesh; simulated data	c,d	Many researchers have pointed out a fundamental flaw in the application of ordinary PCA to the types of variables needed to construct an asset index; namely, that the technique is not meant to be applied to binary and categorical variables. Since an average of 60% of household survey questions used to construct asset indices are binary, this is no minor limitation. Filmer and Pritchett's technique creates spurious correlation through the introduction of dummy variables and for losing directionality of ordinal data, Kolenikov and Angeles propose the use of a slightly amended multivariate technique, originally derived by the same statistician as ordinary PCA. Not only is there greater statistical fidelity, but the status of not owning an asset is also taken into account. The key findings of this proof-of-concept study were that polychoric PCA demonstrated lower misclassification rates, explained a higher proportion of variance, is more robust to the number of categories used, and is more robust to changes in variable coding scheme than the Filmer and Pritchett procedure The two methods demonstrate divergent classifications at the lower end of the SES spectrum with increasing agreement of classification on the upper end of the SES spectrum.
Lindelow, 2006	PCA, Consumpt ion	Global Health	Cross-sectional survey	Yes	Mozambique	b,e	In general, there is some evidence that asset measures may increase the significance of health inequalities. Pro-rich inequalities in immunizations, maternity care, institutional deliveries, and hospital visits were greater when measured with a PCA-derived index than consumption data in Mozambique
Manthalu et al., 2010	PCA	Global Health	Cross-sectional survey	No	Malawi	e,f	A Malawian team went from health to wealth, and found almost no difference between using a PCA index or an index composed of the percentage of children with

							stunting per district with government allocations (spearman rank correlation = 0.96)
McKenzie, 2005	PCA	Economics	Cross-sectional survey	Yes	Mexico	a,d,f,h	One of the earliest researchers to investigate the usefulness of an asset index in inequality research concluded that PCA-based measures in combination with bootstrap prediction methods were highly correlated to expenditure-based inequality measures in Mexico; and importantly, that an index based on durables is more highly correlated with these measures than indices based on housing, utilities, food expenditure, or a combination of these variables
Michelson, 2013	PCA, MCA, Income	Economics	Cross-sectional survey	No	Malawi; Tanzania; Mali; Ghana	a,c,f,g	An expanded set of assets collected to measure progress in the Millenium Villages Project did not perform better than the standard DHS asset mix. MCA and PCA were not significantly different in year over year change and were both more strongly autocorrelated than household income. Transitions out of poverty occur at the same rate using asset indices and household income, with approximately 12-20% of the lowest quartile households classified as highest quartile households after two years. PCA index was more strongly correlated with locally identified factors indicating poverty (female-headedness of household, dependency ratios, and household food insecurity) than household income .
Mohanty, 2009	PCA	Global Health	Cross-sectional survey	No	India	c,e,f	Asset indices may be more directly associated with these outcomes than household expenditure or income because health and education are more representative of long-run household SES than monetary highs or lows. Unmet healthcare need can be underestimated in rural areas and overestimated in urban areas due to the urban bias inherent in PCA indices. Building a national index compared to combining separate urban and rural PCA-derived indices in India

							resulted in 39% of households being classified in the same quintile, 50% to have moved to an adjacent quintile, and 10% to have moved to the farthest quintile
Mohsena et al., 2010	PCA, Count measure	Global Health	Cross-sectional survey	No	Bangladesh	c,e,f	Using a basic count measure outperforms PCA in discriminating households more at risk for stunting, wasting, and underweight. Their use of a simple count of radio, television, bicycle, motorcycle, telephone, and electricity to construct wealth quintiles resulted in 49.1% of households in the poorest quintile and only 4.2% of the richest quintile having all three outcomes of interest, while the PCA index produced equivalent percentages of 28.6% and 11.4%, respectively
Moser and Felton, 2007	Polychoric PCA	Economics	Cross-sectional survey	No	Ecuador	e,f,g	Reporting errors are known to affect even the most carefully planned and executed household consumption surveys due to recall error, exclusion of some expenses, choice of deflator, and currency exchange fluctuations. Indoor plumbing, which may only be missing from a small percentage of the poorest households of a population can still be a very useful predictor of household SES
Ngo and Christiaensen, 2018	PCA, DIHOPIT, Consumption	Economics	Cross-sectional survey	No	Ghana, Malawi, Rwanda, Tanzania, and Uganda	b,c,f, g,i	PCA correlates more strongly with consumption than inverse frequency weighting or DIHOPIT regression, but these differences are not significant. Adding a few binary consumption variables on food and clothing purchases increased identification of the poor in rural settings by 9%, but made no difference in urban settings. Weaker correlation among highest income country and in rural sample

Nkonki et al., 2011	PCA	Global Health	Cross-sectional survey	Yes	South Africa	a,e	Non-significant association of mother-to-child HIV transmission and child mortality to a PCA-derived asset index
Nwaru et al., 2012	PCA	Global Health	Cross-sectional survey	No	China	c,e	Low to moderate correlation with maternal and child health indicators as an outcome of interest; although both an occupational index and educational index found equally, if not contradictory, weak associations
Opuni et al., 2011	PCA, Consumption	Global Health	Cross-sectional survey	Yes	Tanzania	b,c,e,i	Could not identify a pattern of AIDS distribution in Kenya whether PCA-derived index, household consumption, or "traditional wealth" asset indices were used. Contrary to claims that asset indices derived from standardized household surveys cannot be relied upon in countries with traditional conceptions of wealth, a "traditional wealth index" constructed to represent Kenyan cultural constructions of wealth was nearly identical to standard PCA of household assets
Reidpath and Ahmadi, 2014	Polychoric PCA, MSA, Consumption	Global Health	Cross-sectional survey	Yes	Vietnam	b,c,e,g	Mokken Scale Analysis is a nonparametric technique which relies on Guttman scales of items which are increasingly "harder" to answer. Using a combination of positive ownership of assets with the difficulty of eliciting a positive response, MSA is able to rank households along a latent SES gradient . Key assumptions include unidimensionality of SES, local independence of variables, monotonicity of responses, and invariant item ordering. An empirical application of the technique found very high Pearson product moment correlation with a polychoric PCA index (r=0.96) with a lower correlation to household expenditure (r=0.59). Reducing a 17 item asset index to 11 items with polychoric PCA resulted in much lower concordance with both expenditure (r=0.57 v r=0.41) and an MSA derived asset index (r=0.98 v r=0.68)

Rohner et al., 2012	PCA	Global Health	Cross-sectional survey	No	Ivory Coast	c,e	Used rigorous biometric measures of nutritional status while accounting for the effect of malarial infection, age, and residency. The PCA-derived poverty index outperformed the count score by capturing significant socioeconomic inequalities in anemia, stunting, and wasting in children and women of reproductive age.
Sahn and Stifel, 2003	PCA, Consumption	Economics	Cross-sectional survey	Yes	Cote d'Ivoire, Ghana, Jamaica, Madagascar, Nepal, Pakistan, Papua New Guinea, Peru, South Africa, Vietnam	b,e	Consumption data, such as that measured by the Living Standards and Measurement Studies, can be extremely time consuming and expensive to collect. Multi-country comparative studies suggests that the use of PCA-derived asset indices resulted in smoother declines in stunting by wealth quintiles when compared to predicted household consumption in 10 countries
Smits and Steendijk, 2013	PCA, MCA, FA, Categorical PCA	Economics	Cross-sectional survey	No	97 developing countries	a,c,d, e, h,i	Can overcome the difficulty of incomparability of many survey items by grouping accessories into cheap and expensive utensil categories. An asset index applicable to 165 household surveys across 97 LMIC is developed. Although these results were obtained with ordinary PCA, sensitivity checks with MCA, factor analysis, and categorical PCA did not change the results. This international wealth index is robust to removal of any region from analysis (Pearson correlation coefficient ≥ 0.996), removal of any time period (Pearson correlation coefficient ≥ 0.997), and removal of any one asset (Pearson correlation coefficient ≥ 0.986). Good agreement between the international wealth index and DHS country-specific indices, country-specific poverty levels, life expectancy, and most strongly with the Human Development Index. The authors assert that reasonable estimates of purchasing power parity (PPP) poverty levels can be placed at 30th percentile of the index equivalent to PPP$1.25 a day and 50th percentile at PPP$2.00 a day

Tusting et al., 2016	PCA, Income	Global Health	Prospective cohort	No	Uganda	a,c,e, g	Dropping household construction variables from PCA index resulted in a significant association with human biting rate becoming insignificant, even though the two indices are highly correlated (Spearman's rho = 0.93)
Ucar, 2015	PCA, Income, Consumption	Economics	Cross-sectional survey	No	Turkey	a,b	Asset index was more moderately associated with consumption and income, with 54.1% being in the lowest quintile for both asset index and consumption, an 47.1% in the lowest quintile for both asset index and income.
Van Leth et al., 2011	PCA, Income, Consumption	Global Health	Cross-sectional survey	No	Bangladesh, Kenya, Philippines, Vietnam	a,b,e	Focused review of the use of PCA to derive asset indices specifically for tuberculosis surveys concluded that the method more consistently identified inequities in health than income or expenditure surveys
Vandemoortele, 2014	PCA, IRT	Economics	Cross-sectional survey	No	Malawi	c,f	The basic idea of IRT is that observed assets (whether they are dichotomous, polytomous, nominal, or ordinal) which demonstrate the most discrimination according to a latent trait (SES) are given larger weights, which are then assessed for reliability with a non-parametric bootstrap. The two key assumptions of normal distribution of data and independence of variables offer no improvement to the existing PCA approach, and is acknowledged to be more time consuming. High correlation with a PCA index (Spearman rank correlation = 0.88).
Vu et al., 2011	PCA	Global Health	Cross-sectional survey	No	Vietnam	d,e,f	PCA-derived asset quintiles are correlated with low birthweight, education level, and occupation in the Vietnamese context
Vyas and Kumaranayake, 2006	PCA	Global Health	Methods	No	Brazil, Ethiopia	a,b,c, f,g	The supposed urban bias of PCA is not misclassification, but an accurate representation of the relative affluence of urban households

Ward, 2014	Polychoric PCA, Income	Economics	Cross-sectional survey	Yes	China	a,f,g,h,i	A large multiyear pooled analysis in China. Found negative factor weights for all agricultural assets, leading them to suggest that secondary principal components weights (which were positive) could be used in these cases. Alternatively, urban and rural households were disaggregated and separate indices were constructed, which led to agricultural assets having positive weights for rural households and negative weights for urban households. Even removal of all agricultural assets has been shown to have little effect on household rankings in China, with 90 percent of households staying in the same wealth quintile. Using variance of PCA to track inequality of SES has been applied to Chinese survey data, which appears to have great promise for inequality research moving forward
Wittenberg and Leibbrandt, 2017	PCA	Economics	Cross-sectional survey	No	South Africa	a,f,g,h	Care must be taken before applying inequality measures to asset indices - Gini coefficient can only be applied to the absence or presence of real assets, and Cowell-Flachaire approaches can be applied to categorical variables. Having a common asset will usually imply a negative factor loading with PCA, MCA, or factor analysis, which could perversely rank the household as poorer than one lacking the asset at all. Assets can be pooled over time if care is taken with variables like landlines and cell phones, which can be combined into one "phone" asset. Asset inequality fell from a Gini coefficient of 0.47 to 0.29 from 1993 to 2008 in South Africa.
Zeller et al., 2006	PCA, Income	Economics	Cross-sectional survey	No	Bangladesh, Kazakhstan, Peru, and Uganda	a,c,f,i	PCA generally has more error in classifying poverty than quantile, ordinary least squares, probit, and linear probability models in Bangladesh, Kazakhstan, Peru, and

							Uganda, but with good enough performance to be investigated further

Chapter 3. Measuring Health Inequalities in Low- and Middle-Income Countries Using Household Income, Consumption, or Assets: Does it Make a Difference?

Preface

This chapter continues the line of research laid out in Chapter 2 by investigating how the choice of household SES indicator (household income, consumption, and wealth indices) as measures of SES affects the magnitude of health inequalities in low- and middle-income countries (LMICs). To establish a baseline association among the three primary measures of SES, this study compiled 22 country-years of LSMS data and calculated concentration indices, relative indices of inequality, and slope indices of inequality for child deaths, stunting, and underweight. A special focus was put on the interaction between absolute and relative inequality levels with country-income level and the year the surveys were conducted.

I conceived of this study in conjunction with Dr. Karen Grépin in November 2016. I then extracted all required microdata and conducted data analysis before writing the manuscript for this chapter. I received significant input into the interpretation and writing of this chapter from my committee members of Dr. Michel Grignon, Dr. Karen Grépin, and Dr. Michelle Dion and incorporated their revisions into this final version of the study.

Measuring Health Inequalities in Low- and Middle-Income Countries Using Household Income, Consumption, or Assets: Does it Make a Difference?

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Abstract

Despite a voluminous literature examining health inequalities in low- and middle-income countries (LMICs), there has been no systematic comparison of the three most commonly used measures to quantify household SES – income, consumption, and asset indices. Microdata from 22 Living Standards Measurement Study (LSMS) surveys were compiled and concentration indices, relative indices of inequality, and slope indices of inequality were calculated for underweight, stunting, and child deaths using income, consumption, and asset indices (as well as a related hybrid predicted income method). Meta-analysis of subgroups of survey year (pre-1995, 1995-2004, and post-2004), outcome (child deaths, stunting, and underweight), and World Bank country-income (low, low-middle, and upper-middle) was then conducted. Asset indices (and hybrid income proxy) result in the largest magnitudes of health inequalities for 11 of the 12 different overall outcomes, as well as a majority of every country-income and survey year subgroupings. There is no clear trend of health inequality magnitudes changing over time, but results do identify larger magnitudes of health inequality as country-income levels increase. There is no significant difference between relative and absolute measures of inequality, but these results indicate that the hybrid predicted income measure behaves more similarly to asset indices than the household income they are supposed to model. Although the primary results are not statistically significant at the 95% level, they are highly suggestive that health inequality magnitudes may be affected by the choice of household SES measure and should be studied in further detail.

Introduction

All bivariate measures of health inequality require two variables – a health outcome and a measure of socioeconomic status (SES). In the field of global health, much scrutiny has been paid to the manner in which health outcomes are measured, modeled, scaled, weighted, and quantified; but relatively scant research has been conducted on the effect of how different methods of measuring SES itself can have on the magnitude of health inequalities. Despite the myriad of methods that have been employed to measure SES in global health, no systematic comparison of how the choice of methods affects the magnitudes of social health inequality has been conducted. In order to address this gap in the global health literature, this study will empirically evaluate how different measures of SES affect the magnitude of wealth-related health inequalities across 22 household surveys conducted in low and middle-income countries (LMICs).

The three most widely used measures of SES that have been used as the basis to calculate health inequalities in global health are income, consumption[1], and asset indices[2] (Sahn and Stifel, 2003). Income is the primary method of quantifying SES in high-income countries, but in many low- and middle-income countries, income can be highly variable from month to month, may be incorrectly reported by survey respondents, and may be an inaccurate signifier of a household's SES if a large part of a household's spending comes from savings or loans (Bouis, 1994; Galobardes et al., 2007; Howe et al.,

[1] For the purposes of this article all mentions of consumption are interchangeable with expenditure or consumption-expenditure.
[2] Also referred to as a wealth index, household wealth index, or DHS index.

2012). One solution to many of these issues that has been widely used in international household surveys and development literature is to measure households' expenditures over a certain time interval broken down into broad consumption categories. Proponents of these household consumption measures cite the advantages of capturing the effect of income smoothing through savings and loans, resulting in measures that are more consistent from month to month, and that may be more representative of a household's permanent SES (Deaton and Zaidi, 2002; Friedman, 1957). In practice. however, household expenditure data usually takes at least an hour to collect, resulting in lengthy and expensive surveys, and even then, may be affected by recall bias, observer bias, and a high attrition rate (Bollen et al., 2002; Howe et al., 2012).

In response to these challenges, a method of quantifying a household's assets into a single SES index was developed using household assets widely available in standardized household surveys in a seminal work by Filmer and Pritchett (2001). Asset indices are now the most widely used method to quantify SES in global health household surveys of low- and middle-income countries because assets can be quickly and objectively measured by surveyors, remain relatively stable over time, and pre-calculated indices are now included in the most widely used health surveys including Demographic and Health Surveys (DHS) and Multiple Indicator Cluster Surveys (MICS) (Houweling and Kunst, 2010; Howe et al., 2012; Rutstein and Johnson, 2004). Despite these advantages, there has been considerable debate over how best to calculate asset indices (Booysen et al., 2008; Kolenikov and Angeles, 2009; Montgomery et al., 2000;

Vandemoortele, 2014) and the resulting measures can be difficult to interpret or lack a meaningful scale (Ferguson et al., 2003; Filmer and Pritchett, 2001).

A more recent innovation to address the issue of scale proposes to simulate household income by assigning each centile of the SES spectrum, as determined by asset indices, a country- and year-specific simulated income distribution (Harttgen and Vollmer, 2013). The researchers developing this method justify its use with the argument that relative rankings of households according to asset wealth and income are similar, but rather than a tenuous assumption, another way of conceptualizing this method is as a way of converting asset indices to a meaningful context-specific interval scale. Although this method has shown promise when applied to household surveys in LMICs (Fink et al., 2017), there is no published systematic comparison with actual household income or consumption-based health inequality measures. This means that although relative household rankings are based on the asset index and absolute differences between those households are based on simulated income distributions, there is no evidence determining whether this new construct results in health inequality magnitudes more closely resembling those based on asset indices or household income.

While other measures of SES including education, social class, subjective social standing, and multidimensional poverty measures have been used to measure health inequalities; income, consumption, and asset indices share a common goal of measuring social standing through financial well-being regardless of country or social institutions present in those countries. Education level is widely used as a proxy of SES, especially in lower income countries, but takes aim at a different dimension of social wellbeing than financial indicators. Educational strata are also affected by methodological issues such as assuming each year of education is equally indicative of an increase in SES and is of equal quality for each student (Howe et al., 2012). More importantly, the incomparability of education levels across even regional jurisdictions coupled with the fact that it is more indicative of community-level social development than household-level SES can lead to the conclusion that education is a useful, but imprecise proxy of household SES. Each of the measures discussed clearly suffer from practical and theoretical disadvantages and each has a legitimate claim to measuring at least one real dimension of household SES. Nevertheless, many authors have taken the explicit or implicit assumption that one method is superior to the others rather than studying the effect each method has on the magnitude of social health inequalities empirically (Fink et al., 2017; Sahn and Stifel, 2003). This study makes no normative assumption that any method of measuring SES is implicitly superior, nor that measures that result in larger magnitudes of wealth-related inequalities in health are more accurately representing household SES. Rather, each measure has utility for global health research that is contingent on careful measurement and interpretation.

Despite the possibility that SES measures can have a large impact on the magnitude of social health inequalities, a critical interpretive synthesis of existing literature (Poirier, 2018) found that only three studies have compared the use of different methods with the same microdata in more than one country,[3] and none have compared all

[3] Filmer and Pritchett (2001) also systematically investigate more than one country, but only examine the effect on educational attainment inequalities.

three measures of income, consumption, and asset indices. The largest study of its type conducted by Wagstaff and Watanabe (2003) compared equivalized household consumption with asset indices using Living Standards Measurement Study (LSMS) data in 19 countries. Their findings that differences in concentration indices of underweight and stunting were slightly larger using consumption with the difference significant in fewer than a quarter of the cases led them to conclude that there was likely no difference between the two measures. Another study by Sahn and Stifel (2003) predicted standardized anthropometric height-for-age Z-scores for 12 country-years, finding little difference between the two measures, but highlighting cases where the asset index did point to larger inter-quintile (rich-poor) differences than consumption. Filmer and Scott (2012) briefly examined the ratio of child deaths to births, finding that per capita expenditures result in smaller inter-quintile differences than asset indices in four out of eight countries analyzed, with the remainder having no significant difference. Although not a primary study of a SES measures' impact on health inequalities, Howe et al.'s (2009) review of asset index and consumption concordance (including single-country studies) found that health inequalities were larger for consumption in two studies, three studies found larger inequalities using asset indices, and one study found mixed results. In sum, not only is there no systematic comparison of income with asset indices, but the few studies that have compared wealth-related health inequalities using both consumption and asset indices have resulted in very conflicting conclusions.

Howe et al. (2009) also speculate on reasons for this discordance. Among the entire 17 study set included for analysis, Howe et al. found higher agreement between consumption and asset indices in middle income settings, urban areas, and when more and diverse indicators were included in asset indices. Country-income level could theoretically affect asset index performance if a household's spending on non-asset goods, such as food expenses, is systematically correlated with country-level income (Filmer and Scott, 2012). Alternatively, if the amount of household spending that is captured by asset indices increases as countries become richer, then asset index comparability with income and consumption will tend to increase as time goes on due to the general tendency of country income-levels to increase. Relatedly, the tendency of asset prices to fall, and especially as importation of cheaper household durables from Asia have become more common, may result in a divergence between asset wealth and both income and consumption (Johnston and Abreu, 2016). Bivariate health inequality measures also depend heavily on the health outcome being measured. There is evidence, for example, that inequality in child mortality measured using the DHS asset index becomes larger with increasing urbanization (Lindelow, 2006) or when countries decrease their overall rates of child mortality over time (Wang, 2003), meaning that the effect of global improvements in child mortality and other health outcomes (Li et al., 2017) may systematically affect the measurement of wealth-related health inequalities over time.

Lastly, the methods used to calculate social health inequalities have a great influence on the conclusions that are reached, especially depending on whether relative or absolute differences are emphasized. In theory, measures of absolute difference, such as interquartile differences or slope index of inequality (SII), would result in greater inequalities and be more sensitive to differences in scale of measures of SES (Ontario Agency for Health Protection and Promotion (Public Health Ontario), 2013). The concentration index, which measures relative inequality and may be more sensitive to changes in health outcomes at the middle of the SES spectrum may also be affected by different orderings of households depending on the measure of SES used (Gastwirth, 2016; O’Donnell et al., 2008). If the goal of these summary measures is to capture the entirety of the SES spectrum, then some measures such as the concentration index, the relative index of inequality (RII), and the SII are more appropriate than other measures such as interquartile differences, but more generally, each measure can be said to represent different normative judgements applied to the measurement of health inequalities (Harper et al., 2010; Hosseinpoor et al., 2018). In sum, the methods by which inequality is calculated, the health outcomes under study, the year in which the study is conducted, and the country-income level of the population may all affect how different SES measures affect inequalities in health, but there has been no systematic comparison of income, consumption, and asset indices to even establish a baseline relationship between the three primary measures of SES.

To establish a baseline association among the three primary measures of SES, this study compiled 22 country-years of LSMS data and calculated concentration indices, RIIs, and SIIs for child deaths, stunting, and underweight using household income, consumption, and asset indices as measures of SES. Every publicly available survey containing data on income, consumption, household assets, and child health outcomes was then systematically compiled using methods described below, followed by calculating asset indices and assigning a hybrid income proxy according to each country-year. Three measures of inequality of concentration index, RII, and SII were then calculated for each outcome, after which the magnitudes of each summary measure were compared using meta-analytic techniques and broken down according to survey year, country-income level, and health outcome to investigate the ways in which the effect of each SES measure may be shifting over time and space.

Methods

The largest internationally standardized survey of household living standards is the World Bank's LSMS, which has been conducted over 100 times in LMICs around the world (O'Donnell et al., 2008). Due to their focus on living standards, some, but not all, of these studies capture data on household income, consumption, and/or assets; a feature which is not present in DHS or MICS. Additionally, a subset of LSMS surveys capture information on select health outcomes, although these are limited in number compared to health-focused surveys. This study used the World Bank's LSMS Dataset Finder (World Bank, 2018) to identify every survey that contained each of income, consumption data, household assets, and data on either 1) child deaths, or 2) child anthropometrics. These outcomes were selected because they were the most commonly available measures in LSMS surveys, can be easily and objectively compared across borders, and are widely accepted as sensitive indicators of the population's health as a whole (Anderson et al., 1995; Black et al., 2010; Pelletier et al., 1995).

Every survey was closely examined to ensure direct comparability and data from each of 22 surveys was compiled, as summarized in Appendix Table 1.[4] Each health measure was calculated from raw height, weight, age, and fertility data, even if already included in the survey as precalculated variables, in order to ensure comparability. Child deaths and births for women aged 15-49 were included for analysis to replicate commonly used DHS methods (Corsi et al., 2012), and a simple ratio of deaths to births was used as a proxy for infant mortality.[5] Child nutrition outcomes of stunting and underweight were calculated as being more than two standard deviations from the 2006 WHO child growth standards for height and weight for age (in months) using Stata command zscore06 for all children under the age of five (Leroy, 2011; Mercedes, 2006).

Household income and consumption data were pulled directly from their respective modules and kept in local currencies because all health inequality calculations were conducted within survey country-years. Although some studies choose to use per capita or equivalized household income and consumption (Filmer and Scott, 2012; Sahn and Stifel, 2003), household income and consumption was selected for this study. Household income and consumption are more directly comparable to the dimension of SES measured by the asset index because the unit of measurement is the household rather than the individual, and household SES is more stable due to intra-household income or

[4] A maximum of two survey years (in order of most recently conducted) per country was used to prevent overrepresentation of select countries. Only surveys that contained pre-calculated household consumption and income modules and were available for public use were compiled for this study (i.e. no special permission needed from a country statistical agency).
[5] No survey weights were used because the outcome of interest is the household SES measure itself, not population health or wealth estimates. Mortality ratios could not be calculated for Nigeria because a births per woman variable was not present in LSMS data.

consumption substitution in the case of shocks (Baird et al., 2011; Friedman, 1957). Asset indices were then calculated using Kolenikov and Angeles' (2009) update of Filmer and Pritchett's (2001) original PCA methods.[6] Every household commodity in each survey wave was included for calculation of the asset indices, resulting in a range of 10 to 37 assets per survey. Finally, a "hybrid" income proxy method was used to map an estimated household income to each country-year's relative ranking of asset index wealth centiles. This was done by dividing each survey's households into 100 equal parts according to the relative ranking determined by the asset index, and then assigning each of those centiles a predicted income according to the year and country in which the survey was conducted using an open-access dataset (Fink, 2016; Fink et al., 2017). Summary statistics of all health outcomes and SES measures are presented in Table 1.

Wealth-related inequalities in health outcomes were then calculated using three methods of concentration index, RII, and SII. The value of the concentration index corresponds to two times the area between the line of equality and the concentration curve; or the percentage of the total outcome of interest that would have to be redistributed from the richest half to the poorest half of the population. It is worth noting that concentration index magnitudes will not change if health and rank difference do not covary, because even if the relative ranking of households changes, a lack of correlation with health would result in no change to the index value (Wagstaff and Watanabe, 2003).

[6] This method was chosen because a review of the literature on asset index construction using household surveys (Poirier, 2018) identified polychoric PCA as a more statistically appropriate, easily calculated, and reliable indicator of household SES. Despite these advantages, the two methods are almost always highly correlated (Spearman correlation coefficient > 0.90).

We used O'Donnell et al.'s (2016) *conindex* command based on the convenient regression method to calculate index values and standard errors, with Wagstaff corrections for bounded health outcome of stunting, underweight, and ratio of child deaths (Kakwani et al., 1997; O'Donnell et al., 2008; Wagstaff, 2005). Concentration index values were calculated for income, consumption, and asset index values as measures of SES, but the hybrid income proxy method was not used because household orderings are based entirely on asset index values, meaning there would be no difference except for loss of granularity after converting to centiles.

The SII can be interpreted as the absolute difference in health outcome between the richest and poorest household, taking into account the entire distribution of households in a regression, while the RII is a ratio measure of the prevalence of the health outcome of the poorest households compared to the richest households, again taking the entire distribution of households into account via regression (Hosseinpoor et al., 2013; Khang et al., 2008) These health inequality measures were calculated using a generalized linear model (GLM) with a logarithmic link for RIIs and an identity link for SIIs using methods described by Ernstsen et al. (2012). Household rankings for these methods use ridits of income, consumption, and hybrid income proxy calculated using methods described by Bross (1958), meaning that the scale of differences in household wealth is taken into account. Unlike the concentration index, the hybrid income proxy was used in lieu of the asset index, because both the SII and RII require an interval, rather than ordinal SES measure. Taken together, these three metrics measure scale-independent SES against relative health inequality (concentration index), scale dependent

SES against relative health inequality (RII), and scale dependent SES against absolute health inequality (SII).

In addition to presenting survey-by-survey results, results were aggregated using meta-analytic techniques to combine the aggregate survey-by-survey results into one unified measure of association. The pooling of aggregate data was conducted using a random-effects inverse-variance model with DerSimonian-Laird estimate of tau^2. Each inequality estimate was aggregated by survey wave with standard errors and analyzed using random effects for generic effect measures with the *admetan* command (Fisher, 2015; Higgins et al., 2009), and repeated for subgroups of survey year (pre-1995, 1995-2004, and post-2004), outcome (child deaths, stunting, and underweight), and World Bank country-income (low, low-middle, and upper-middle). Overall effect sizes, as well as inequality magnitudes of each subgrouping, were then examined for significant differences between the three major SES measurement methods of income, consumption, and asset indices (or income proxy hybrid for RII and SII).

Results

In most countries, there was a positive association between all three measures of income, consumption, and the asset index. Centiles of income, consumption, and asset indices were plotted against each other for each country in Figures 1-3 to examine the strength of association at different points in the SES distribution.[7] There is a fairly strong and monotonic increase in income for an equivalent increase in consumption in almost every country, with the exception of a relatively flatter distribution in Nigeria for both 2010 and 2012; possibly due to the relatively small sample sizes for Nigerian income data (N=501; 471, respectively). Consumption centiles are also positively associated with asset centiles, albeit somewhat less monotonically, except for a small decrease at the top of the South African asset wealth spectrum and a flat distribution with small decrease at the top of the Tajikistani asset wealth spectrum. Finally, income centiles display a highly variable association with asset index centiles in Cote d'Ivoire and Kyrgyzstan, but generally display a concave, positive overall association. There is no inherent reason to expect strong concordance between these measures in every context, but the strength of agreement between all three measures is notable and indicates that all three measures of SES are related at some level.

Disaggregated health outcome prevalence for stunting, underweight, and child death ratios are presented for survey-specific quintiles (i.e. populations divided into five equal parts) in Appendix Tables 2-3, and kernel-weighted local polynomial plots for each outcome are presented in Appendix Figures 1-3. As expected, there is a decline in prevalence for every outcome over each quintile using all three SES measures. Detailed comparisons of social inequality measures for stunting, underweight, and child death ratios are presented for income, consumption, and asset indices (or hybrid income proxy

[7] No graphs of the predicted income hybrid measure were generated because these would have been identical to asset index graphs.

for RII and SII) using concentration indices in Tables 2-4, RIIs in Tables 5-7, and SIIs in Tables 8-10.[8] Concentration index values are larger in magnitude (i.e. higher inequality) using asset indices for all three outcomes. Overall there are significant concentration index differences between SES measures in 12 of 52 comparisons for stunting, three of 52 comparisons for underweight, and two of 42 comparisons for child deaths. RII values are larger in magnitude (i.e. higher inequality) using hybrid income proxies for all three outcomes. Overall there are significant RII differences between SES measures in 9 of 52 comparisons for stunting, 4 of 52 comparisons for underweight, and 0 of 42 comparisons for child deaths. SII values are larger in magnitude (i.e. higher inequality) using asset indices for all three outcomes. Overall there are significant SII differences between SES measures in 11 of 51 comparisons for stunting, 3 of 49 comparisons for underweight, and 0 of 42 comparisons for child deaths. Most inequality indices were not significantly different from each other, but when they were, asset index-derived indices most often resulted in larger inequalities.

Meta-analysis of all concentration indices indicated no significant difference in the magnitude of inequality between SES measures for outcomes of stunting, underweight, and child deaths (Figure 4). Combining all health outcomes for meta-analysis (Table 11) does not change the result, although asset indices result in the largest magnitudes for every outcome. Meta-analysis of RIIs (Figure 5) reveals a very similar pattern, with all SES measures resulting in magnitudes of inequality that are not

[8] SIIs could not be calculated for Panama 1997 and Peru 1994 (underweight only) because GLM models would not converge

statistically different. The hybrid income proxy, which is based on the household asset index, results in the largest magnitudes of inequality for RIIs (Table 12), except for underweight, which is largest using an income measure. Finally, SII results also indicate non-statistically different magnitudes of inequality for every outcome and SES measure (Figure 6). Like the RII, the SII is largest using the hybrid income proxy for three out of the four outcomes; with inequalities in child deaths being equal using both income and hybrid income proxy (Table 13).

Next, inequality measures were broken down by country-income level and by era (Tables 11-13). Concentration index values clearly increase as countries become richer. Asset indices again result in higher concentration index values in 11 out of 12 instances, although none of the differences are statistically significant. While there are no clear secular changes in concentration index levels, there are hints of a slight increase in the 1995-2004 era. Yet again, there are no statistically different index values, but a suggestive trend emerges, with asset indices resulting in the largest values in seven out of eight comparisons prior to 2005, but income resulting in the largest magnitudes in all four post-2005 comparisons. The clear trend of higher inequalities among richer countries is replicated with RII measures. Once again, there are no significant differences between SES measures, and the hybrid income proxy results in the highest inequality levels in nine of 12 comparisons. Over time, post-2005 RII values are slightly lower than previous eras, but there is no clear time trend mediating SES measures to inequality magnitudes. Finally, SII magnitudes are also largest in higher-income countries (albeit with smaller differences than concentration indices and RIIs), but dominant SES measures change depending on country-income level. The largest SII magnitudes in low-income countries result from the hybrid income proxy in three out of four cases, but income results in the largest magnitudes in all four cases for low-middle income countries and consumption in all four cases in upper-middle income countries. The SII points to generally decreasing inequality over time, and there is no clear time trend mediating SES measures to inequality magnitudes.

Discussion

This first systematic investigation of the effect of SES measures on health inequality magnitudes suggests that the use of asset indices, and the hybrid income proxy based on them, may result in larger magnitudes of inequality than either household consumption or income. The results are tenuous because the relatively small number of studies available for analysis results in wide confidence intervals, but the fact that asset indices (and hybrid income proxy) result in the largest magnitudes of health inequalities for 11 of the 12 different overall outcomes, as well as a majority of every country-income and survey year subgroupings, is strongly indicative of a real difference. Thinking through these results through the lens of risk may allow for even stronger interpretation. A global health researcher may not place much stock in a statistically insignificant pooled effect size, but faced with the risk of a simple change in SES measure resulting in a concentration index for stunting going from to -0.07 to -0.19 in Ghana or going from 0.03

to -0.14 for underweight in Nigeria, the possibility of SES measure having a large impact on the magnitudes of health inequalities becomes more clear.

While we do not observe a clear time trend for health inequality magnitudes postulated by other authors (Wang, 2003), we do replicate results suggesting larger magnitudes of health inequality as country-income levels increase (Filmer and Scott, 2012). In theory, asset indices may be more appropriate measures of household SES in lower income countries because a greater percentage of survey respondents may receive no regular income and consumption patterns may be more irregular and difficult to measure (Bollen et al., 2002; Howe et al., 2012). We find no clear evidence to support this theory, although SII magnitudes were largest in magnitude with the hybrid income proxy for low-income countries only. We also find mixed evidence supporting the idea that any SES measure is resulting in larger magnitudes as time goes on. Moreover, although larger concentration index values shifted from asset indices to household income in more recent survey years, RII and SII trends are inconclusive. Differences between SES measures according to health outcomes did emerge with greater divergence between SES measures for stunting and underweight than child deaths. This may be a statistical effect due to higher prevalence levels affecting the magnitudes of difference between SES measures, or may be indicative of differences between permanent and transitory household SES levels affecting shorter-term and longer-term health outcomes differently.

Lastly, the similarities between absolute and relative inequality measures reveal two important findings. First, the fact that differences in absolute inequalities between lower and higher-income countries are smaller than those of relative health inequalities may be due to lower overall disease prevalence along the entire SES spectrum in the richer countries, with faster progress among higher earners within richer countries (Harper et al., 2010). Second, the finding that, just like the asset indices they are based on, the hybrid income proxy method results in larger inequality measures than income or consumption in most of the cases observed provides evidence that this new method (Fink et al., 2017; Harttgen and Vollmer, 2013) may perform more similarly to asset indices than the household incomes they are supposed to simulate. This is not an issue of measurement error, but researchers using the new method should recognize that although the absolute scale of predicted income is similar to actual household income, the underlying SES construct it is measuring may be closer to that measured by asset indices.

A major strength of this study is that it is the first ever systematic comparison of income, consumption, and asset indices on magnitudes of health inequalities using the same microdata for several countries. While compiling disparate estimations of inequality magnitudes can be suggestive (Howe et al., 2009), rigorous and systematic analysis of microdata is the only way to overcome the uncertainty associated with these efforts. This study also compared only health outcomes that are directly measured and comparable across countries and survey years, and every survey used in analysis is a standardized LSMS survey. In addition, this is the first study to incorporate the new hybrid income proxy measure to investigate the impact of SES measures on health inequality magnitudes. However, by limiting the study to these directly comparable household surveys containing income, consumption, and assets, the size of the compiled dataset was effectively limited to a small number of studies. If more surveys were included for analysis, either by obtaining non-public surveys or by analyzing surveys that did not contain household income or consumption modules, the suggestive differences observed may have become statistically significant at the 95% confidence level. The study was also limited by small sample sizes reporting household income in some survey waves, but this is a limitation inherent in the collection of income data from low income countries motivating many to use consumption or asset measures rather than income data. It is also possible that the countries sampled by the World Bank, or the countries that chose to include health modules, may be systematically different than countries sampled for DHS or MICS surveys.

These results matter for global health researchers, for multilateral organizations, and for development economists. Global health researchers should be cognizant that their choice of SES measure is not innocuous, as choosing an asset index over household income may represent a more permanent marker of household SES and may result in a larger magnitude of inequality. Although this study takes no normative stance on the presence of larger inequalities being a marker of a superior SES measure, the mere presence of difference must be acknowledged and accounted for. This is why multilateral organizations such as the World Bank, USAID, and UNICEF should investigate the effects of their preferred SES measures more thoroughly and inform country partners and researchers of the implications of their choices. Finally, development economists should begin studying the pathways linking SES, whether it is measured using income, consumption, or household assets, with health outcomes. If magnitudes of social health inequality are systematically different depending on the choice of household SES measure, there must be a causal link mediating SES and health through one or more pathways that have yet to be fully identified. There is clearly more research to be done with a more comprehensive set of household surveys and health outcomes, but the apparent increase in the magnitude of health inequalities with the use of asset indices to measure household SES suggests that income, consumption, and asset indices are not as equal as commonly assumed.

Table 1. Summary of health outcome prevalence for all Living Standards Measurement Surveys (LSMS) included for analysis. All outcomes are not population weighted, and are therefore not indicators of population-level health.

Survey Code	Country	Year	Mean Child Death Ratio	Prevalence Stunting	Prevalence Underweight
ALB_2002	Albania	2002	0.03	0.43	0.10
BRA_1996	Brazil	1996	0.04	0.20	0.06
CIV_1987	Cote d'Ivoire	1987	0.12	0.18	0.10
CIV_1988	Cote d'Ivoire	1988	0.12	0.19	0.11
GHA_1988	Ghana	1988	0.14	0.34	0.22
GHA_2009	Ghana	2009	0.06	0.29	0.22
GTM_2000	Guatemala	2000	0.07	0.50	0.17
GUY_1992	Guyana	1992	0.07	0.14	0.13
KGZ_1997	Kyrgyzstan	1997		0.37	0.10
KGZ_1998	Kyrgyzstan	1998	0.03	0.41	0.14
NGA_2010	Nigeria	2010		0.37	0.28
NGA_2012	Nigeria	2012		0.21	0.11
PAK_1991	Pakistan	1991	0.13	0.44	0.38
PAN_1997	Panama	1997	0.02	0.20	0.06
PAN_2003	Panama	2003	0.03	0.29	0.06
PER_1994	Peru	1994	0.06	0.34	0.09
TJK_2007	Tajikistan	2007	0.06	0.38	0.15
TLS_2007	Timor-Leste	2007	0.07	0.45	0.42
TZA_2010	Tanzania	2010		0.32	0.13
UGA_2011	Uganda	2011	0.11	0.21	0.08
UGA_2013	Uganda	2013	0.09	0.21	0.07
ZAF_1993	South Africa	1993	0.10	0.26	0.13

Table 2. Stunting concentration index values for each survey wave with income, consumption, and asset index comparison.[21]

		Income					Consumption					Assets					SES Measure Comparisons		
Country	Year	Obs.	Index value	Std. error	UCI	LCI	Obs.	Index value	Std. error	UCI	LCI	Obs.	Index value	Std. error	UCI	LCI	Inc. vs. Cons.	Inc. vs. Assets	Cons. Vs. Assets
Albania	2002	1338	-0.08	0.03	-0.02	-0.14	1338	-0.01	0.03	0.05	-0.07	1333	-0.03	0.03	0.03	-0.09	Same	Same	Same
Brazil	1996	1647	-0.21	0.04	-0.14	-0.28						1762	-0.25	0.03	-0.18	-0.31		Same	
Cote d'Ivoire	1987	2215	-0.12	0.03	-0.06	-0.18	2233	-0.17	0.03	-0.11	-0.23	2206	-0.09	0.03	-0.03	-0.15	Same	Same	Same
Cote d'Ivoire	1988	2105	-0.09	0.03	-0.02	-0.15	2121	-0.14	0.03	-0.08	-0.20	2117	-0.04	0.03	0.02	-0.10	Same	Same	Same
Ghana	1988						2906	-0.07	0.02	-0.03	-0.12	2898	-0.19	0.02	-0.15	-0.24			Lower
Ghana	2009						2931	-0.07	0.02	-0.02	-0.11	2607	-0.18	0.02	-0.14	-0.23			Lower
Guatemala	2000	5743	-0.22	0.01	-0.19	-0.25	5743	-0.28	0.01	-0.25	-0.31	5743	-0.28	0.01	-0.26	-0.31	Lower	Lower	Same
Guyana	1992	601	-0.04	0.07	0.09	-0.17	601	-0.11	0.07	0.02	-0.24	601	0.03	0.07	0.16	-0.10	Same	Same	Same
Kyrgyzstan	1997	1162	-0.06	0.04	0.00	-0.13	1163	-0.14	0.03	-0.08	-0.21	1113	0.01	0.04	0.08	-0.06	Same	Same	Higher
Kyrgyzstan	1998	1689	-0.06	0.03	-0.01	-0.12	1727	-0.08	0.03	-0.02	-0.13	1643	-0.02	0.03	0.04	-0.07	Same	Same	Same
Nigeria	2010	282	-0.27	0.07	-0.13	-0.40	2576	-0.05	0.02	0.00	-0.09	2404	-0.15	0.02	-0.10	-0.19	Higher	Same	Lower
Nigeria	2012	205	0.07	0.10	0.27	-0.12	2737	-0.04	0.03	0.02	-0.09	2766	-0.06	0.03	-0.01	-0.11	Same	Same	Same
Pakistan	1991	3911	-0.12	0.02	-0.08	-0.15	3916	-0.09	0.02	-0.05	-0.13	3903	-0.14	0.02	-0.11	-0.18	Same	Same	Same
Panama	1997						2294	-0.52	0.03	-0.46	-0.57	2292	-0.61	0.03	-0.55	-0.66	Lower	Lower	Same
Panama	2003	2922	-0.24	0.02	-0.20	-0.29	2922	-0.35	0.02	-0.30	-0.39	2922	-0.44	0.02	-0.40	-0.48			Lower
Peru	1994	2296	-0.28	0.02	-0.23	-0.32	2296	-0.34	0.02	-0.30	-0.39	2228	-0.38	0.02	-0.33	-0.43	Same	Lower	Same
Tajikistan	2007						2701	-0.02	0.02	0.02	-0.07	2694	-0.15	0.02	-0.10	-0.19			Lower
Timor-Leste	2007						3937	0.06	0.02	0.09	0.02	3937	0.04	0.02	0.07	0.00			Same
Tanzania	2010						2971	-0.16	0.02	-0.12	-0.20	2993	-0.18	0.02	-0.13	-0.22			Same
Uganda	2011	2276	-0.09	0.03	-0.03	-0.15	2511	-0.11	0.03	-0.05	-0.16	2504	-0.15	0.03	-0.09	-0.21	Same	Same	Same
Uganda	2013	187	-0.17	0.12	0.06	-0.40	2583	-0.13	0.03	-0.08	-0.19	2580	-0.13	0.03	-0.07	-0.18	Same	Same	Same
South Africa	1993	4876	-0.21	0.02	-0.17	-0.24	4960	-0.22	0.02	-0.18	-0.25	4967	-0.20	0.02	-0.16	-0.24	Same	Same	Same
Median			-0.12					-0.11					-0.15						
Average			-0.14					-0.14					-0.16						
Max			0.07					0.06					0.04						
Min			-0.28					-0.52					-0.61						

[21] For income, consumption, and asset columns red cells indicate the highest levels of inequality, yellow the middle value, and green the lowest levels. For comparison columns, green indicates a statistically significant (95%) lower level and red a significantly higher level.

Table 3. Underweight concentration index values for each survey wave with income, consumption, and asset index comparison.[22]

		Income					Consumption					Assets					SES Measure Comparisons		
Country	Year	Obs.	Index value	Std. error	UCI	LCI	Obs.	Index value	Std. error	UCI	LCI	Obs.	Index value	Std. error	UCI	LCI	Inc. vs. Cons.	Inc. vs. Assets	Cons. Vs. Assets
Albania	2002	1338	-0.15	0.05	-0.05	-0.26	1338	-0.06	0.05	0.04	-0.17	1333	-0.04	0.05	0.07	-0.14	Same	Same	Same
Brazil	1996	1647	-0.24	0.06	-0.12	-0.36						1762	-0.28	0.06	-0.16	-0.39		Same	
Cote d'Ivoire	1987	2215	-0.06	0.04	0.02	-0.14	2233	-0.05	0.04	0.02	-0.13	2206	-0.11	0.04	-0.03	-0.19	Same	Same	Same
Cote d'Ivoire	1988	2105	-0.05	0.04	0.03	-0.13	2121	-0.07	0.04	0.01	-0.15	2117	-0.10	0.04	-0.02	-0.18	Same	Same	Same
Ghana	1988						2906	-0.05	0.03	0.00	-0.10	2898	-0.18	0.03	-0.13	-0.23			Lower
Ghana	2009						2931	-0.07	0.03	-0.02	-0.12	2607	-0.11	0.03	-0.06	-0.16			Same
Guatemala	2000	5743	-0.20	0.02	-0.16	-0.24	5743	-0.24	0.02	-0.20	-0.28	5743	-0.26	0.02	-0.22	-0.30	Same	Same	Same
Guyana	1992	601	-0.04	0.07	0.10	-0.18	601	-0.14	0.07	-0.01	-0.28	601	-0.06	0.07	0.08	-0.20	Same	Same	Same
Kyrgyzstan	1997	1162	-0.15	0.06	-0.04	-0.26	1163	-0.13	0.06	-0.03	-0.24	1113	0.06	0.06	0.18	-0.05	Same	Same	Same
Kyrgyzstan	1998	1689	0.02	0.04	0.10	-0.06	1727	0.05	0.04	0.13	-0.03	1643	-0.04	0.04	0.04	-0.12	Same	Same	Same
Nigeria	2010	282	-0.22	0.08	-0.06	-0.37	2576	0.03	0.03	0.08	-0.02	2404	-0.14	0.03	-0.09	-0.19	Higher	Same	Lower
Nigeria	2012	205	0.01	0.14	0.29	-0.27	2737	-0.06	0.03	0.00	-0.13	2766	-0.07	0.03	0.00	-0.14	Same	Same	Same
Pakistan	1991	3911	-0.11	0.02	-0.08	-0.15	3916	-0.11	0.02	-0.07	-0.14	3903	-0.14	0.02	-0.11	-0.18	Same	Same	Same
Panama	1997						2294	-0.43	0.05	-0.33	-0.53	2292	-0.51	0.05	-0.41	-0.61			Same
Panama	2003	2922	-0.27	0.05	-0.18	-0.36	2922	-0.32	0.05	-0.23	-0.40	2922	-0.44	0.04	-0.36	-0.53	Same	Same	Same
Peru	1994	2296	-0.33	0.04	-0.25	-0.41	2296	-0.35	0.04	-0.27	-0.43	2228	-0.39	0.04	-0.31	-0.48	Same	Same	Same
Tajikistan	2007						2701	0.03	0.03	0.09	-0.03	2694	-0.06	0.03	0.00	-0.13			Same
Timor-Leste	2007						3937	0.01	0.02	0.04	-0.03	3937	-0.01	0.02	0.03	-0.04			Same
Tanzania	2010						2971	-0.12	0.03	-0.06	-0.18	2993	-0.14	0.03	-0.08	-0.20			Same
Uganda	2011	2276	-0.15	0.05	-0.06	-0.24	2511	-0.23	0.04	-0.14	-0.31	2504	-0.20	0.04	-0.12	-0.29	Same	Same	Same
Uganda	2013	187	0.04	0.20	0.42	-0.35	2583	-0.13	0.04	-0.04	-0.21	2580	-0.20	0.04	-0.12	-0.29	Same	Same	Same
South Africa	1993	4876	-0.16	0.02	-0.11	-0.21	4960	-0.14	0.02	-0.09	-0.18	4967	-0.11	0.02	-0.06	-0.16	Same	Same	Same
Median			-0.15					-0.11					-0.13						
Average			-0.13					-0.12					-0.16						
Max			0.04					0.05					0.06						
Min			-0.33					-0.43					-0.51						

[22] For income, consumption, and asset columns red cells indicate the highest levels of inequality, yellow the middle value, and green the lowest levels. For comparison columns, green indicates a statistically significant (95%) lower level and red a significantly higher level.

Table 4. Child deaths concentration index values for each survey wave with income, consumption, and asset index comparison.[23]

		Income					Consumption					Assets					SES Measure Comparisons		
Country	Year	Obs.	Index value	Std. error	UCI	LCI	Obs.	Index value	Std. error	UCI	LCI	Obs.	Index value	Std. error	UCI	LCI	Inc. vs. Cons.	Inc. vs. Assets	Cons. Vs. Assets
Albania	2002	2662	-0.25	0.04	-0.17	-0.32	2662	-0.18	0.04	-0.10	-0.25	2655	-0.22	0.04	-0.15	-0.30	Same	Same	Same
Brazil	1996	3020	-0.31	0.03	-0.24	-0.37						3241	-0.34	0.03	-0.28	-0.40		Same	
Cote d'Ivoire	1987	1002	-0.16	0.04	-0.09	-0.23	1015	-0.23	0.04	-0.16	-0.30	1002	-0.25	0.04	-0.18	-0.32	Same	Same	Same
Cote d'Ivoire	1988	1061	-0.08	0.03	-0.01	-0.15	1067	-0.12	0.03	-0.05	-0.19	1065	-0.19	0.03	-0.13	-0.26	Same	Same	Same
Ghana	1988						1813	-0.11	0.02	-0.06	-0.15	1810	-0.12	0.02	-0.07	-0.16			Same
Ghana	2009						2835	-0.13	0.03	-0.07	-0.18	2526	-0.26	0.03	-0.20	-0.32			Lower
Guatemala	2000	5929	-0.14	0.02	-0.11	-0.18	5929	-0.18	0.02	-0.14	-0.22	5929	-0.17	0.02	-0.13	-0.21	Same	Same	Same
Guyana	1992	936	-0.13	0.05	-0.03	-0.22	936	-0.07	0.05	0.02	-0.16	936	-0.04	0.05	0.05	-0.14	Same	Same	Same
Kyrgyzstan	1998	2377	-0.09	0.04	0.00	-0.18	2433	0.00	0.04	0.08	-0.09	2326	-0.03	0.04	0.05	-0.12	Same	Same	Same
Pakistan	1991	4557	-0.11	0.02	-0.08	-0.14	4564	-0.13	0.02	-0.10	-0.16	4533	-0.15	0.02	-0.12	-0.18	Same	Same	Same
Panama	1997						3495	-0.35	0.04	-0.27	-0.42	3487	-0.37	0.04	-0.29	-0.44			Same
Panama	2003	4522	-0.09	0.04	-0.02	-0.16	4522	-0.22	0.04	-0.15	-0.29	4521	-0.25	0.04	-0.17	-0.32	Same	Lower	Same
Peru	1994	2922	-0.22	0.03	-0.17	-0.28	2922	-0.25	0.03	-0.20	-0.31	2841	-0.27	0.03	-0.21	-0.32	Same	Same	Same
Tajikistan	2007						4481	-0.08	0.03	-0.03	-0.13	4454	-0.04	0.03	0.01	-0.09			Same
Timor-Leste	2007						3258	-0.14	0.02	-0.10	-0.19	3258	-0.14	0.02	-0.09	-0.19			Same
Uganda	2011	1602	-0.14	0.03	-0.09	-0.19	1748	-0.13	0.03	-0.08	-0.18	1753	-0.13	0.03	-0.08	-0.18	Same	Same	Same
Uganda	2013	152	-0.07	0.09	0.11	-0.25	2129	-0.12	0.02	-0.07	-0.16	2125	-0.08	0.02	-0.03	-0.13	Same	Same	Same
South Africa	1993	6828	-0.19	0.02	-0.15	-0.22	6940	-0.23	0.02	-0.19	-0.26	6964	-0.21	0.02	-0.17	-0.24	Same	Same	Same
Median			-0.14					-0.13					-0.18						
Average			-0.15					-0.16					-0.18						
Max			-0.07					0.00					-0.03						
Min			-0.31					-0.35					-0.37						

[23] For income, consumption, and asset columns red cells indicate the highest levels of inequality, yellow the middle value, and green the lowest levels. For comparison columns, green indicates a statistically significant (95%) lower level and red a significantly higher level.

Table 5. Stunting RII values for each survey wave with income, consumption, and asset index comparison.[24]

		Income				Consumption				Hybrid				SES Measure Comparisons		
Country	Year	RII	LCI	UCI	Obs.	RII	LCI	UCI	Obs.	RII	LCI	UCI	Obs.	Inc. vs. Cons.	Inc. vs. Hybrid	Cons. Vs. Hybrid
Albania	2002	1.30	1.05	1.59	1,338	1.03	0.84	1.26	1,338	1.12	0.90	1.39	1,333	Same	Same	Same
Brazil	1996	2.86	2.03	4.03	1,647					3.44	2.46	4.81	1,762		Same	
Cote d'Ivoire	1987	1.81	1.32	2.46	2,215	2.29	1.69	3.13	2,233	1.56	1.14	2.13	2,206	Same	Same	Same
Cote d'Ivoire	1988	1.52	1.12	2.06	2,105	1.97	1.45	2.68	2,121	1.23	0.90	1.66	2,117	Same	Same	Same
Ghana	1988					1.32	1.11	1.57	2,906	2.02	1.70	2.38	2,898			Lower
Ghana	2009					1.33	1.10	1.62	2,931	2.19	1.78	2.70	2,607			Lower
Guatemala	2000	1.86	1.71	2.03	5,743	2.20	2.02	2.40	5,743	2.15	1.97	2.34	5,743	Same	Same	Same
Guyana	1992	1.24	0.63	2.46	601	1.77	0.90	3.51	601	0.86	0.44	1.69	601	Same	Same	Same
Kyrgyzstan	1998	1.27	0.98	1.64	1,162	1.70	1.32	2.20	1,163	0.98	0.76	1.27	1,113	Same	Same	Higher
Kyrgyzstan	1998	1.25	1.02	1.52	1,689	1.31	1.07	1.59	1,727	1.06	0.87	1.29	1,643	Same	Same	Same
Nigeria	2010	2.42	1.48	3.95	282	1.20	1.00	1.43	2,576	1.75	1.45	2.10	2,404	Higher	Same	Lower
Nigeria	2012	0.72	0.29	1.89	205	1.19	0.93	1.52	2,737	1.31	1.03	1.68	2,766	Same	Same	Same
Pakistan	1991	1.44	1.28	1.62	3,911	1.35	1.19	1.52	3,916	1.57	1.40	1.78	3,903	Same	Same	Same
Panama	1997					16.45	11.85	23.26	2,294	27.78	19.92	40.00	2,292			Same
Panama	2003	2.86	2.34	3.48	2,922	4.65	3.79	5.71	2,922	7.81	6.33	9.71	2,922	Lower	Lower	Lower
Peru	1994	2.93	2.41	3.57	2,296	3.79	3.12	4.61	2,296	4.29	3.52	5.24	2,228	Same	Same	Same
Tajikistan	2007					1.08	0.92	1.28	2,701	1.72	1.46	2.03	2,694			Lower
Timor-Leste	2007					0.83	0.74	0.94	3,937	0.88	0.78	0.99	3,937			Same
Tanzania	2010					1.94	1.61	2.33	2,971	2.01	1.68	2.40	2,993			Same
Uganda	2011	1.54	1.17	2.04	2,276	1.67	1.28	2.17	2,511	2.04	1.56	2.67	2,504	Same	Same	Same
Uganda	2013	2.44	0.72	8.26	187	1.86	1.44	2.42	2,583	1.80	1.39	2.33	2,580	Same	Same	Same
South Africa	1993	2.46	2.08	2.89	4,876	2.64	2.24	3.12	4,960	2.41	2.04	2.84	4,967	Same	Same	Same
Median		1.67				1.70				1.77						
Average		1.87				2.55				3.27						
Max		2.93				16.45				27.78						
Min		0.72				0.83				0.86						

[24] For income, consumption, and asset index columns red cells indicate the highest levels of inequality, yellow the middle value, and green the lowest levels. For comparison columns, green indicates a statistically significant (95%) lower level and red a significantly higher level.

Table 6. Underweight RII values for each survey wave with income, consumption, and asset index comparison.[25]

		Income				Consumption				Hybrid				SES Measure Comparisons		
Country	Year	RII	LCI	UCI	Obs.	RII	LCI	UCI	Obs.	RII	LCI	UCI	Obs.	Inc. vs. Cons.	Inc. vs. Hybrid	Cons. Vs. Hybrid
Albania	2002	2.29	1.32	3.97	1,338	1.41	0.82	2.44	1,338	1.21	0.70	2.09	1,333	Same	Same	Same
Brazil	1996	4.07	2.00	8.26	1,647					5.21	2.59	10.53	1,762		Same	
Cote d'Ivoire	1987	1.37	0.89	2.08	2,215	1.33	0.88	2.02	2,233	1.81	1.17	2.78	2,206	Same	Same	Same
Cote d'Ivoire	1988	1.29	0.84	1.99	2,105	1.46	0.95	2.24	2,121	1.73	1.12	2.65	2,117	Same	Same	Same
Ghana	1988					1.27	1.00	1.61	2,906	2.20	1.75	2.79	2,898			Higher
Ghana	2009					1.41	1.11	1.78	2,931	1.68	1.30	2.16	2,607			Same
Guatemala	2000	2.69	2.20	3.28	5,743	3.33	2.72	4.08	5,743	3.57	2.92	4.37	5,743	Same	Same	Same
Guyana	1992	1.21	0.59	2.51	601	2.10	1.01	4.35	601	1.36	0.66	2.80	601	Same	Same	Same
Kyrgyzstan	1998	2.30	1.26	4.18	1,162	2.10	1.15	3.82	1,163	0.71	0.39	1.30	1,113	Same	Same	Same
Kyrgyzstan	1998	0.88	0.59	1.33	1,689	0.78	0.52	1.17	1,727	1.20	0.80	1.81	1,643	Same	Same	Same
Nigeria	2010	2.52	1.25	5.08	282	0.88	0.71	1.09	2,576	1.83	1.46	2.29	2,404	Lower	Same	Higher
Nigeria	2012	0.96	0.21	4.37	205	1.41	0.98	2.03	2,737	1.47	1.02	2.11	2,766	Same	Same	Same
Pakistan	1991	1.50	1.31	1.72	3,911	1.49	1.29	1.71	3,916	1.71	1.48	1.96	3,903	Same	Same	Same
Panama	1997					14.97	7.69	29.41	2,294	30.49	14.77	66.67	2,292			
Panama	2003	4.90	2.87	8.40	2,922	6.54	3.77	11.36	2,922	17.01	9.35	31.25	2,922	Same	Higher	Same
Peru	1994	6.85	4.17	11.36	2,296	7.75	4.69	12.82	2,296	10.20	6.06	17.24	2,228	Same	Same	Same
Tajikistan	2007					0.87	0.63	1.19	2,701	1.38	1.01	1.88	2,694			Same
Timor-Leste	2007					0.98	0.86	1.11	3,937	1.02	0.90	1.16	3,937			Same
Tanzania	2010					1.87	1.36	2.58	2,971	2.04	1.49	2.80	2,993			Same
Uganda	2011	2.28	1.37	3.77	2,276	3.72	2.27	6.06	2,511	3.11	1.91	5.08	2,504	Same	Same	Same
Uganda	2013	0.82	0.09	7.25	187	2.05	1.27	3.30	2,583	3.15	1.93	5.13	2,580	Same	Same	Same
South Africa	1993	2.27	1.76	2.92	4,876	2.04	1.58	2.63	4,960	1.75	1.36	2.25	4,967	Same	Same	Same
Median		2.27				1.49				1.78						
Average		2.39				2.85				4.36						
Max		6.85				14.97				30.49						
Min		0.82				0.78				0.71						

[25] For income, consumption, and asset columns red cells indicate the highest levels of inequality, yellow the middle value, and green the lowest levels. For comparison columns, green indicates a statistically significant (95%) lower level and red a significantly higher level.

Table 7. Child death RII values for each survey wave with income, consumption, and asset index comparison.[26]

		Income				Consumption				Hybrid				SES Measure Comparisons		
Country	Year	RII	LCI	UCI	Obs.	RII	LCI	UCI	Obs.	RII	LCI	UCI	Obs.	Inc. vs. Cons.	Inc. vs. Hybrid	Cons. Vs. Hybrid
Albania	2002	4.46	2.03	9.80	2,662	2.87	1.33	6.17	2,662	3.75	1.72	8.20	2,655	Same	Same	Same
Brazil	1996	6.45	3.44	12.20	3,020					8.20	4.42	15.15	3,241		Same	
Cote d'Ivoire	1987	2.37	1.32	4.27	1,002	3.52	1.93	6.41	1,015	3.95	2.16	7.25	1,002	Same	Same	Same
Cote d'Ivoire	1988	1.54	0.88	2.70	1,061	1.87	1.06	3.30	1,067	2.82	1.59	5.00	1,065	Same	Same	Same
Ghana	1988					1.74	1.17	2.58	1,813	1.82	1.23	2.70	1,810			Same
Ghana	2009					2.04	1.23	3.38	2,835	4.50	2.53	8.00	2,526			Same
Guatemala	2000	2.26	1.61	3.16	5,929	2.81	2.00	3.94	5,929	2.65	1.89	3.72	5,929	Same	Same	Same
Guyana	1992	2.00	0.89	4.50	936	1.47	0.66	3.30	936	1.27	0.56	2.86	936	Same	Same	Same
Kyrgyzstan	1998	1.69	0.78	3.68	2,377	1.03	0.49	2.17	2,433	1.23	0.57	2.63	2,326	Same	Same	Same
Pakistan	1991	1.80	1.39	2.33	4,557	1.96	1.51	2.54	4,564	2.20	1.69	2.85	4,533	Same	Same	Same
Panama	1997					9.01	3.88	21.28	3,495	10.36	4.41	24.39	3,487			Same
Panama	2003	1.70	0.91	3.18	4,522	3.76	1.96	7.19	4,522	4.44	2.30	8.62	4,521	Same	Same	Same
Peru	1994	3.58	2.18	5.88	2,922	4.31	2.60	7.09	2,922	4.76	2.86	7.94	2,841	Same	Same	Same
Tajikistan	2007					1.60	1.07	2.40	4,481	1.25	0.84	1.88	4,454			Same
Timor-Leste	2007					2.24	1.45	3.45	3,258	2.18	1.42	3.36	3,258			Same
Uganda	2011	2.09	1.28	3.42	1,602	1.96	1.22	3.15	1,748	1.95	1.22	3.13	1,753	Same	Same	Same
Uganda	2013	1.50	0.23	10.00	152	1.93	1.20	3.12	2,129	1.57	0.99	2.51	2,125	Same	Same	Same
South Africa	1993	2.76	2.14	3.56	6,828	3.51	2.71	4.55	6,940	3.13	2.42	4.03	6,964	Same	Same	Same
Median		2.09				2.04				2.74						
Average		2.63				2.80				3.45						
Max		6.45				9.01				10.36						
Min		1.50				1.03				1.23						

[26] For income, consumption, and asset columns red cells indicate the highest levels of inequality, yellow the middle value, and green the lowest levels. For comparison columns, green indicates a statistically significant (95%) lower level and red a significantly higher level.

Table 8. Stunting SII values for each survey wave with income, consumption, and asset index comparison.[27]

		Income				Consumption				Hybrid				SES Measure Comparisons		
Country	Year	SII	LCI	UCI	Obs.	SII	LCI	UCI	Obs.	SII	LCI	UCI	Obs.	Inc. vs. Cons.	Inc. vs. Hybrid	Cons. Vs. Hybrid
Albania	2002	-0.12	-0.21	0.03	1,338	-0.01	-0.11	0.08	1,338	-0.05	-0.14	0.04	1,333	Same	Same	Same
Brazil	1996	-0.19	-0.26	-0.13	1,647					-0.22	-0.28	-0.16	1,762		Same	
Cote d'Ivoire	1987	-0.10	-0.16	0.05	2,215	-0.15	-0.21	0.10	2,233	-0.07	-0.13	0.02	2,206	Same	Same	Same
Cote d'Ivoire	1988	-0.08	-0.14	0.02	2,105	-0.12	-0.18	0.07	2,121	-0.04	-0.09	0.02	2,117	Same	Same	Same
Ghana	1988					-0.10	-0.16	0.04	2,906	-0.28	-0.34	-0.22	2,898			Lower
Ghana	2009					-0.09	-0.15	0.03	2,931	-0.23	-0.29	-0.17	2,607			Lower
Guatemala	2000	-0.33	-0.37	-0.29	5,743	-0.42	-0.46	-0.38	5,743	-0.43	-0.47	-0.39	5,743	Lower	Lower	Same
Guyana	1992	-0.03	-0.13	0.07	601	-0.09	-0.19	0.01	601	0.02	-0.08	0.12	601	Same	Same	Same
Kyrgyzstan	1998	-0.09	-0.19	0.00	1,162	-0.21	-0.30	-0.11	1,163	0.01	-0.09	0.11	1,113	Same	Same	Higher
Kyrgyzstan	1998	-0.09	-0.17	0.01	1,689	-0.11	-0.19	0.03	1,727	-0.03	-0.11	0.06	1,643	Same	Same	Same
Nigeria	2010	-0.41	-0.61	-0.22	282	-0.07	-0.13	0.00	2,576	-0.21	-0.27	-0.14	2,404	Higher	Same	Lower
Nigeria	2012	0.08	-0.12	0.28	205	-0.04	-0.09	0.02	2,737	-0.06	-0.12	0.01	2,766	Same	Same	Same
Pakistan	1991	-0.17	-0.23	-0.12	3,911	-0.13	-0.19	0.08	3,916	-0.21	-0.27	-0.16	3,903	Same	Same	Same
Panama	1997															
Panama	2003	-0.30	-0.36	-0.25	2,922	-0.41	-0.47	-0.36	2,922	-0.49	-0.54	-0.44	2,922	Lower	Lower	Same
Peru	1994	-0.38	-0.44	-0.32	2,296	-0.47	-0.54	-0.41	2,296	-0.53	-0.59	-0.47	2,228	Same	Lower	Same
Tajikistan	2007					-0.03	-0.10	0.03	2,701	-0.21	-0.27	-0.15	2,694			Lower
Timor-Leste	2007					0.08	0.03	0.14	3,937	0.06	0.00	0.11	3,937			Same
Tanzania	2010					-0.21	-0.26	-0.15	2,971	-0.25	-0.30	-0.19	2,993			Same
Uganda	2011	-0.10	-0.15	0.04	2,276	-0.11	-0.17	0.06	2,511	-0.15	-0.21	0.10	2,504	Same	Same	Same
Uganda	2013	-0.11	-0.27	0.05	187	-0.14	-0.20	0.08	2,583	-0.14	-0.19	0.08	2,580	Same	Same	Same
South Africa	1993	-0.25	-0.30	-0.21	4,876	-0.26	-0.30	-0.22	4,960	-0.24	-0.28	-0.20	4,967	Same	Same	Same
Median		-0.11				-0.12				-0.21						
Average		-0.17				-0.15				-0.18						
Max		0.08				0.08				0.06						
Min		-0.41				-0.47				-0.53						

[27] For income, consumption, and asset index columns red cells indicate the highest levels of inequality, yellow the middle value, and green the lowest levels. For comparison columns, green indicates a statistically significant (95%) lower level and red a significantly higher level.

Table 9. Underweight SII values for each survey wave with income, consumption, and asset index comparison.[28]

		Income				Consumption				Hybrid				SES Measure Comparisons		
Country	Year	SII	LCI	UCI	Obs.	SII	LCI	UCI	Obs.	SII	LCI	UCI	Obs.	Inc. vs. Cons.	Inc. vs. Hybrid	Cons. Vs. Hybrid
Albania	2002	-0.09	-0.15	0.04	1,338	-0.04	-0.10	0.02	1,338	-0.02	-0.08	0.04	1,333	Same	Same	Same
Brazil	1996	-0.08	-0.11	0.04	1,647					-0.08	-0.11	0.05	1,762		Same	
Cote d'Ivoire	1987	-0.04	-0.08	0.01	2,215	-0.03	-0.08	0.01	2,233	-0.06	-0.10	0.01	2,206	Same	Same	Same
Cote d'Ivoire	1988	-0.03	-0.07	0.02	2,105	-0.04	-0.08	0.01	2,121	-0.06	-0.10	0.01	2,117	Same	Same	Same
Ghana	1988					-0.06	-0.11	0.00	2,906	-0.21	-0.26	-0.15	2,898			Lower
Ghana	2009					-0.08	-0.13	0.03	2,931	-0.12	-0.17	0.06	2,607			Same
Guatemala	2000	-0.18	-0.21	-0.15	5,743	-0.22	-0.25	-0.19	5,743	-0.25	-0.28	-0.22	5,743	Same	Lower	Same
Guyana	1992	-0.03	-0.12	0.07	601	-0.11	-0.21	0.01	601	-0.04	-0.14	0.05	601	Same	Same	Same
Kyrgyzstan	1998	-0.08	-0.14	0.02	1,162	-0.07	-0.13	0.01	1,163	0.03	-0.03	0.09	1,113	Same	Same	Same
Kyrgyzstan	1998	0.02	-0.04	0.07	1,689	0.04	-0.02	0.10	1,727	-0.03	-0.09	0.03	1,643	Same	Same	Same
Nigeria	2010	-0.26	-0.43	0.09	282	0.04	-0.02	0.10	2,576	-0.17	-0.23	-0.11	2,404	Same	Same	Lower
Nigeria	2012	0.00	-0.14	0.15	205	-0.04	-0.08	0.00	2,737	-0.05	-0.09	0.00	2,766	Same	Same	Same
Pakistan	1991	-0.16	-0.22	-0.11	3,911	-0.15	-0.21	-0.10	3,916	-0.20	-0.25	-0.15	3,903	Same	Same	Same
Panama	1997															
Panama	2003	-0.09	-0.12	0.06	2,922	-0.10	-0.12	0.07	2,922	-0.11	-0.13	0.09	2,922	Same	Same	Same
Peru	1994	-0.14	-0.17	-0.11	2,296	-0.15	-0.19	-0.12	2,296					Same		
Tajikistan	2007					0.02	-0.03	0.07	2,701	-0.05	-0.10	0.00	2,694			Same
Timor-Leste	2007					0.01	-0.04	0.06	3,937	-0.01	-0.06	0.04	3,937			Same
Tanzania	2010					-0.08	-0.12	0.04	2,971	-0.11	-0.15	0.06	2,993			Same
Uganda	2011	-0.06	-0.10	0.03	2,276	-0.09	-0.13	0.06	2,511	-0.08	-0.12	0.05	2,504	Same	Same	Same
Uganda	2013	0.02	-0.13	0.17	187	-0.06	-0.09	0.02	2,583	-0.09	-0.12	0.05	2,580	Same	Same	Same
South Africa	1993	-0.12	-0.16	0.09	4,876	-0.10	-0.13	0.07	4,960	-0.09	-0.13	0.06	4,967	Same	Same	Same
Median		-0.08				-0.06				-0.08						
Average		-0.08				-0.07				-0.09						
Max		0.02				0.04				0.03						
Min		-0.26				-0.22				-0.25						

[28] For income, consumption, and asset columns red cells indicate the highest levels of inequality, yellow the middle value, and green the lowest levels. For comparison columns, green indicates a statistically significant (95%) lower level and red a significantly higher level.

Table 10. Child death SII values for each survey wave with income, consumption, and asset index comparison.[29]

		Income				Consumption				Hybrid				SES Measure Comparisons		
Country	Year	SII	LCI	UCI	Obs.	SII	LCI	UCI	Obs.	SII	LCI	UCI	Obs.	Inc. vs. Cons.	Inc. vs. Hybrid	Cons. Vs. Hybrid
Albania	2002	-0.04	-0.06	0.02	2,662	-0.03	-0.06	0.01	2,662	-0.04	-0.06	0.02	2,655	Same	Same	Same
Brazil	1996	-0.07	-0.09	0.05	3,020					-0.08	-0.10	0.06	3,241		Same	
Cote d'Ivoire	1987	-0.11	-0.17	0.04	1,002	-0.14	-0.21	0.08	1,015	-0.17	-0.23	0.10	1,002	Same	Same	Same
Cote d'Ivoire	1988	-0.06	-0.13	0.01	1,061	-0.07	-0.14	0.01	1,067	-0.12	-0.19	0.06	1,065	Same	Same	Same
Ghana	1988					-0.08	-0.13	0.02	1,813	-0.09	-0.14	0.03	1,810			Same
Ghana	2009					-0.05	-0.08	0.02	2,835	-0.08	-0.11	0.05	2,526			Same
Guatemala	2000	-0.05	-0.07	0.03	5,929	-0.07	-0.09	0.05	5,929	-0.06	-0.09	0.04	5,929	Same	Same	Same
Guyana	1992	-0.06	-0.11	0.00	936	-0.03	-0.09	0.03	936	-0.02	-0.07	0.04	936	Same	Same	Same
Kyrgyzstan	1998	-0.02	-0.04	0.01	2,377	0.00	-0.03	0.02	2,433	-0.01	-0.03	0.02	2,326	Same	Same	Same
Pakistan	1991	-0.08	-0.11	0.04	4,557	-0.08	-0.12	0.05	4,564	-0.11	-0.15	0.08	4,533	Same	Same	Same
Panama	1997					-0.04	-0.05	0.02	3,495	-0.04	-0.05	0.03	3,487			Same
Panama	2003	-0.01	-0.03	0.00	4,522	-0.03	-0.04	0.01	4,522	-0.03	-0.05	0.02	4,521	Same	Same	Same
Peru	1994	-0.08	-0.11	0.05	2,922	-0.08	-0.11	0.06	2,922	-0.09	-0.11	0.06	2,841	Same	Same	Same
Tajikistan	2007					-0.03	-0.05	0.00	4,481	-0.01	-0.04	0.01	4,454			Same
Timor-Leste	2007					-0.05	-0.08	0.02	3,258	-0.05	-0.08	0.02	3,258			Same
Uganda	2011	-0.08	-0.13	0.03	1,602	-0.07	-0.12	0.02	1,748	-0.08	-0.13	0.03	1,753	Same	Same	Same
Uganda	2013	-0.03	-0.16	0.11	152	-0.06	-0.10	0.02	2,129	-0.04	-0.09	0.00	2,125	Same	Same	Same
South Africa	1993	-0.10	-0.13	0.08	6,828	-0.11	-0.14	0.09	6,940	-0.11	-0.13	0.08	6,964	Same	Same	Same
Median		-0.06				-0.06				-0.07						
Average		-0.06				-0.06				-0.07						
Max		-0.01				0.00				-0.01						
Min		-0.11				-0.14				-0.17						

[29] For income, consumption, and asset columns red cells indicate the highest levels of inequality, yellow the middle value, and green the lowest levels. For comparison columns, green indicates a statistically significant (95%) lower level and red a significantly higher level.

Table 11. Meta-analytic pooling of aggregate concentration index data for death ratio, stunting, underweight, and combined outcomes with subgroup analysis for country-income level and survey year

Concentration Index		**Death Ratio**	**LCI**	**UCI**	**Stunting**	**LCI**	**UCI**	**Underweight**	**LCI**	**UCI**	**Combined**	**LCI**	**UCI**
All	Assets	-0.18	-0.22	-0.14	-0.17	-0.23	-0.10	-0.16	-0.21	-0.11	-0.17	-0.20	-0.14
	Consumption	-0.16	-0.19	-0.13	-0.15	-0.20	-0.09	-0.12	-0.17	-0.07	-0.14	-0.17	-0.11
	Income	-0.16	-0.19	-0.12	-0.14	-0.19	-0.10	-0.14	-0.19	-0.10	-0.15	-0.17	-0.13
Country Income	L Assets	-0.11	-0.16	-0.06	-0.12	-0.16	-0.08	-0.12	-0.16	-0.08	-0.12	-0.14	-0.09
	L Consumption	-0.11	-0.13	-0.09	-0.10	-0.12	-0.07	-0.09	-0.13	-0.04	-0.09	-0.11	-0.08
	L Income	-0.12	-0.14	-0.09	-0.09	-0.12	-0.07	-0.08	-0.15	-0.02	-0.10	-0.12	-0.08
	LM Assets	-0.23	-0.28	-0.17	-0.18	-0.31	-0.05	-0.18	-0.28	-0.08	-0.19	-0.26	-0.13
	LM Consumption	-0.20	-0.25	-0.16	-0.17	-0.29	-0.04	-0.14	-0.24	-0.04	-0.17	-0.23	-0.11
	LM Income	-0.17	-0.22	-0.12	-0.15	-0.22	-0.08	-0.16	-0.24	-0.07	-0.16	-0.20	-0.12
	UM Assets	-0.26	-0.35	-0.18	-0.30	-0.46	-0.14	-0.28	-0.50	-0.06	-0.28	-0.35	-0.20
	UM Consumption	-0.22	-0.25	-0.19	-0.28	-0.41	-0.16	-0.22	-0.40	-0.05	-0.24	-0.30	-0.18
	UM Income	-0.20	-0.30	-0.09	-0.22	-0.25	-0.19	-0.21	-0.29	-0.14	-0.21	-0.25	-0.17
Survey Year	Pre-1995 Assets	-0.18	-0.23	-0.14	-0.15	-0.23	-0.07	-0.16	-0.22	-0.10	-0.17	-0.20	-0.13
	Pre-1995 Consumption	-0.16	-0.22	-0.11	-0.17	-0.24	-0.09	-0.13	-0.19	-0.06	-0.15	-0.19	-0.12
	Pre-1995 Income	-0.15	-0.19	-0.11	-0.15	-0.21	-0.09	-0.13	-0.20	-0.06	-0.14	-0.18	-0.11
	1995-2004 Assets	-0.23	-0.32	-0.15	-0.23	-0.39	-0.08	-0.22	-0.35	-0.08	-0.23	-0.30	-0.15
	1995-2004 Consumption	-0.19	-0.28	-0.10	-0.23	-0.36	-0.10	-0.19	-0.32	-0.06	-0.20	-0.27	-0.14
	1995-2004 Income	-0.18	-0.26	-0.10	-0.15	-0.22	-0.08	-0.16	-0.25	-0.08	-0.16	-0.20	-0.12
	Post-2005 Assets	-0.13	-0.19	-0.06	-0.12	-0.18	-0.06	-0.11	-0.16	-0.06	-0.12	-0.15	-0.09
	Post-2005 Consumption	-0.12	-0.14	-0.10	-0.06	-0.12	-0.01	-0.06	-0.12	-0.01	-0.08	-0.11	-0.05
	Post-2005 Income	-0.13	-0.18	-0.08	-0.12	-0.24	0.00	-0.15	-0.22	-0.07	-0.13	-0.17	-0.08

Table 12. Meta- analytic pooling of aggregate RII data for death ratio, stunting, underweight, and combined outcomes with subgroup analysis for country-income level and survey year

RII		Death Ratio	LCI	UCI		Stunting	LCI	UCI		Underweight	LCI	UCI		Combined	LCI	UCI
All	Consumption	2.149	1.78	2.519		1.781	1.516	2.047		1.54	1.29	1.79		1.779	1.61	1.947
	Hybrid	2.288	1.831	2.745		1.886	1.593	2.179		1.779	1.472	2.085		1.918	1.729	2.107
	Income	2.142	1.787	2.497		1.776	1.519	2.033		1.878	1.469	2.287		1.867	1.679	2.056
Country Income	L Consumption	1.743	1.466	2.02		1.451	1.283	1.618		1.402	1.109	1.696		1.467	1.331	1.604
	L Hybrid	1.698	1.319	2.078		1.617	1.333	1.901		1.646	1.311	1.981		1.64	1.456	1.824
	L Income	1.839	1.437	2.241		1.374	1.251	1.497		1.398	0.96	1.836		1.405	1.273	1.537
	LM Consumption	2.637	1.999	3.274		1.85	1.343	2.358		1.567	1.134	2.001		1.863	1.564	2.162
	LM Hybrid	2.849	2.147	3.552		1.775	1.261	2.29		1.895	1.266	2.524		1.967	1.641	2.293
	LM Income	2.263	1.585	2.942		1.758	1.356	2.16		2.049	1.286	2.812		1.914	1.609	2.219
	UM Consumption	3.536	2.67	4.402		3.597	1.627	5.567		3.881	-0.446	8.208		3.343	2.44	4.247
	UM Hybrid	4.162	1.968	6.355		4.435	1.817	7.053		5.405	0.148	10.662		3.923	2.821	5.024
	UM Income	2.617	1.294	3.94		2.616	2.303	2.929		3.284	1.496	5.071		2.607	2.257	2.956
Survey Year	Pre-1995 Consumption	2.359	1.703	3.016		2.122	1.589	2.655		1.562	1.234	1.89		1.986	1.707	2.266
	Pre-1995 Hybrid	2.453	1.804	3.102		1.919	1.428	2.409		1.825	1.491	2.16		2	1.723	2.277
	Pre-1995 Income	2.183	1.644	2.722		1.912	1.4	2.424		1.627	1.181	2.073		1.883	1.613	2.153
	1995-2004 Consumption	2.532	1.153	3.911		2.279	1.535	3.023		2.496	1.101	3.891		2.281	1.759	2.803
	1995-2004 Hybrid	3.173	1.622	4.725		2.362	1.63	3.095		2.135	0.927	3.343		2.316	1.796	2.836
	1995-2004 Income	2.215	1.37	3.061		1.767	1.359	2.176		2.461	1.33	3.593		1.96	1.613	2.307
	Post-2005 Consumption	1.882	1.484	2.28		1.344	1.086	1.602		1.238	0.986	1.489		1.372	1.206	1.538
	Post-2005 Hybrid	1.779	1.207	2.352		1.694	1.271	2.116		1.691	1.289	2.092		1.7	1.464	1.937
	Post-2005 Income	2.061	1.011	3.11		1.485	0.796	2.175		2	1.116	2.884		1.617	1.232	2.001

Table 13. Meta- analytic pooling of aggregate SII data for death ratio, stunting, underweight, and combined outcomes with subgroup analysis for country-income level and survey year

SII		Death Ratio	LCI	UCI	Stunting	LCI	UCI	Underweight	LCI	UCI	Combined	LCI	UCI
All	Consumption	-0.039	-0.052	-0.026	-0.156	-0.236	-0.076	-0.065	-0.102	-0.028	-0.094	-0.125	-0.064
	Hybrid	-0.041	-0.056	-0.027	-0.181	-0.256	-0.106	-0.089	-0.132	-0.047	-0.115	-0.15	-0.08
	Income	-0.041	-0.057	-0.024	-0.174	-0.231	-0.117	-0.079	-0.117	-0.042	-0.106	-0.137	-0.074
Country Income	L Consumption	-0.036	-0.058	-0.015	-0.122	-0.166	-0.077	-0.061	-0.102	-0.019	-0.073	-0.097	-0.049
	L Hybrid	-0.033	-0.055	-0.011	-0.153	-0.217	-0.089	-0.089	-0.146	-0.033	-0.1	-0.136	-0.063
	L Income	-0.038	-0.066	-0.01	-0.107	-0.154	-0.059	-0.056	-0.122	0.01	-0.07	-0.102	-0.037
	LM Consumption	-0.048	-0.068	-0.029	-0.151	-0.318	0.016	-0.061	-0.126	0.004	-0.093	-0.149	-0.038
	LM Hybrid	-0.051	-0.072	-0.03	-0.167	-0.327	-0.008	-0.088	-0.169	-0.006	-0.114	-0.178	-0.05
	LM Income	-0.055	-0.082	-0.028	-0.198	-0.314	-0.083	-0.094	-0.154	-0.033	-0.123	-0.176	-0.07
	UM Consumption	-0.052	-0.127	0.022	-0.335	-0.488	-0.182	-0.099	-0.168	-0.029	-0.17	-0.314	-0.026
	UM Hybrid	-0.051	-0.092	-0.01	-0.318	-0.491	-0.145	-0.091	-0.144	-0.038	-0.163	-0.281	-0.045
	UM Income	-0.047	-0.102	0.007	-0.252	-0.307	-0.196	-0.089	-0.141	-0.037	-0.137	-0.227	-0.048
Survey Year	Pre-1995 Consumption	-0.071	-0.101	-0.04	-0.196	-0.313	-0.079	-0.091	-0.138	-0.044	-0.123	-0.172	-0.074
	Pre-1995 Hybrid	-0.076	-0.115	-0.038	-0.196	-0.323	-0.068	-0.112	-0.177	-0.047	-0.137	-0.198	-0.076
	Pre-1995 Income	-0.072	-0.103	-0.04	-0.175	-0.269	-0.08	-0.086	-0.142	-0.03	-0.113	-0.159	-0.068
	1995-2004 Consumption	-0.026	-0.044	-0.007	-0.238	-0.387	-0.088	-0.079	-0.188	0.031	-0.115	-0.19	-0.04
	1995-2004 Hybrid	-0.03	-0.047	-0.014	-0.205	-0.372	-0.038	-0.077	-0.189	0.035	-0.108	-0.183	-0.033
	1995-2004 Income	-0.024	-0.04	-0.008	-0.195	-0.282	-0.108	-0.085	-0.157	-0.012	-0.108	-0.159	-0.056
	Post-2005 Consumption	-0.041	-0.061	-0.022	-0.071	-0.142	0	-0.027	-0.06	0.005	-0.048	-0.074	-0.022
	Post-2005 Hybrid	-0.039	-0.064	-0.014	-0.148	-0.235	-0.061	-0.078	-0.118	-0.038	-0.098	-0.136	-0.061
	Post-2005 Income	-0.066	-0.136	0.003	-0.131	-0.292	0.03	-0.048	-0.122	0.026	-0.078	-0.138	-0.019

Figure 1. Kernel-weighted local polynomial plot of income centiles vs consumption centiles

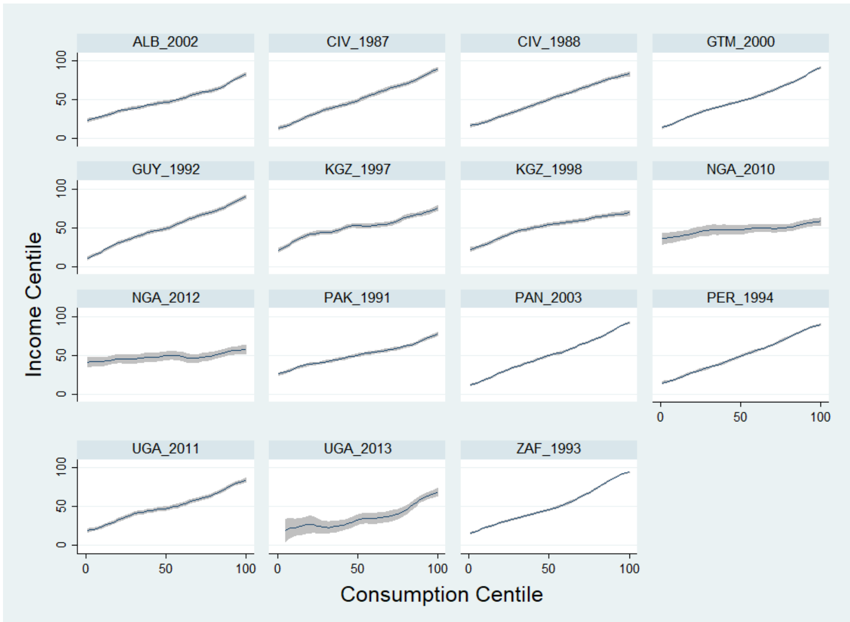


Figure 2. Kernel-weighted local polynomial plot of income centiles vs asset index centiles

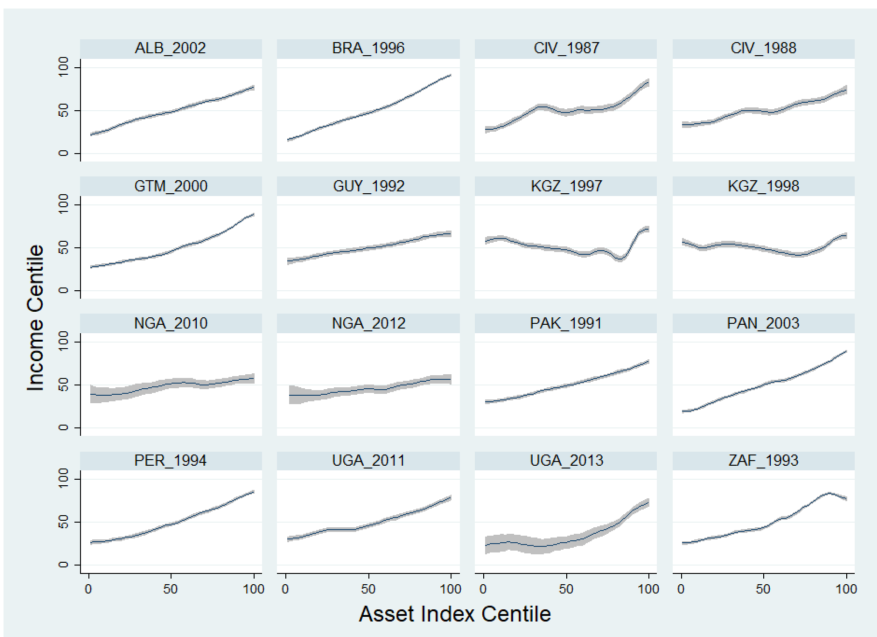


Figure 3. Kernel-weighted local polynomial plot of consumption centiles vs asset index centiles

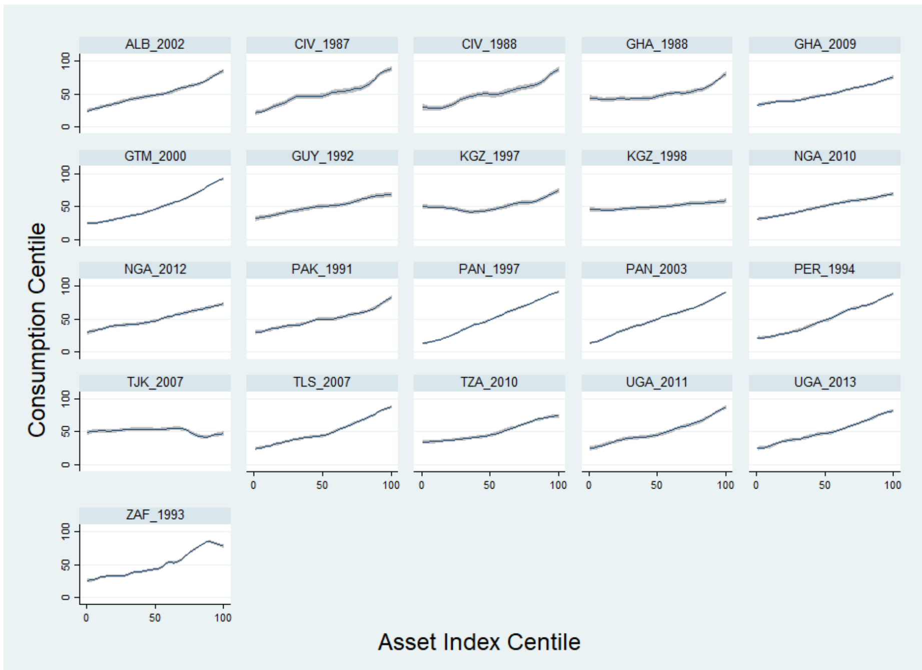


Figure 4. Forest plot comparisons of concentration indices using income, consumption, and assets for stunting (left), underweight (center), and child death ratios (right)

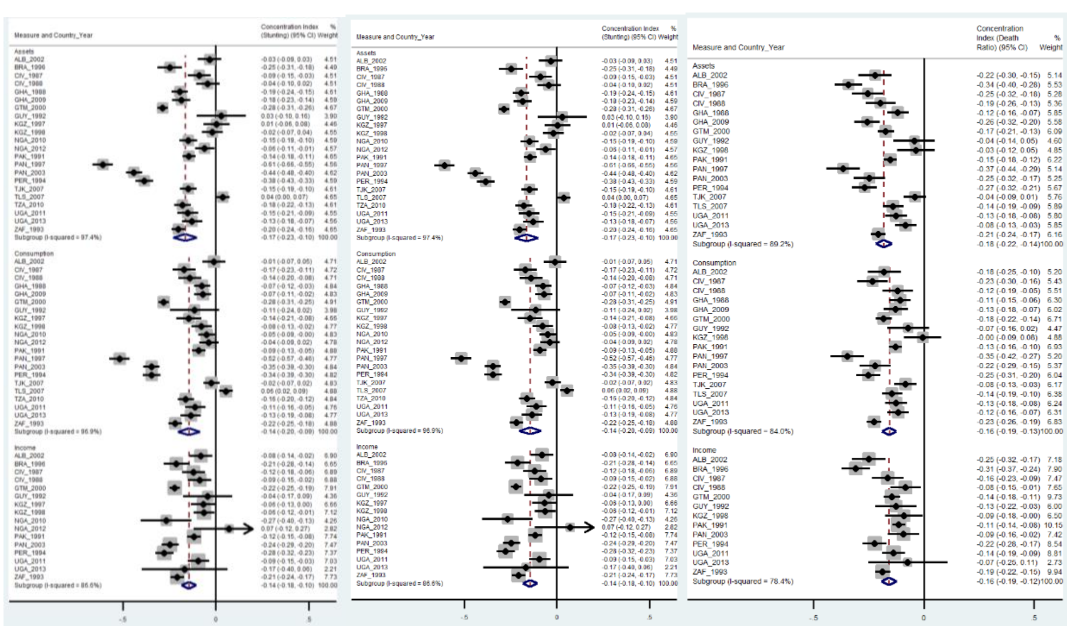


Figure 5. Forest plot comparisons of RII values using income, consumption, and income proxy hybrid for stunting (left), underweight (center), and child death ratios (right)

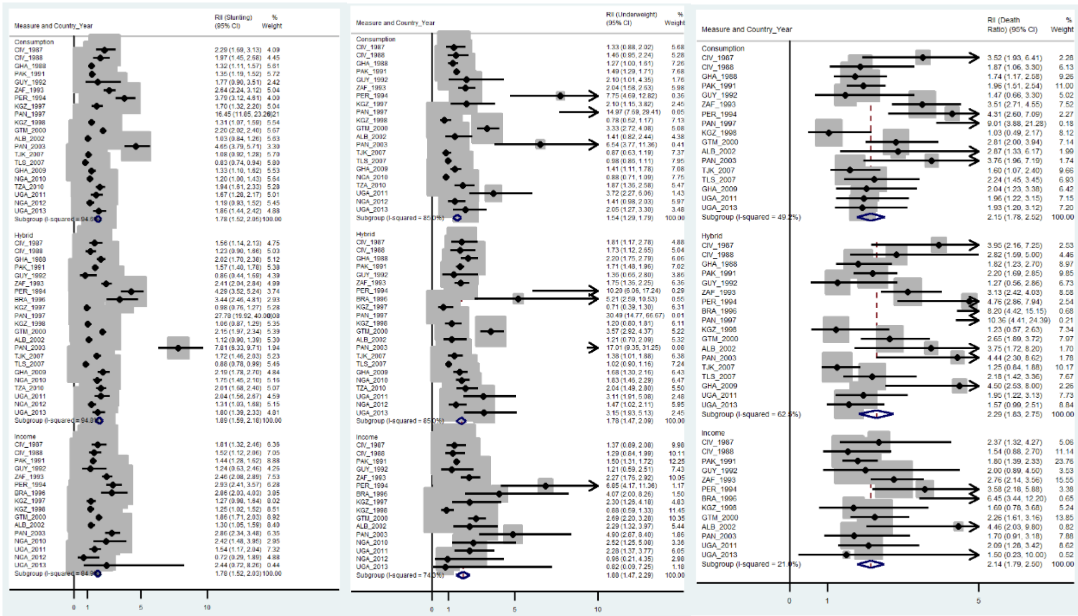
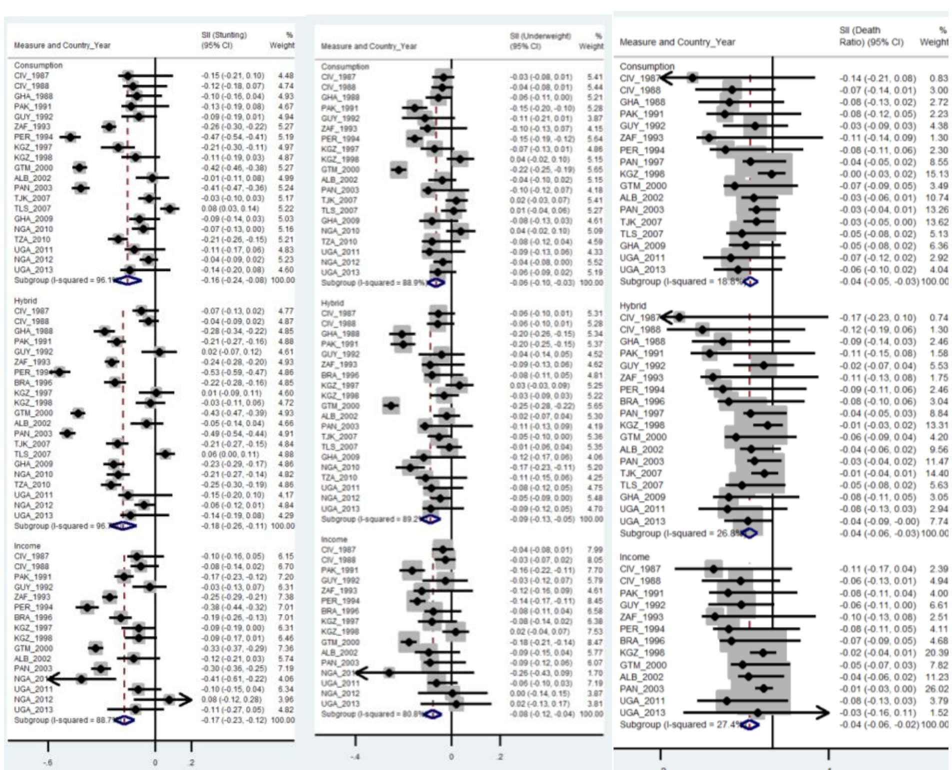


Figure 6. Forest plot comparisons of SII values using income, consumption, and income proxy hybrid for stunting (left), underweight (center), and child death ratios (right)



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Appendix Table 1. Living Standards Measurement Survey (LSMS) Characteristics

Survey Code	Country	Year	Income Level	Survey Name	Primary Investigators	Sample Size[30]
ALB_2002	Albania	2002	Low-Middle	Living Standards Measurement Survey 2002 (Wave 1 Panel)	Institute of Statistics of Albania	3,599
BRA_1996	Brazil	1996	Upper-Middle	Living Standards Measurement Study Survey 1996-1997	Instituto Brasileiro de Geografia e Estatísticai / Brazilian Geographical and Statistical institute (IBGE)	4,940
CIV_1987	Cote d'Ivoire	1987	Low-Middle	Enquête Permanente Auprès des Ménages 1987-1988 (Wave 3 Panel)	Direction de la Statistique - Ministère de l'Economie et des Finances	1,600
CIV_1988	Cote d'Ivoire	1988	Low-Middle	Enquête Permanente Auprès des Ménages 1988-1989 (Wave 4 Panel)	Direction de la Statistique - Ministère de l'Economie et des Finances	1,600
GHA_1988	Ghana	1988	Low	Living Standards Survey II 1988-1989	Ghana Statistical Service (GSS)	3,104
GHA_2009	Ghana	2009	Low	Socioeconomic Panel Survey: 2009-2010	Institute of Statistical, Social and Economic Research - University of Ghana	4,972
GTM_2000	Guatemala	2000	Low-Middle	Encuesta Nacional sobre Condiciones de Vida 2000	Instituto Nacional de Estadística (INE)	7,276
GUY_1992	Guyana	1992	Low	Living Standards Measurements Survey 1992	Bureau of Statistics - Ministry of Finance	1,818
KGZ_1997	Kyrgyzstan	1997	Low	Poverty Monitoring Survey 1997	National Statistical Committee (NATSTATCOM)	2,876
KGZ_1998	Kyrgyzstan	1998	Low	Poverty Monitoring Survey 1998	National Statistical Committee (NATSTATCOM)	2,979
NGA_2010	Nigeria	2010	Low	General Household Survey, Panel 2010	National Bureau of Statistics (NBS) - Federal Government of Nigeria (FGN)	4,935
NGA_2012	Nigeria	2012	Low	General Household Survey, Panel 2012-2013	National Bureau of Statistics (NBS) - Federal Government of Nigeria (FGN)	4,814
PAK_1991	Pakistan	1991	Low	Integrated Household Survey 1991	Federal Bureau of Statistics (FBS)	4,799
PAN_1997	Panama	1997	Low-Middle	Encuesta de Niveles de Vida 1997	Ministerio de Planificacion y Politica Economica	4,945

[30] Sample size refers to the number of households containing information on at least one of income, consumption, or asset index. Samples may differ for each health outcome or individual SES measure.

PAN_2003	Panama	2003	Upper-Middle	Encuesta de Niveles de Vida 2003	Ministerio de Economía y Finanzas (MEF)	6,363
PER_1994	Peru	1994	Low-Middle	Encuesta Nacional de Hogares sobre Medición de Niveles de Vida 1994	Instituto Nacional de Estadística (INE)	3,623
TJK_2007	Tajikistan	2007	Low	Living Standards Survey 2007	State Statistical Agency	4,860
TLS_2007	Timor-Leste	2007	Low-Middle	Survey of Living Standards 2007 and Extension 2008	National Statistics Directorate	4,477
TZA_2010	Tanzania	2010	Low	National Panel Survey 2010-2011	National Bureau of Statistics - Ministry of Finance, Tanzania	3,924
UGA_2011	Uganda	2011	Low	National Panel Survey 2011-2012	Uganda Bureau of Statistics (UBOS) - Ministry of Finance, Planning and Economic Development	2,837
UGA_2013	Uganda	2013	Low	National Panel Survey 2013-2014	Uganda Bureau of Statistics - Government of Uganda	3,119
ZAF_1993	South Africa	1993	Upper-Middle	Integrated Household Survey 1993	Southern Africa Labour and Development Research Unit	8,810

Appendix Table 2. Survey and quintile-specific prevalence for stunting and underweight using income, consumption, and assets

	Income					Consumption					Assets				
Country quintile	N	Sex (% female)	Mean age (months)	Stunting (prevalence)	Underweight (prevalence)	N	Sex (% female)	Mean age (months)	Stunting (prevalence)	Underweight (prevalence)	N	Sex (% female)	Mean age (months)	Stunting (prevalence)	Underweight (prevalence)
ALB_2002															
1	335	0.430	32.6	0.442	0.125	279	0.466	32.9	0.391	0.115	367	0.493	32.6	0.460	0.106
2	221	0.439	29.9	0.516	0.154	263	0.452	32.2	0.490	0.106	312	0.429	31.1	0.429	0.122
3	308	0.458	31.1	0.435	0.078	260	0.458	31.0	0.469	0.100	246	0.419	31.7	0.382	0.069
4	222	0.446	31.7	0.428	0.117	251	0.406	30.6	0.414	0.120	191	0.476	29.8	0.435	0.110
5	252	0.413	30.5	0.361	0.052	285	0.404	29.6	0.414	0.081	217	0.346	30.2	0.456	0.111
BRA_1996															
1	435	0.485	30.1	0.301	0.092						560	0.473	29.8	0.293	0.089
2	397	0.511	31.0	0.176	0.065						419	0.549	30.2	0.189	0.057
3	332	0.509	30.4	0.181	0.045						344	0.445	31.6	0.163	0.044
4	276	0.536	31.5	0.167	0.029						244	0.553	30.8	0.164	0.029
5	207	0.507	30.3	0.116	0.024						195	0.533	32.8	0.108	0.031
CIV_1987															
1	249	0.498	31.4	0.233	0.104	201	0.547	31.3	0.244	0.090	426	0.472	31.8	0.228	0.131
2	345	0.493	32.3	0.214	0.099	370	0.484	31.1	0.224	0.119	496	0.484	31.7	0.179	0.119
3	479	0.480	31.5	0.188	0.115	505	0.487	32.5	0.208	0.119	484	0.488	32.2	0.155	0.085
4	559	0.487	32.4	0.174	0.131	593	0.464	32.9	0.174	0.106	447	0.494	32.9	0.177	0.087
5	571	0.504	33.9	0.135	0.068	564	0.509	33.5	0.112	0.085	353	0.518	34.2	0.164	0.091
CIV_1988															
1	233	0.459	29.2	0.240	0.150	200	0.470	28.7	0.290	0.140	387	0.463	30.9	0.204	0.124
2	369	0.496	32.3	0.203	0.106	352	0.494	31.6	0.216	0.122	467	0.450	31.8	0.216	0.124
3	417	0.520	32.4	0.201	0.098	467	0.505	32.3	0.203	0.111	459	0.510	33.5	0.170	0.118
4	537	0.443	33.0	0.196	0.102	526	0.475	33.3	0.173	0.089	448	0.520	32.7	0.172	0.078
5	549	0.519	34.5	0.149	0.100	576	0.497	34.9	0.148	0.101	356	0.511	35.2	0.194	0.090
GHA_1988															
1						365	0.493	33.4	0.362	0.230	655	0.501	32.8	0.389	0.263
2						511	0.503	30.6	0.348	0.233	603	0.514	33.1	0.443	0.274
3						603	0.493	33.7	0.406	0.250	678	0.509	33.6	0.382	0.258
4						686	0.520	33.2	0.340	0.206	549	0.486	32.8	0.279	0.166
5						741	0.495	34.1	0.286	0.201	413	0.492	33.2	0.157	0.099
GHA_2009															
1						414	0.478	34.5	0.297	0.232	926	0.524	34.3	0.362	0.241
2						625	0.522	34.2	0.301	0.246	545	0.475	34.1	0.301	0.251
3						678	0.501	34.2	0.326	0.230	416	0.466	34.5	0.252	0.216
4						618	0.494	35.0	0.270	0.223	378	0.513	34.7	0.238	0.169
5						596	0.503	35.0	0.233	0.168	342	0.494	34.9	0.173	0.164
GTM_2000															
1	1,205	0.491	29.0	0.589	0.222	1,192	0.484	29.3	0.637	0.236	1559	0.509	29.3	0.604	0.227
2	1,318	0.489	29.9	0.581	0.211	1,391	0.494	29.8	0.578	0.223	1392	0.481	29.3	0.585	0.224
3	1,271	0.500	30.3	0.496	0.164	1,272	0.501	29.9	0.499	0.153	1188	0.481	30.8	0.536	0.166
4	1,088	0.497	30.2	0.427	0.136	1,117	0.498	29.8	0.415	0.136	941	0.514	30.5	0.336	0.090
5	819	0.490	29.4	0.309	0.078	771	0.490	30.4	0.248	0.053	663	0.477	29.3	0.216	0.045
GUY_1992															
1	113	0.446	31.4	0.150	0.124	94	0.478	30.7	0.170	0.117	120	0.470	29.4	0.133	0.150

2	114	0.450	29.6	0.149	0.140	126	0.448	31.6	0.151	0.183	133	0.447	29.5	0.113	0.120
3	131	0.473	29.6	0.130	0.130	111	0.445	30.6	0.162	0.144	128	0.445	28.9	0.172	0.141
4	118	0.436	30.8	0.161	0.144	149	0.514	28.9	0.148	0.121	122	0.508	32.6	0.156	0.115
5	125	0.524	29.7	0.120	0.096	121	0.442	29.6	0.083	0.066	98	0.469	31.0	0.133	0.102
KGZ_1997															
1	154	0.468	38.0	0.390	0.143	140	0.493	40.4	0.436	0.150	320	0.500	38.3	0.338	0.106
2	181	0.486	37.3	0.398	0.122	233	0.468	36.7	0.421	0.124	294	0.476	38.4	0.395	0.068
3	243	0.535	39.2	0.391	0.111	246	0.476	38.0	0.431	0.093	237	0.511	37.9	0.435	0.122
4	293	0.485	38.5	0.365	0.082	250	0.512	37.5	0.348	0.084	164	0.512	37.8	0.372	0.116
5	291	0.491	36.7	0.326	0.082	294	0.517	38.3	0.272	0.085	98	0.500	36.8	0.255	0.122
KGZ_1998															
1	283	0.516	36.0	0.466	0.152	294	0.432	37.4	0.459	0.095	506	0.471	35.3	0.433	0.140
2	338	0.501	36.8	0.408	0.121	378	0.525	36.9	0.452	0.159	433	0.519	37.8	0.397	0.150
3	304	0.510	38.1	0.431	0.138	337	0.497	35.5	0.409	0.145	286	0.489	37.4	0.434	0.154
4	361	0.457	36.6	0.391	0.133	384	0.505	37.0	0.370	0.143	275	0.467	37.1	0.433	0.131
5	403	0.483	35.6	0.385	0.159	334	0.467	36.4	0.377	0.150	143	0.486	35.5	0.350	0.119
NGA_2010															
1	62	0.463	33.4	0.484	0.258	326	0.460	32.3	0.377	0.218	502	0.482	31.6	0.416	0.315
2	67	0.524	31.9	0.507	0.418	512	0.508	31.4	0.422	0.285	530	0.435	31.7	0.415	0.330
3	56	0.439	29.2	0.321	0.196	582	0.467	31.4	0.368	0.313	495	0.490	31.1	0.343	0.267
4	55	0.438	28.1	0.364	0.164	578	0.498	30.4	0.315	0.285	492	0.491	31.1	0.333	0.260
5	42	0.622	28.3	0.095	0.095	578	0.459	31.5	0.370	0.277	385	0.459	30.4	0.242	0.174
NGA_2012															
1	43	0.442	30.6	0.140	0.093	297	0.448	30.8	0.249	0.128	673	0.478	31.4	0.218	0.123
2	44	0.477	29.3	0.273	0.023	556	0.496	32.0	0.218	0.133	597	0.461	31.6	0.261	0.127
3	59	0.593	28.8	0.220	0.153	643	0.474	30.2	0.215	0.112	498	0.504	30.1	0.183	0.106
4	22	0.455	33.8	0.182	0.091	635	0.490	31.5	0.198	0.096	537	0.471	31.1	0.214	0.110
5	37	0.486	34.2	0.189	0.054	606	0.474	31.6	0.216	0.111	461	0.497	31.0	0.174	0.082
PAK_1991															
1	685	0.512	29.8	0.463	0.413	618	0.518	29.9	0.500	0.437	759	0.503	29.3	0.478	0.480
2	761	0.524	29.2	0.498	0.423	727	0.527	29.9	0.470	0.406	767	0.527	30.2	0.499	0.374
3	775	0.503	30.0	0.489	0.426	768	0.487	29.9	0.445	0.397	879	0.522	30.7	0.504	0.407
4	788	0.509	29.4	0.411	0.340	887	0.516	28.8	0.419	0.370	818	0.484	29.3	0.379	0.339
5	902	0.479	29.1	0.357	0.308	916	0.479	29.2	0.390	0.309	680	0.479	27.5	0.319	0.279
PAN_1997															
1						525	0.488	28.6	0.430	0.120	724	0.453	29.3	0.452	0.127
2						578	0.462	29.3	0.230	0.080	479	0.503	29.4	0.136	0.048
3						434	0.493	28.9	0.113	0.035	440	0.493	26.9	0.077	0.020
4						427	0.492	29.1	0.082	0.014	370	0.503	29.4	0.046	0.016
5						330	0.533	28.7	0.039	0.009	279	0.538	29.3	0.043	0.011
PAN_2003															
1	718	0.506	29.2	0.421	0.102	659	0.496	28.4	0.487	0.106	948	0.487	29.2	0.500	0.117
2	600	0.440	30.3	0.297	0.060	725	0.469	30.0	0.303	0.070	651	0.467	30.0	0.266	0.046
3	609	0.496	28.9	0.284	0.049	569	0.480	29.9	0.257	0.046	563	0.481	29.6	0.179	0.023
4	561	0.480	30.0	0.210	0.037	534	0.466	29.7	0.204	0.030	442	0.466	29.8	0.143	0.025
5	418	0.500	31.8	0.167	0.024	435	0.515	32.0	0.110	0.016	318	0.535	32.1	0.104	0.016
PER_1994															
1	561	0.503	29.3	0.453	0.152	567	0.488	29.6	0.490	0.164	668	0.497	28.9	0.488	0.156
2	542	0.494	30.8	0.415	0.107	559	0.533	29.8	0.435	0.095	568	0.487	30.4	0.451	0.102
3	460	0.525	30.4	0.317	0.061	462	0.463	30.5	0.292	0.063	428	0.507	30.4	0.257	0.047
4	389	0.478	29.8	0.257	0.046	407	0.516	30.9	0.199	0.039	340	0.456	30.7	0.135	0.029
5	344	0.466	29.1	0.148	0.032	301	0.463	28.8	0.130	0.030	224	0.547	30.4	0.098	0.018
TJK_2007															
1						305	0.485	30.7	0.407	0.141	570	0.495	30.7	0.461	0.156

2						430	0.488	32.1	0.393	0.165	539	0.464	30.5	0.425	0.167
3						495	0.491	29.6	0.354	0.123	628	0.467	29.4	0.389	0.156
4						635	0.444	30.2	0.422	0.137	589	0.497	29.3	0.319	0.143
5						836	0.490	28.7	0.360	0.163	368	0.462	30.0	0.299	0.095
TLS_2007															
1						476	0.492	30.2	0.429	0.424	723	0.499	29.1	0.426	0.443
2						756	0.499	29.8	0.413	0.402	777	0.493	30.1	0.425	0.390
3						838	0.505	30.9	0.438	0.427	748	0.489	31.7	0.455	0.421
4						876	0.508	31.4	0.468	0.419	822	0.505	31.2	0.471	0.436
5						991	0.474	29.7	0.474	0.424	867	0.489	30.0	0.459	0.409
TZA_2010															
1						427	0.482	28.0	0.410	0.185	775	0.471	28.3	0.381	0.159
2						568	0.514	28.6	0.375	0.158	738	0.505	28.9	0.364	0.168
3						641	0.487	29.0	0.309	0.122	594	0.517	28.9	0.345	0.133
4						680	0.491	29.1	0.293	0.121	478	0.533	29.2	0.241	0.098
5						655	0.530	28.8	0.232	0.105	408	0.522	28.3	0.157	0.074
UGA_2011															
1	455	0.477	29.5	0.222	0.088	362	0.459	29.3	0.224	0.122	544	0.489	29.9	0.276	0.123
2	459	0.519	30.0	0.240	0.105	518	0.500	30.2	0.234	0.097	521	0.482	30.5	0.186	0.063
3	468	0.506	30.5	0.222	0.068	560	0.536	30.1	0.223	0.071	489	0.540	31.4	0.233	0.082
4	426	0.474	31.6	0.192	0.073	551	0.510	30.6	0.211	0.065	506	0.512	30.6	0.194	0.071
5	468	0.553	31.6	0.156	0.043	520	0.542	31.7	0.138	0.040	444	0.541	30.1	0.119	0.034
UGA_2013															
1	57	0.509	30.8	0.211	0.035	419	0.504	27.6	0.232	0.086	619	0.502	30.2	0.236	0.103
2	40	0.375	30.5	0.150	0.025	538	0.517	28.6	0.247	0.087	533	0.527	28.1	0.225	0.081
3	28	0.286	33.8	0.107	0.143	555	0.497	29.7	0.243	0.085	535	0.503	29.3	0.236	0.080
4	28	0.607	31.0	0.071	0.071	562	0.514	29.8	0.181	0.064	496	0.504	29.4	0.214	0.054
5	34	0.706	35.1	0.147	0.000	509	0.519	30.6	0.138	0.051	397	0.514	29.8	0.098	0.038
ZAF_1993															
1	1,099	0.496	29.5	0.334	0.168	953	0.461	30.5	0.366	0.159	1654	0.481	29.9	0.323	0.138
2	1,097	0.491	29.6	0.290	0.129	1,031	0.490	29.1	0.296	0.141	1196	0.493	29.9	0.281	0.165
3	1,020	0.480	30.6	0.282	0.158	1,123	0.508	29.4	0.240	0.136	898	0.510	29.4	0.247	0.131
4	1,036	0.499	30.0	0.212	0.103	1,205	0.496	30.4	0.231	0.118	675	0.505	30.2	0.178	0.089
5	622	0.513	30.4	0.113	0.053	648	0.522	30.7	0.114	0.065	544	0.496	31.0	0.118	0.053

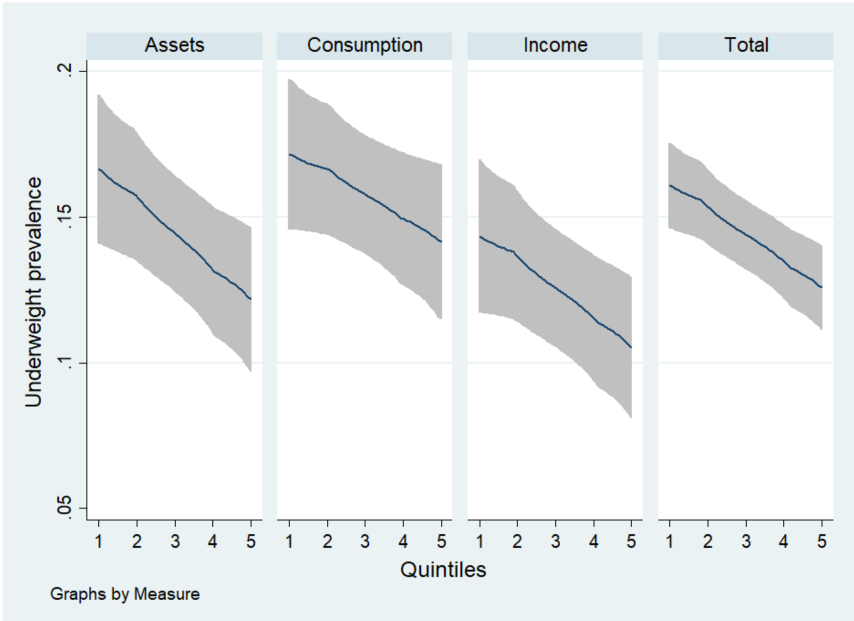
Appendix Table 3. Survey and quintile-specific prevalence for births, deaths, and child death ratio using income, consumption, and assets

	Income				Consumption				Assets			
Country quintile	N	Births (mean)	Deaths (mean)	Death ratio	N	Births (mean)	Deaths (mean)	Death ratio	N	Births (mean)	Deaths (mean)	Death ratio
ALB_2002												
1	517	3.29	0.23	0.048	441	2.87	0.16	0.037	551	3.31	0.24	0.050
2	450	2.94	0.16	0.042	490	3.00	0.18	0.041	558	2.95	0.13	0.030
3	604	2.72	0.11	0.027	549	2.78	0.14	0.034	536	2.70	0.12	0.030
4	518	2.63	0.09	0.022	579	2.73	0.11	0.027	491	2.45	0.08	0.022
5	573	2.26	0.05	0.015	603	2.46	0.06	0.016	519	2.28	0.05	0.017
BRA_1996												
1	541	3.39	0.42	0.085					662	3.94	0.49	0.089
2	609	3.08	0.24	0.047					700	2.99	0.20	0.048
3	626	2.81	0.18	0.042					686	2.57	0.16	0.039
4	624	2.58	0.14	0.033					619	2.48	0.12	0.027
5	620	2.33	0.05	0.014					574	2.13	0.05	0.016
CIV_1987												
1	161	3.81	0.66	0.166	160	3.98	0.83	0.200	187	4.79	0.98	0.184
2	199	4.14	0.63	0.142	211	4.15	0.68	0.148	219	4.38	0.67	0.147
3	214	4.28	0.63	0.118	223	4.38	0.59	0.097	204	4.31	0.70	0.124
4	209	4.31	0.56	0.106	222	3.89	0.50	0.110	208	3.67	0.35	0.093
5	215	3.91	0.47	0.085	199	4.02	0.36	0.060	184	3.23	0.22	0.050
CIV_1988												
1	169	4.04	0.73	0.140	161	4.27	0.86	0.160	207	4.77	0.97	0.177
2	201	4.42	0.70	0.130	211	4.08	0.65	0.139	230	4.85	0.79	0.139
3	226	4.13	0.56	0.125	238	4.56	0.70	0.115	222	4.41	0.70	0.124
4	243	4.41	0.68	0.121	234	4.18	0.58	0.104	214	3.52	0.34	0.093
5	222	4.05	0.47	0.096	223	3.98	0.38	0.100	192	3.36	0.26	0.067
GHA_1988												
1					258	3.79	0.86	0.195	377	4.37	0.84	0.161
2					345	3.69	0.66	0.140	361	4.06	0.79	0.179
3					387	4.02	0.70	0.149	381	4.19	0.74	0.141
4					413	4.06	0.64	0.124	346	3.93	0.53	0.115
5					410	4.12	0.52	0.119	345	3.18	0.38	0.107
GHA_2009												
1					332	3.42	0.30	0.077	695	4.24	0.49	0.092
2					575	3.75	0.34	0.068	491	4.04	0.32	0.061
3					617	3.91	0.36	0.068	441	3.72	0.25	0.049
4					641	3.77	0.34	0.062	463	3.29	0.17	0.035
5					677	3.49	0.20	0.042	442	2.83	0.12	0.031
GTM_2000												
1	1,028	3.92	0.49	0.092	981	3.83	0.51	0.097	1,205	4.67	0.52	0.087
2	1,140	4.33	0.42	0.075	1,161	4.36	0.43	0.076	1,221	4.48	0.47	0.080
3	1,200	4.16	0.39	0.067	1,248	4.21	0.42	0.075	1,220	4.16	0.40	0.069
4	1,268	3.98	0.31	0.053	1,262	4.12	0.29	0.049	1,170	3.41	0.25	0.056
5	1,257	3.31	0.23	0.049	1,277	3.18	0.20	0.042	1,113	2.84	0.14	0.035
GUY_1992												
1	168	3.19	0.35	0.077	136	3.14	0.30	0.072	208	3.32	0.39	0.084
2	187	3.13	0.44	0.092	208	3.04	0.38	0.077	202	2.94	0.28	0.064
3	196	2.66	0.26	0.070	201	2.66	0.26	0.082	185	2.78	0.26	0.064
4	208	2.63	0.24	0.072	214	2.89	0.30	0.068	191	2.65	0.26	0.063
5	195	2.97	0.19	0.041	195	2.87	0.22	0.052	168	2.77	0.26	0.074

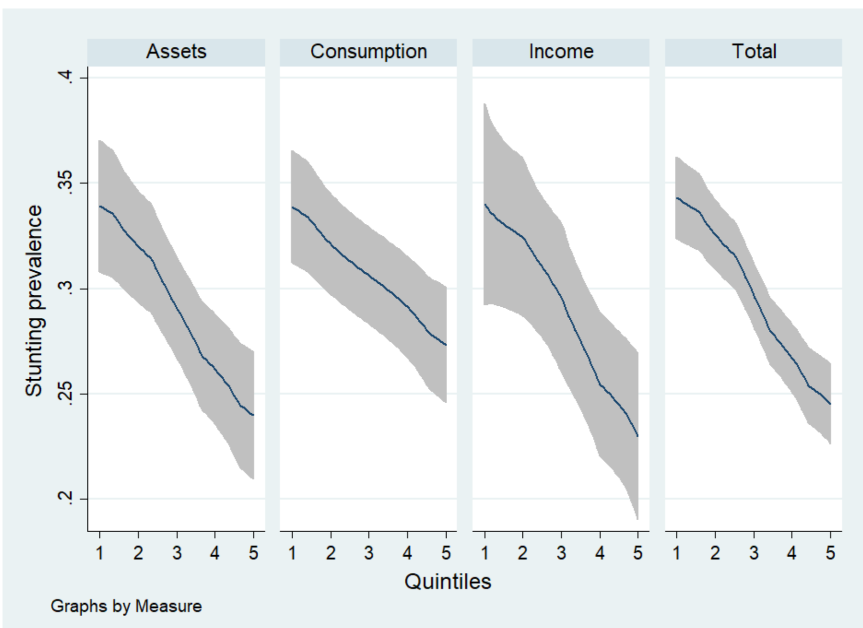
KGZ_1998												
1	423	2.94	0.15	0.038	351	2.59	0.10	0.033	559	3.50	0.13	0.031
2	461	3.09	0.16	0.038	485	3.06	0.12	0.032	538	3.32	0.14	0.035
3	460	3.00	0.12	0.033	506	3.15	0.14	0.039	447	3.34	0.20	0.035
4	515	3.13	0.12	0.026	538	3.36	0.14	0.031	455	2.71	0.13	0.038
5	553	3.03	0.10	0.025	589	2.94	0.15	0.031	362	1.90	0.06	0.023
PAK_1991												
1	807	5.03	0.90	0.160	699	4.46	0.90	0.180	879	4.93	0.91	0.164
2	861	5.09	0.91	0.159	837	4.91	0.81	0.143	915	4.93	0.86	0.157
3	898	5.05	0.73	0.123	911	5.34	0.83	0.134	955	5.06	0.85	0.146
4	956	5.07	0.77	0.127	1,025	5.21	0.73	0.115	927	5.07	0.66	0.108
5	1,073	4.43	0.52	0.100	1,130	4.58	0.57	0.107	895	4.56	0.47	0.083
PAN_1997												
1					522	4.18	0.36	0.056	704	4.50	0.35	0.054
2					683	3.58	0.15	0.026	604	3.55	0.11	0.019
3					702	3.11	0.07	0.015	702	2.86	0.06	0.017
4					790	2.83	0.07	0.019	727	2.61	0.06	0.015
5					798	2.41	0.04	0.009	750	2.29	0.03	0.009
PAN_2003												
1	766	3.65	0.17	0.031	664	3.61	0.21	0.045	939	4.08	0.26	0.048
2	846	3.20	0.14	0.030	903	3.34	0.17	0.032	911	3.19	0.10	0.024
3	940	3.13	0.10	0.024	938	3.14	0.10	0.022	913	2.84	0.08	0.020
4	1,035	2.80	0.10	0.028	1,016	2.78	0.06	0.018	919	2.58	0.05	0.016
5	909	2.41	0.05	0.016	1,001	2.43	0.05	0.017	839	2.29	0.05	0.018
PER_1994												
1	551	4.09	0.54	0.094	530	4.14	0.66	0.109	591	4.30	0.59	0.104
2	577	3.92	0.49	0.091	574	3.87	0.43	0.084	604	4.13	0.56	0.094
3	576	3.55	0.35	0.061	599	3.59	0.32	0.055	577	3.49	0.29	0.056
4	625	3.26	0.24	0.046	634	3.27	0.23	0.046	588	3.06	0.14	0.033
5	594	3.00	0.15	0.035	586	2.96	0.14	0.036	482	2.71	0.11	0.032
TJK_2007												
1					645	3.10	0.29	0.082	910	3.81	0.30	0.064
2					827	3.45	0.26	0.059	909	3.61	0.28	0.066
3					912	3.51	0.27	0.065	945	3.52	0.25	0.059
4					954	3.66	0.25	0.054	948	3.18	0.21	0.056
5					1,143	3.45	0.22	0.052	742	3.10	0.21	0.056
TLS_2007												
1					433	3.62	0.53	0.109	595	4.28	0.57	0.101
2					613	4.00	0.48	0.084	605	4.53	0.49	0.080
3					656	4.58	0.46	0.072	625	4.32	0.45	0.073
4					720	4.56	0.39	0.063	689	4.38	0.36	0.060
5					838	4.54	0.35	0.054	746	4.16	0.31	0.055
UGA_2011												
1	286	4.95	0.86	0.136	241	4.90	0.86	0.138	329	4.99	0.81	0.132
2	314	5.19	0.81	0.127	340	4.84	0.79	0.124	328	5.37	0.77	0.110
3	316	4.93	0.68	0.106	380	5.01	0.68	0.111	344	5.35	0.80	0.123
4	333	4.94	0.64	0.104	380	5.06	0.65	0.102	381	4.98	0.65	0.112
5	353	4.61	0.45	0.073	407	4.63	0.42	0.071	371	3.81	0.30	0.060
UGA_2013												
1	59	3.44	0.41	0.124	372	3.61	0.58	0.121	532	4.11	0.59	0.105
2	41	2.59	0.17	0.040	513	3.60	0.49	0.104	526	3.76	0.44	0.094
3	40	2.88	0.18	0.053	569	3.55	0.43	0.093	571	3.83	0.52	0.104
4	56	1.89	0.16	0.065	647	3.83	0.42	0.087	605	3.39	0.38	0.089
5	47	2.55	0.30	0.082	742	2.84	0.26	0.068	605	2.28	0.18	0.068

ZAF_1993												
1	1,349	3.34	0.54	0.132	1,137	3.32	0.65	0.161	1,635	3.55	0.63	0.140
2	1,305	3.18	0.50	0.122	1,326	3.16	0.46	0.118	1,604	3.04	0.41	0.113
3	1,371	3.02	0.39	0.100	1,529	2.96	0.36	0.092	1,370	2.81	0.32	0.086
4	1,597	2.79	0.31	0.083	1,686	2.84	0.29	0.076	1,296	2.59	0.25	0.077
5	1,314	2.45	0.15	0.054	1,373	2.59	0.19	0.056	1,170	2.55	0.19	0.052

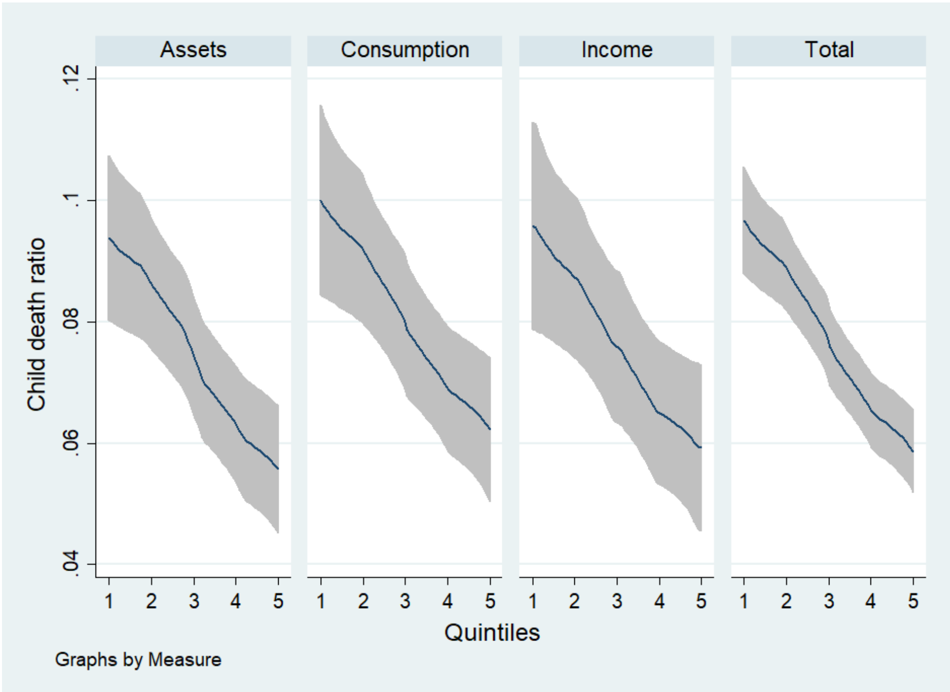
Appendix Figure 1. Kernel-weighted local polynomial plot of prevalence of underweight by quintile divided by assets, consumption, income, and all SES measures



Appendix Figure 2. Kernel-weighted local polynomial plot of prevalence of stunting by quintile divided by assets, consumption, income, and all SES measures



Appendix Figure 3. Kernel-weighted local polynomial plot of prevalence of child death ratio by quintile divided by assets, consumption, income, and all SES measures



Chapter 4. Transnational Wealth-Related Health Inequality Measurement

Preface

At the time of writing, this article has been published in Social Science & Medicine – Population Health and is available as an open-access (CC BY-NC-ND 4 licensed) article at https://doi.org/10.1016/j.ssmph.2018.10.009. This chapter uses the knowledge gained from Chapter 2 and begins the work of justifying and demonstrating a transnational approach to measuring health inequalities. Limitations and potential analytical errors of the country-by-country approach are identified before laying out in detailed steps how a transnational analysis can be conducted using an asset index. This method is then conducted using an empirical example of Haiti and the Dominican Republic, uncovering previously unrecognized transnational health inequalities.

I conceived of this study in conjunction with Dr. Michel Grignon in August 2016. I then compiled all necessary data and conducted all data analysis before writing the manuscript for this chapter. I received significant input into the interpretation and writing of this chapter from my committee members of Dr. Michel Grignon, Dr. Karen Grépin, and Dr. Michelle Dion and incorporated their revisions into this final version of the study.

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Transnational Wealth-Related Health Inequality Measurement

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Abstract

The study of international differences in wealth-related health inequalities has traditionally consisted of country-by-country comparisons using own-country relative measures of socioeconomic status, which effectively ignores absolute differences in both wealth and health that can differ between and within countries. To address these limitations, we propose an alternative approach: that of constructing a transnational measure of wealth-related health inequality. To illustrate the limitations of the country-by-country approach, we simulate the impact of changes in wealth and health inequalities both between and within countries on cross-country measures of health inequality and find at least five errors that may arise using country-by-country methods. We then empirically demonstrate the transnational approach to wealth-related health inequalities between and within Haiti and the Dominican Republic, the two constituent countries of the island of Hispaniola, using data from their respective Demographic and Health Surveys. Transnational socioeconomic rankings reveal a large and increasing divergence in wealth between the two countries, which would be ignored using the county-by-country approach. We find that wealth-related inequalities in long-term children's health outcomes are larger than inequalities in short-term health outcomes, and decompositions of the influence of place-based variables on these inequalities reveal country of residence to be the most important factor for long-term outcomes, while urban/rural residence and subnational regions are more important for short-term health outcomes. The significance of this novel methodological approach in relation to conventional health inequality research, including hidden dimensions of wealth-related health inequalities, for example

the urbanized “middle class” distribution of HIV and a hidden unequal burden of wasting among children uncovered by the transnational approach are discussed, and errors in gauging changes in inequality over time using a country-by-country approach are highlighted. Using the transnational approach can help to measure important trends in wealth-related health inequalities across countries that more commonly used methods traditionally overlook.

Introduction

Health inequality research has matured into a well-recognized field with dedicated journals, funding sources, and institutional support within governmental and non-governmental agencies. With the advent of the Sustainable Development Goals (SDG), reducing inequalities within and between countries as detailed in Goal 10 is now an explicitly recognized global objective demanding internationally standardized measurement techniques (United Nations, 2015). While some effort has been made towards developing indices to measure global convergence in health outcomes across countries (Sachs et al., 2016), empirical research quantifying and comparing socioeconomic inequality in achieving SDG health targets at a multi-country level has been limited. There have been calls for additional research to investigate health inequalities at this level (GBD 2015 SDG Collaborators, 2016; Hosseinpoor and Bergen, 2016; McKinnon et al., 2014), but the methodological foundation for international comparisons in health inequalities has yet to be formally developed. Given the limited attention that has been given to this topic in the global health inequality measurement field, there is a need for the development of new measures to compare health inequalities across countries and over time.

Most studies of wealth-related health inequalities are typically limited to a single country or subregion (i.e. province, state, district, etc.) and use summary measures such as the concentration index, relative index of inequality, slope index of inequality, generalized entropy index, or similar measure to quantify inequality (Kakwani et al., 1997; Marmot et al., 1991). The most common ranking measures of socioeconomic status (SES) that health inequality researchers have used include years of education (Fortson, 2008), income (Mújica et al., 2014), and household expenditure (Mokdad et al., 2015), however, in global health the most commonly used measure across countries is the household asset index (Davidson R. Gwatkin et al., 2007; McKinnon et al., 2014; Van De Poel et al., 2008; Wang, 2003). This technique is based on an accounting procedure that records the presence of typical household assets and calculates an index, often using the method of principal components analysis (PCA) adapted for household SES ranking by Filmer and Pritchett (2001), to calculate the relative well-being of households. The wealth index is now included as a standard feature in all Demographic and Health Surveys (DHS) as both a raw score and as quintiles of households ranked by raw score (Rutstein, 2008).[1] The validity and implicit value judgements of each measure of inequality have been well described for single-unit studies (Harper et al., 2010), but an increasing number of researchers are now using these measures of SES to construct measures of health inequality across more than one country or subregion and over time.

In response to the increasing interest being paid to comparisons of inequalities in global health, some studies have begun compiling, comparing, and even averaging health inequality summary measures across countries using a country-by-country approach (Li et al., 2017; McKinnon et al., 2014; Strømme and Norheim, 2017). Although the need for such research to guide the SDGs is clear, the growing body of studies that have used this country-by-county method have generated somewhat counter-intuitive results; especially

[1] An alternative approach of polychoric PCA offers the advantages of not requiring the creation of dummy variables, includes the lack of ownership of assets in the score, and has been demonstrated to perform at least as well as the original PCA methodology (Filmer and Scott, 2012; Kolenikov and Angeles, 2009).

when there are large differences in disease prevalence and wealth levels between countries. As one illustrative example in Latin America and the Caribbean, researchers have either found that Haiti and Colombia have similarly very low inequalities in health (Arsenault et al., 2017; McKinnon et al., 2014; Paraje, 2009; Van De Poel et al., 2008), or are polar opposites of very high and very low inequality in health (Cardona et al., 2013; Gakidou and King, 2000; Wagstaff, 2002a), with some even presenting conflicting conclusions within the same study. It is possible that these conflicting findings can be attributed to the use of different methods of combining absolute and relative health inequality measures between two countries with very different levels of absolute wealth and health but similar patterns of disease distribution. This is because if the poorer country has a high burden of disease throughout the SES spectrum of its population, a summary measure of wealth-related health inequality may still be quite low, and conversely, a rich country with a very low burden of disease may not result in a large summary measure due to semi-random dispersion in its distribution. The effects of ignoring these differences can be further exacerbated by comparing countries over time. If there are larger increases in absolute wealth in one country or changes in the distribution of wealth in either country, making comparisons with the assumption of relative wealth parity would become invalid; even if the distribution of health outcomes within each unit does not change (Hosseinpoor et al., 2016; Wagstaff et al., 2014). The effects of ever-changing living standards between countries and the varying levels in health inequalities both within and between countries have therefore been continually analyzed as distinct and unrelated phenomena.

In addition to the variety of measurement errors that can arise from different combinations of health and wealth inequalities, the method by which wealth is measured can also have a distortionary effect. Since household asset indices calculated using the most common method of PCA have no meaningful scale (Filmer and Pritchett, 2001), the magnitude of wealth inequality may appear to be different even if absolute wealth levels are equal, or else may appear to be the same even when vast differences in wealth present. If researchers use a scale-dependent measure of inequality or attempt to compare two countries with separately calculated asset indices, this illusion can lead to the appearance of differences in health inequalities even when none are present. Stated differently, it may be clear that a household earning $50,000 is qualitatively different than a household earning $10,000, even if both households are in the highest-earning quintiles of their respective countries, but this difference can be less apparent to researchers if both households have an identical 5.5 household asset index value in the survey data. In sum, depending on the method used to quantify SES and absolute inequalities in health and wealth, comparing the magnitude of wealth-related health inequalities across countries using a country-by-country approach can produce misleading results– a methodological blindness which we propose to address using a new approach.

In this paper, we develop a new methodology to compare estimates of wealth-related health inequalities between countries and over time, an approach we call the transnational approach. To demonstrate its usefulness and the limitations of the country-by-country approach, we first demonstrate the distortionary effects of differences in health and disease prevalence within and between countries on overall differences in health inequalities across countries using simulated survey data. Second, we empirically construct measures of health inequalities across two countries, Haiti and the Dominican Republic, using both the country-by-country approach and the transnational approach. To do so, we begin with a discussion of specific methodological and practical issues that affected our ability to compare these two countries including selecting which countries to compare, identifying an appropriate data source that is comparable across countries or subregions, measuring SES on a common scale across countries, and deciding on an appropriate health inequality measure for transnational health inequality measurement. Our main finding is that the transnational approach identifies very different trends in cross-country health inequalities and that the transnational approach allows us to observe important differences in health inequalities that we could not observe using the country-by-country approach. We discuss the limitations of this approach and instances when we believe it would be more appropriate than more commonly used approaches to measure differences in health inequalities across countries.

Approaches to comparing health inequalities across countries

Rather than combining disparate measures of wealth and health using a bottom-up country-by-country approach, a top-down transnational approach allows us to address confounders which have affected this emerging field. At the most basic level, the transnational approach is simply the analysis of wealth-related health inequalities with every person or household in the area of study ranked using one unified SES measure rather than attempting to compare two or more countries with separate and incomparable SES rankings. The utility of this type of analysis has previously been demonstrated in the decomposition of health inequalities into within- and between-provincial components in Canada (Jimenez-Rubio et al., 2008).[2] The institutional design of Canada's federated health institutions means it can be treated as a proxy for the study of international health with provinces representing the same type of variation as might be seen in a country-by-country analysis, demonstrating that transnational health inequality analysis is theoretically possible. The primary obstacle to extending this style of analysis to the level of international health lies in the comparison of SES between countries, as one cannot simply use a common currency or an assumption of formal and relatively stable household incomes. However, it is possible to overcome this obstacle using common methods of household asset index creation to extend analysis from the within-country scale to the scale of multiple countries, bringing with it more significant health inequalities and greater policy diversity inherent in international research and leading to findings which are not apparent using any other method.

Although the lack of income or expenditure data in most household health survey of low- and middle-income countries may seem to be a significant challenge, the common practice of using a household asset index to rank SES can be used to generate a transnational ranking. The asset index measures a different dimension of SES than

[2] Similar work comparing within- and between-jurisdictional inequalities in health have been conducted in both high-income (Allanson, 2017) and low- and middle-income countries (Chalasani, 2012; Pulok et al., 2018), but Jimenez-Rubio et al. (2008) provide a useful framework for understanding the general approach.

income or household expenditure that is more indicative of long-term SES than short- or medium-term income, and as such may not yield the same relative rankings (Howe et al., 2009). However, since they are derived from household assets, these indices can be easily measured, remain relatively stable over time, and can be directly compared across national boundaries – all major advantages over income or expenditure data which can fluctuate dramatically and can be difficult to measure accurately in developing contexts (Bollen et al., 2002; Sahn and Stifel, 2003). The main challenge in using this measure comes from the fact that although asset indices effectively rank each household relative to others in the sample, the numeric value of each index has no inherent value – it is an ordinal, but not an interval variable. Nevertheless, with care to ensure all household assets are directly comparable, one can pool two or more household surveys together, create a new transnational asset index using common methods such as PCA, and then analyze the within- and between-country components of health inequalities, as demonstrated by Jimenez-Rubio et al. (2008). While the fundamental approach is straightforward, the consequences of using the transnational approach in place of the currently accepted practice of country-by-country comparisons of international health inequalities are far from trivial.

To demonstrate the differences between the country-by-country approach and transnational approaches to estimating differences in health inequalities, we simulate the theoretical impact of changes in both income[3] and disease inequality within and across

[3] Although most transnational wealth-related inequality issues are related to the use of household asset indices, income is used as the ranking measure in the simulation for ease of understanding.

countries using simulated survey data. A “poorer” country (mean income $30,000) and a “richer” country (mean income $40,000) with normally distributed and overlapping incomes were randomly assigned different prevalence levels of a disease according to transnational quintile, representing the entire SES distribution of both countries divided into five equal parts. Individuals were randomly assigned a hypothetical disease outcome varying randomly from a 0.65-0.75 level in the poorest transnational SES quintile to 0.25-0.35 in the richest transnational quintile. This disease distribution is meant to represent disease outcomes which are more prevalent both in poorer countries and among lower SES status within countries. Parameters of both between- and within-country income inequalities and health inequalities were then varied to observe the relative effect of both transnational and country-specific income-related health inequalities.[4]

[4] Appendix Table 1 presents concentration indices for each scenario.

Table 1. Simulated transnational composition effects for increases and decreases in both within- and between-country health and income inequality.

Variable modified	Direction of modification	Poor country inequality	Rich country inequality	Country-by-country inequality	Transnational inequality	Error #
Health inequality between countries	Convergence (poor reduces disease prevalence more than rich country)	Increase	No change	Increase	Decrease	1
	Divergence (rich reduces disease prevalence more than poor country)	No change	Increase	Increase	Increase	
Income inequality between countries	Convergence (poor catches up to rich)	No change	No change	No change	Decrease	2
	Divergence (rich becomes even wealthier than poor)	No change	No change	No change	Decrease	3
Health inequality within countries	Decrease in richer country	No change	Decrease	Decrease	Decrease	
	Increase in richer country	No change	Increase	Increase	Increase	
	Decrease in poorer country	Decrease	No change	Decrease	Decrease	
	Increase in poorer country	Increase	No change	Increase	Increase	
Income inequality within countries	Decrease in richer country	No change	Decrease	Decrease	Decrease	
	Increase in richer country	No change	No change	No change	Decrease	4
	Decrease in poorer country	Decrease	No change	Decrease	Decrease	
	Increase in poorer country	No change	No change	No change	Decrease	5

In Table 1, we present the differences that each of these effects have on the direction of both within- and between-country health inequalities, several of which would be undetectable or produce counterintuitive results using country-by-country methods. For example, error #1 identifies a situation in which reducing between-country health inequality by improving health outcomes in the poorer country increases health inequality within that country but decreases transnational inequality. Therefore, if a researcher were to use a country-by-country approach and simply count the number of countries that had experienced increases in health inequalities or take an average of country-level health inequalities – a method which has been used in published literature – one would conclude that overall inequality in the two countries had increased rather than decreased. An increase or decrease of between-country income inequality with disease prevalence staying the same, as described in errors #2 and #3, would result in changes to transnational inequality, but country-by-country inequality remaining exactly the same. Similarly, increasing within-country income inequality in either the poorer or richer country, as described in errors #4 and #5, would decrease transnational inequality, but be completely undetected using country-by-country methods. Given the many threats to validity demonstrated in the simulated survey data, there is clearly justification for the use of transnational health inequality research, but the feasibility of doing so using real-world data must first be considered.

Empirical Example: Wealth-Related Health Inequalities in Hispaniola

To best demonstrate the utility of the transnational approach, case selection for our empirical demonstration was guided by three factors – a clearly demarcated jurisdictional or physical boundary for each individual jurisdiction and for the transnational unit, a most-different (i.e. extreme case) case selection approach, and data availability. These criteria were chosen to explore cases which most closely match the simulated composition effects identified in Table 1 while reducing the influence of confounding effects such as differing cultural contexts, conflict zones, or environmental/ecological differences. The contrast afforded by an "extreme case" and "most different case" selection logic has the advantage of highlighting transnational inequalities that may be overlooked using country-by-country methods of analysis (Seawright and Gerring, 2008).[5] These considerations led to the selection of Haiti and the Dominican Republic, which together constitute the island of Hispaniola.

The physical boundary formed by the limits of the shared island provide an ideal and intuitive delimitation for the frame of analysis. The shared terrain has shaped the economic development and the public health challenges faced by both countries, but despite their shared geography, each country has undergone remarkably divergent paths of development. Whether the measure is gross national income (GNI) per capita, human development index, life expectancy, or infant mortality rate; Haiti has long endured the lowest quality of life measures in the Western Hemisphere, and has consistently fared worse than the neighboring Dominican Republic with an 11 year gap in life expectancy and a GNI per capita more than eight times lower than its richer neighbor in 2016 (The World Bank, 2017). The disparity between these countries has not gone unnoticed among health inequality researchers. More than fifteen years ago, Adam Wagstaff posed a prescient question - why is it "that the two countries that occupy the Caribbean island of

[5] While this case selection method is inappropriate for generalizing findings to countries not selected for analysis (Lieberson, 1992), it is appropriate for a study demonstrating the utility of a novel methodology.

Hispaniola-the Dominican Republic and Haiti-have such markedly different levels of inequality in child malnutrition and mortality?” (2002a, p. 10). He concluded that Hispaniola is an illustrative case of the tendency for health inequalities to increase as per capita incomes increase and as concomitant gains in health outcomes begin to take root among those benefiting from economic growth – the same effect identified in our transnational composition effect simulation.

Several studies have investigated health inequalities in Haiti (Arsenault et al., 2017; Danquah et al., 2015; Fenn et al., 2007; Davidson R Gwatkin et al., 2007a) and in the Dominican Republic (Davidson R Gwatkin et al., 2007b; Wagstaff, 2002b) separately. In addition, a number of studies have also contrasted measures of health inequalities across the two countries using country-by-county methods. One study found Haiti to have the largest inequities in health of any country in the Latin American and Caribbean (LAC) region using an index of health and socioeconomic factors, while the Dominican Republic was ranked sixth worst out of 20 total countries in the same analysis (Cardona et al., 2013). In contrast, another cross-country comparison using DHS data noted that although Haiti had the lowest levels of inequality in child malnutrition in the LAC region, this obscured the fact that it had one of the highest absolute levels of child malnutrition in the region (Paraje, 2009). These seemingly contradictory findings can be explained by the limitations in making comparisons across countries using different reference points for both wealth and health; the best performing country in the first case, and own population in the second case. Thus, depending on the reference point, completely contradictory findings can be obtained due to a fundamental tension that cannot be resolved using a country-by-country frame of analysis – more examples of the errors we identified in our simulation. Absolute differences in health inequalities across countries and inequalities within countries can be compared, but the magnitude of wealth-related inequalities among the population of Hispaniola as a whole cannot be measured using the current paradigm.

Having selected cases for analysis, the challenge of identifying an appropriate data source to pool over the two countries was solved using DHS data, which offer seven waves of more than 300 household surveys in over 90 countries with directly comparable health outcomes collected over three decades by international researchers in conjunction with country officials (Corsi et al., 2012). Health outcomes included in these datasets are mainly focused on maternal and child health, but certain countries have chosen to add country-specific modules. Directly measured outcomes always include children's height and weight, and sometimes include laboratory test results for other outcomes such as anemia, human immunodeficiency virus (HIV), and malaria. These direct measures are complemented by self-reported health outcomes regarding child mortality, cough, diarrhea, and fever. An additional advantage of using DHS data is the availability of georeferenced data, which have been previously used to map children's health outcomes across several African countries (Burke et al., 2016; Kazembe and Mpeketula, 2010).[6] Using these techniques, subregional differences within countries can point to

[6] Actual global positioning system (GPS) coordinates are offset by up to five kilometers in rural clusters and up to one kilometer in urban clusters while remaining inside the administrative boundary to protect confidentiality, however, on aggregate, these random displacements do not affect the results (ICF International, 2012).

environmental or political determinants of health that would be overlooked using summary indicators, and more relevant to this study, sharp discontinuities across national boundaries can be suggestive of country-specific determinants of health (Burke et al., 2016).

The Dominican Republic has participated in every wave of DHS since its inception in 1986 (DHS-I to DHS-VI), while Haiti has participated since 1994 (DHS-III to DHS-VI). The analysis was restricted to women of reproductive age and their children, because adult men are only sampled as a subsample of the women's household surveys and the sample is therefore relatively underpowered and non-representative (ICF International, 2012). To capture a variety of distributions of inequalities in health, every health outcome (excluding healthcare utilization variables) present in surveys for both countries were analyzed (Appendix Table 2). Children's nutritional health outcomes are widely recognized to be crucial to public health and are generally more sensitive to living standards than adult health outcomes (Marmot, 2005). Therefore, the directly measured outcomes of underweight, stunting, and wasting were all converted to binary outcomes (z-scores two standard deviations below zero), because of the limited and uncertain influence of positive z-scores on children's health in this context.[7] Self-reported outcomes of children's fever, cough, and diarrhea in the last two weeks were also included as indicators of short-term children's health. From the women's dataset, a ratio of self-reported children's deaths to live births was included as a proxy for infant

[7] Reference standards developed by the DHS for children's height and weight were used rather than the World Health Organization's (WHO) standards to allow direct comparability throughout all survey waves (WHO standards only available for DHS wave 6).

mortality, and blood tests for HIV status were included to observe whether infectious diseases exhibited a different pattern of inequality.[8] All calculations were performed using STATA version 13 (StataCorp LP, College Station, TX) and survey weights were included in all relevant calculations with poststratification adjustment according to each country's population.[9] In addition to these summary measures, georeferenced data was available for both Haiti and the Dominican Republic in waves five and six. Using these georeferenced data, the geography of health inequality throughout Hispaniola was investigated using ArcGIS (ESRI, Redlands, CA). The prevalence of disease for each survey cluster was mapped using global positioning system coordinates, and both spline interpolation and kriging methods were used to produce smoothed disease outcome maps (Auchincloss et al., 2012, 2007). Although waves three and four did not include georeferenced data, the earliest available shared survey (wave three) was analyzed for both countries to track the evolution of inequalities over time.

Despite the DHS offering a rich source of information for health outcomes in both countries, the surveys generally do not contain income or household expenditure data – a common challenge present in many household health surveys. This led us to create a new household asset index for the entire transnational sample for each of DHS waves three (1994-1996), five (years 2005-2007) and six (2012-2013). Household asset data was first

[8] Corrections using Heckman-type selection models have been suggested for use in analyzing HIV status using DHS data due to selection issues associated with nonparticipation rates being higher for HIV testing in particular, however, since bias has been found to only significantly impact male prevalence rates (Bärnighausen et al., 2011), a correction was not performed in this case.
[9] Postweights based on population under 5 for children's recode and women aged 15-49 for women's recode variables using United Nations population data.

closely examined and recoded to ensure direct comparability between both countries before a transnational asset index was calculated for each wave.[10] With socioeconomic ranking of the transnational dataset complete, quantification of wealth-related health inequalities was conducted using the concentration index. We calculated the concentration index using methods described by O'Donnell et al. (2008) and concentration indices for all binary variable outcomes were corrected using the Wagstaff (2005) method.[11] Concentration indices are represented graphically as concentration curves, which represent all individuals ranked in order of lowest to highest SES along the x axis, with the cumulative share of disease plotted on the y axis, usually contrasted against a 45-degree diagonal line of equality for reference. The concentration index has a value ranging between -1 and 1 which corresponds to two times the area between the line of equality and the concentration curve; or the percentage of the total outcome of interest that would have to be redistributed from the richest half to the poorest half of the population to reach a state of equality (Koolman and van Doorslaer, 2004; O'Donnell et al., 2008; Wagstaff et al., 1991). We therefore exploit the fact that the concentration

[10] Only assets included in both country surveys were included for analysis, resulting in a range of 26 (wave three) to 52 (wave six) assets included for analysis. One wealth index was created with the same methodology used by the DHS Program (Filmer and Pritchett, 2001; Rutstein, 2008), including rescaling of rural and urban households with a secondary regression, and another wealth index was calculated using polychoric PCA. Given the more desirable statistical properties of polychoric PCA (Kolenikov and Angeles, 2009) and minimal difference between the two indices, polychoric PCA wealth index values are used as the default in this analysis.

[11] An alternative method of addressing binary outcome variables is the Erreygers method (Erreygers, 2009; Erreygers and Ourti, 2012). Since we are more interested in relative inequality of health than absolute inequality and compare only outcomes of ill health rather than good health the Wagstaff correction is appropriate (Kjellsson and Gerdtham, 2013) and represents the more widely used method in global health literature.

index is unaffected by a non-interval SES variable and proceed to decompose the index into its constituent parts.

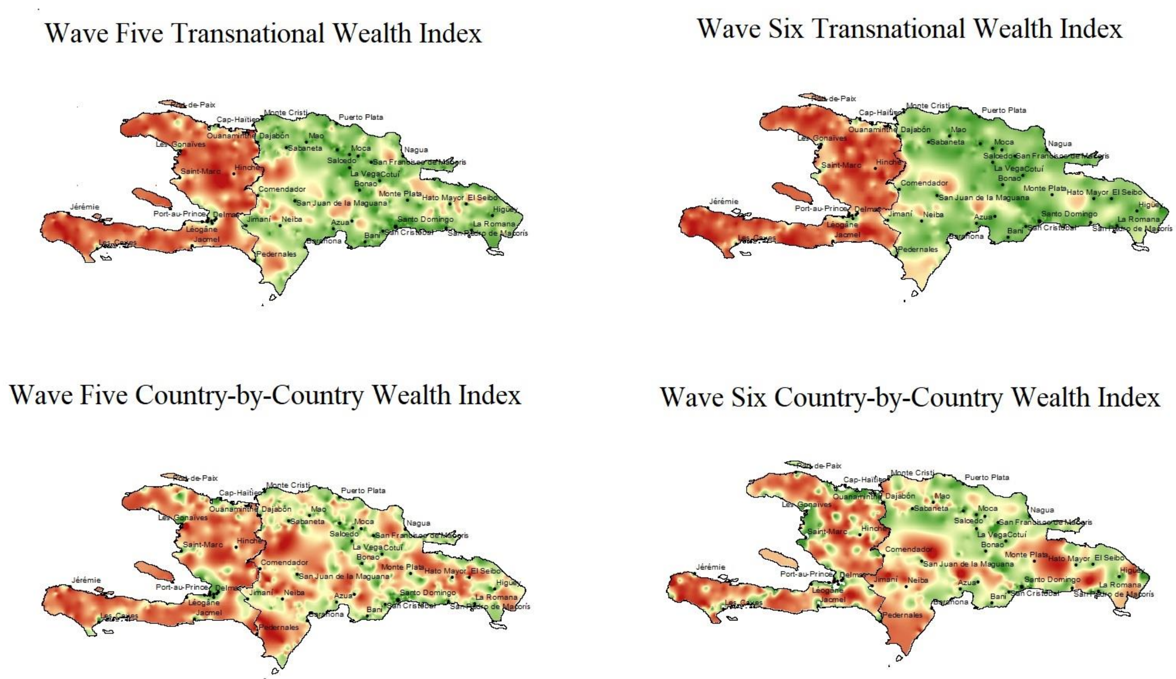
The decomposition of the concentration index has been used to tease out factors which contribute to social inequalities in health as well as whether the factors contribute to larger or smaller inequalities. Studies using this approach do so for two main reasons. The first type attempts to identify possible causal factors which determine population social inequality in health, such as education, national income growth rates, or healthcare system characteristics (Goesling and Firebaugh, 2004; McGrail et al., 2009; Sahn and Younger, 2006). The second approach does not attempt to identify causal factors that explain patterns of inequality, but investigates the relative distribution of inequality among groups, often investigating the degree to which inequalities are distributed *within* geographical regions or *between* geographical regions (Pradhan et al., 2003). Within the Canadian context, for example, studies have decomposed health outcomes and healthcare use inequalities into both causal (Allin, 2008) and distributional (Jimenez-Rubio et al., 2008) types. With respect to our empirical demonstration, using the distributional decomposition approach means that besides removing the possibility of analytical errors demonstrated in the simulation, the transnational approach can identify the ways in which disadvantaged regions shift over time and the degree to which they are distributed between and within countries. Our concentration indices were therefore decomposed into three principal geographical constituents – the cross-country component, the within-country subregional component, and the urban-rural component.[12,13] Having addressed the major challenges of justifying cases for inclusion, using high-quality comparable data, ranking households according to a common SES scale, quantifying the magnitude of inequalities in health on a transnational scale, and decomposing these inequalities according to their distributional components, we proceed to describe the results of the first empirical demonstration of transnational health inequality decomposition in Haiti and the Dominican Republic.

[12] Subregions were recoded in waves five and six to be directly comparable using ten Haitian departments and nine Dominican health regions, however wave three only contained three Haitian divisions (north, metropolitan, south).

[13] Rather than only using within- and cross-country variables to decompose following Jimenez-Rubio (2008), urban-rural status was added to account for a possibly significant confounding factor. Subregions were used as fixed effect variables, while urban-rural and country were used as the primary decomposition variables.

Results

Figure 1. Transnational and country-by-country wealth index spline interpolation for waves five and six

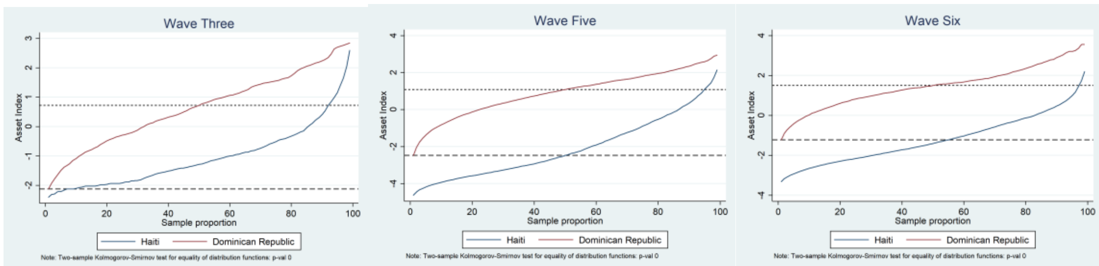


A map of transnational household asset index values (Figure 1, top) from highest (green) to lowest (red) clearly demonstrates a sharp disparity in wealth between the two countries.[14] It is important to note that borders are presented for visual aid only and did not affect wealth index calculation or interpolation in any way. This makes the sharp divide which nearly identically coincides with the Haitian-Dominican border all the more

[14] Alternative specifications of PCA wealth index and kriging interpolation are presented in Appendix Figures 1 and 2, but do not affect these results significantly.

striking. Going past this clear contrast, there are, nonetheless, areas of relative wealth and deprivation in both countries. The Dominican Republic's pockets of relative deprivation are observed in mountainous and rural areas and are fewer in number in wave six. Haiti's pockets of relative affluence are nearly all concentrated around major cities of Port-au-Prince, Cap-Haïtien, Saint Marc, Gonaïves, and Les Cayes. In contrast, mapping country-specific values of the same index values (Figure 1, bottom) displays no such contrast. While the areas of relative wealth within each country are the same, there is no discernible wealth disparity between countries, an effect which is guaranteed by the use of country-by-country methods, and which could produce counterintuitive results if interpreted naively. In effect, the country-by-country maps are a visual representation of how wealth data can be misleadingly used to erase real and meaningful differences in household SES.

Figure 2. Pen's Parades of polychoric PCA wealth indices for waves three (left), five (center) and six (right)



Pen's Parades presented in Figure 2 order each country's households from lowest to highest SES from left to right according to each wave's transnational asset index values – a comparison which would be impossible using country-by-country analysis.[15,16] Although the units of the index are not inherently meaningful, the relative standing of each household within each wave reveals that Dominican respondents are consistently wealthier than their Haitian counterparts.[17] Even more revealing, Dominicans are increasingly wealthier as time goes on. In wave three, both the "poorest" and the "wealthiest" Haitian respondents were almost as wealthy as the equivalent Dominican

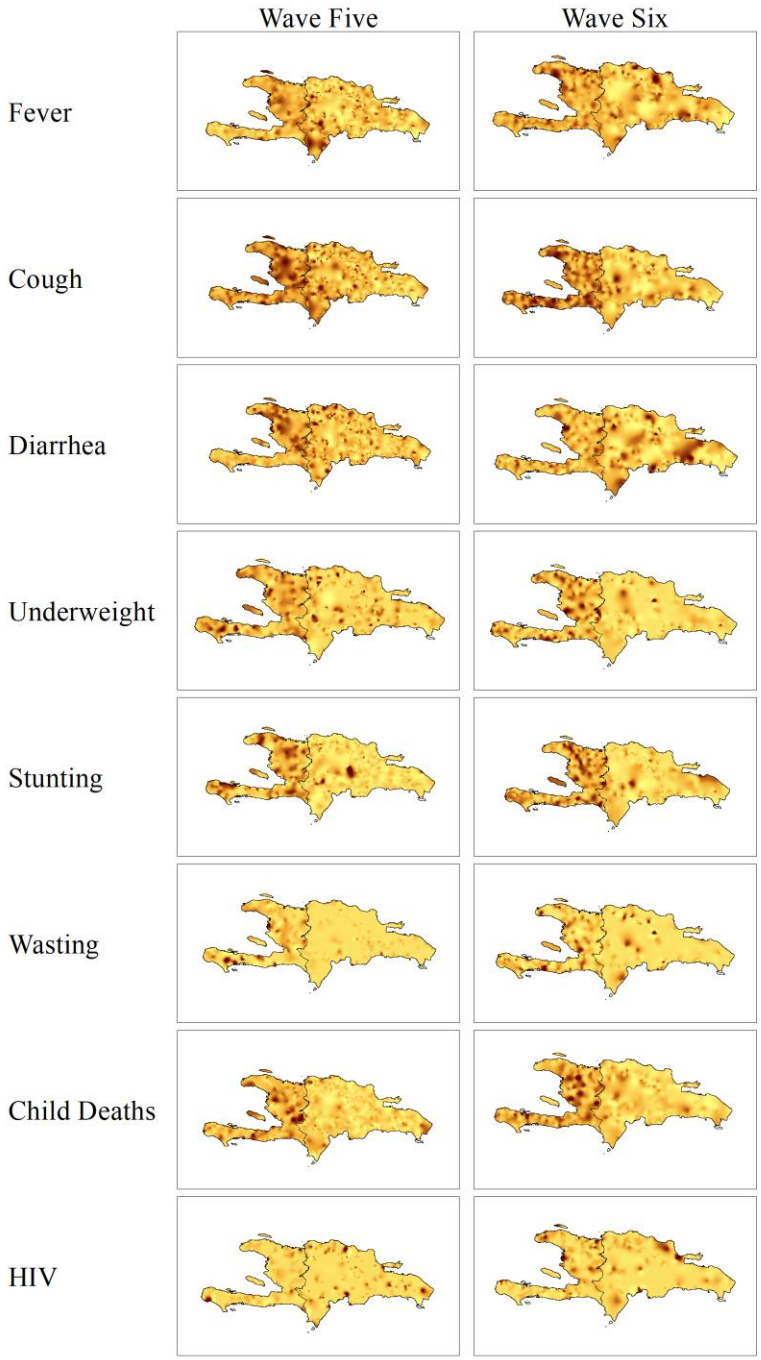
[15] PCA and polychoric PCA wealth indices performed very similarly overall, and closely matched the original wealth index calculated by DHS staff (Appendix Table 3). For example, the spearman's rho between the wave six transnational PCA wealth index and DHS wealth index are for the Dominican Republic (0.92) and Haiti (0.90). The same values between the polychoric PCA index and the original DHS index are 0.90 and 0.88 for the Dominican Republic and Haiti respectively, and PCA and polychoric PCA wealth indices reached a spearman's rho of 0.97 for the transnational sample. Differences due to dropping variables not present in both datasets were therefore minimal, and transnational PCA and polychoric PCA wealth indices were more similar to each other than to the DHS indices in every wave.

[16] Two reference lines have been added at the level of the lowest wealth index centile and the median wealth index value for the Dominican Republic.

[17] Reference lines within each survey wave can be used to compare countries, but cannot be used to compare other survey waves.

respondents. In wave five, however, the poorest Dominican respondents were about at wealthy as the median Haitian respondents, and the wealth disparity only worsened in wave six, recreating several conditions identified as potential confounding in the simulated survey data.

Figure 3. Health outcome maps for DHS waves five (left) and six (right) for fever, cough, diarrhea, underweight, stunting, wasting, child deaths, and HIV status (top to bottom)



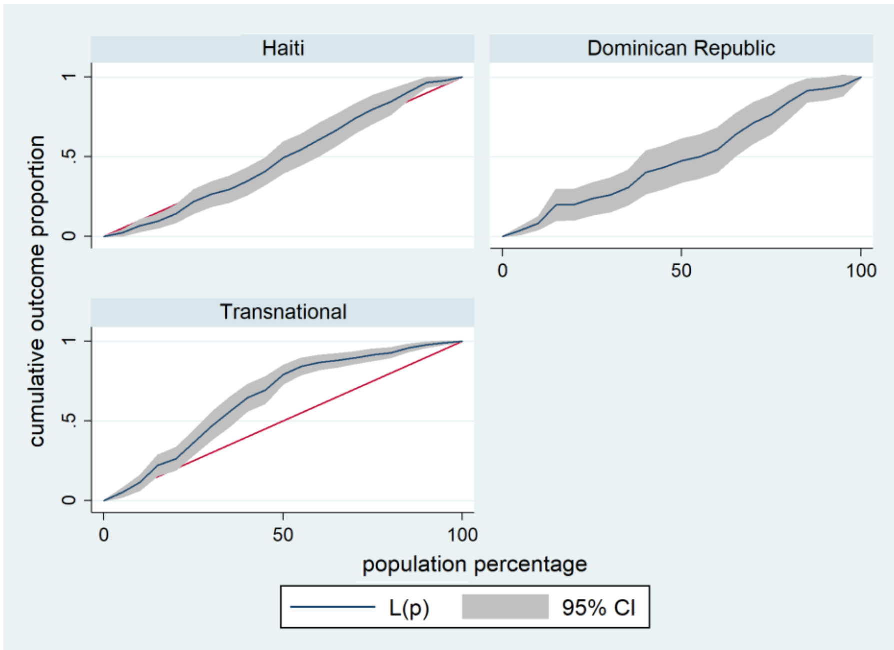
Moving from wealth to health, maps of health outcomes (Figure 3) represent higher prevalence of each outcome with red shading.[18] The acute children's health outcomes seen in the top three rows of Figure 3 are fairly evenly dispersed throughout both countries, with the exception of cough, which appears to be slightly more prevalent in Haiti. In contrast, there are clearly more high-prevalence clusters for the three long-term outcomes of underweight, stunting, and wasting on the Haitian side of the border. Health outcomes from the women's surveys, however, display two very different distributions of disease. Just as long-term children's health outcomes, child deaths are clearly more prevalent on the Haitian side of the border, but high-prevalence clusters of HIV appear to be spread evenly throughout the island.[19]

[18] Wave three data were not georeferenced. Borders are presented for visual aid only and did not affect interpolation.
[19] An effect similar to the one seen in Figure 2 would be observed for health outcomes if interpolation was conducted separately for each country, but since this would be an artifact of interpolation methods rather than data analysis (anthropometry is always measured on the same scale), no additional maps or analysis were conducted.

Table 2. Concentration indices for Haiti, the Dominican Republic, and transnational sample with a country-by-country average and differences between both countries and survey waves

Wave Three	Haiti	DR	Haiti-DR Difference	p-value	Country-by-country	Transnational		
Stunting	-0.275	-0.452	-0.177	0.00*	-0.364	-0.495		
Underweight	-0.254	-0.492	-0.238	0.00*	-0.373	-0.537		
Wasting	-0.125	-0.176	-0.051	0.69	-0.151	-0.400		
Diarrhea	-0.061	-0.135	-0.073	0.06	-0.098	-0.208		
Fever	-0.085	-0.068	0.016	0.68	-0.077	-0.158		
Cough	-0.065	-0.094	-0.03	0.42	-0.080	-0.159		
Child Deaths	-0.069	-0.189	-0.12	0.00*	-0.129	-0.259		
Wave Five	Haiti	DR	Haiti-DR Difference	p-value	Country-by-country	Transnational	Country-by-country change	Transnational change
Stunting	-0.316	-0.265	0.051	0.31	-0.291	-0.579	0.073	-0.084
Underweight	-0.23	-0.314	-0.084	0.13	-0.272	-0.694	0.101	-0.157
Wasting	0.007	0.01	0.003	0.97	0.009	-0.503	0.159	-0.103
Diarrhea	-0.06	-0.061	-0.001	0.98	-0.061	-0.186	0.038	0.022
Fever	-0.041	-0.02	0.021	0.6	-0.031	-0.120	0.046	0.038
Cough	-0.045	-0.056	-0.011	0.79	-0.051	-0.233	0.029	-0.074
HIV	0.044	-0.266	-0.31	0.00*	-0.111	-0.339		
Child Deaths	-0.116	-0.135	-0.019	0.36	-0.126	-0.278	0.004	-0.019
Wave Six	Haiti	DR	Haiti-DR Difference	p-value	Country-by-country	Transnational	Country-by-country change	Transnational change
Stunting	-0.246	-0.265	-0.019	0.78	-0.256	-0.413	0.035	0.166
Underweight	-0.215	-0.273	-0.058	0.42	-0.244	-0.388	0.028	0.306
Wasting	-0.111	-0.034	0.077	0.42	-0.073	-0.290	-0.081	0.213
Diarrhea	-0.015	-0.106	-0.091	0.04*	-0.061	-0.068	0.000	0.118
Fever	-0.017	-0.053	-0.036	0.34	-0.035	-0.073	-0.005	0.047
Cough	0.036	-0.066	-0.102	0.01*	-0.015	-0.219	0.036	0.014
HIV	0.082	-0.322	-0.404	0.00*	-0.120	-0.245	-0.009	0.094
Child Deaths	-0.071	-0.133	-0.061	0.03*	-0.102	-0.234	0.024	0.044

Figure 4. Wave five wasting concentration curves for Haiti, Dominican Republic, and transnational samples

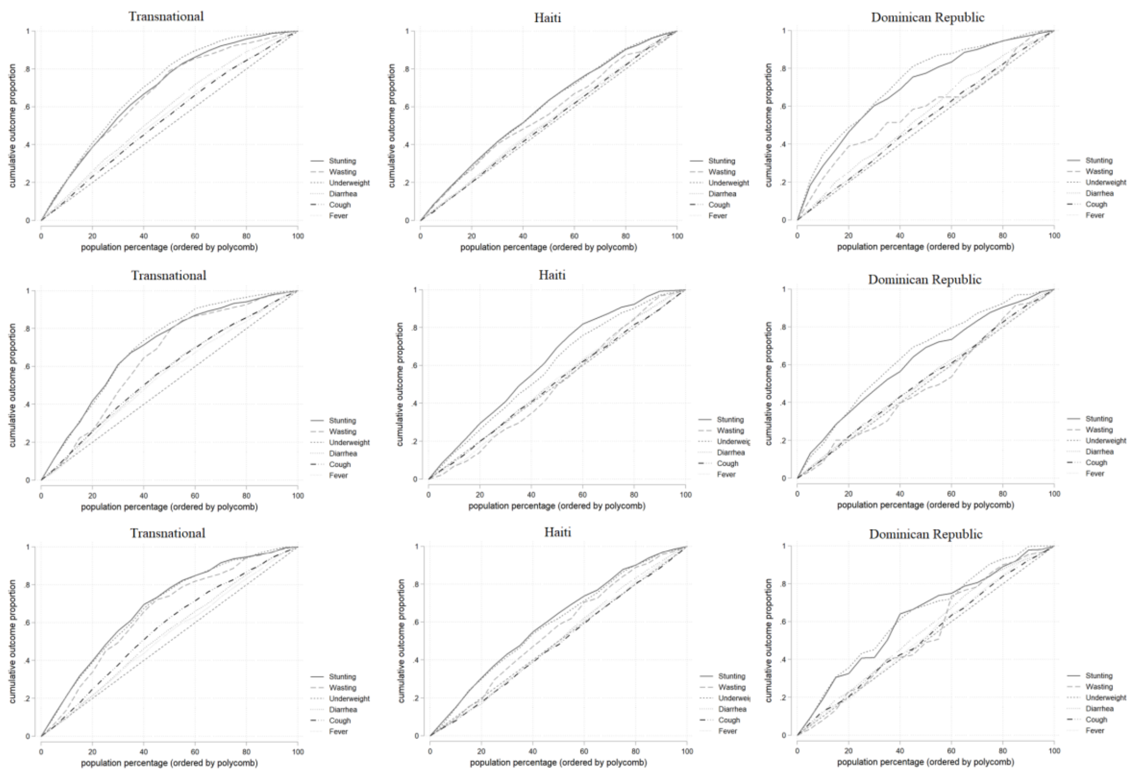


Delving deeper into these outcomes, Haitian survey respondents more frequently reported higher rates for every negative health outcome than respondents in the Dominican Republic.[20] Concentration indices for each of these outcomes are presented in Table 2. Country-by-country concentration indices indicate a significant difference between Haiti and the Dominican Republic at the 95% level in only eight of 23 outcomes analyzed, with child deaths and HIV status most likely to be significantly different. In contrast, the transnational sample consistently results in higher concentration indices, which is caused both by the disparities in wealth between the two countries and by the higher prevalence

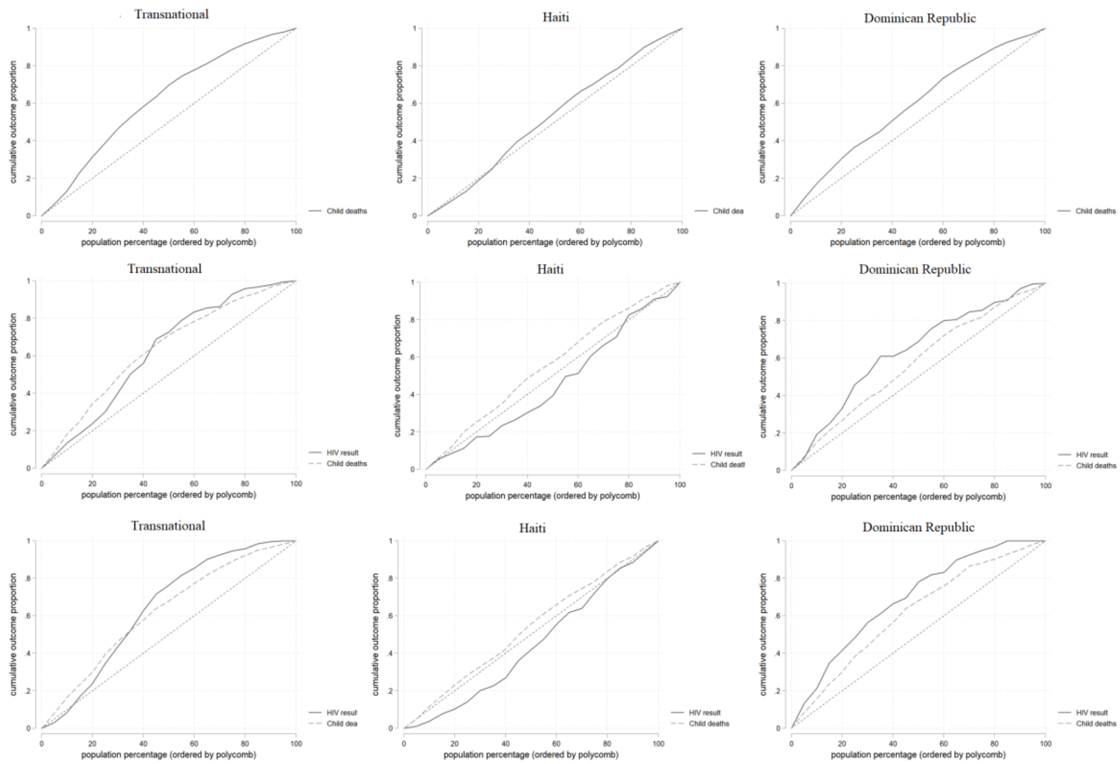
[20] Descriptive statistics for health outcomes and wealth indices in waves three, five, and six are available in Appendix Tables 4-9.

of each outcome in Haiti – yet another hidden effect predicted in the simulation exercise. This effect can be more clearly seen by plotting the concentration curves. For example, Figure 4 shows that for the outcome of wasting in wave five, both Haiti and the Dominican Republic have no significant wealth-related inequalities in the distribution of wasting within their borders, however, due to the much higher prevalence in the lower SES country, the transnational sample has a highly significant pro-rich inequality of distribution for the island as a whole. Finally, changes in wealth-related health inequalities over time for both the country-by-country approach and for the transnational approach result in diametrically opposite conclusions in eight out of the fifteen measures that can be compared from wave to wave, and there are large differences in magnitude for those that are at least aligned in direction.

Panel 1. Concentration curves for children's health outcomes in wave three (top), wave five (middle), and wave six (bottom) for transnational sample, Haiti, and Dominican Republic

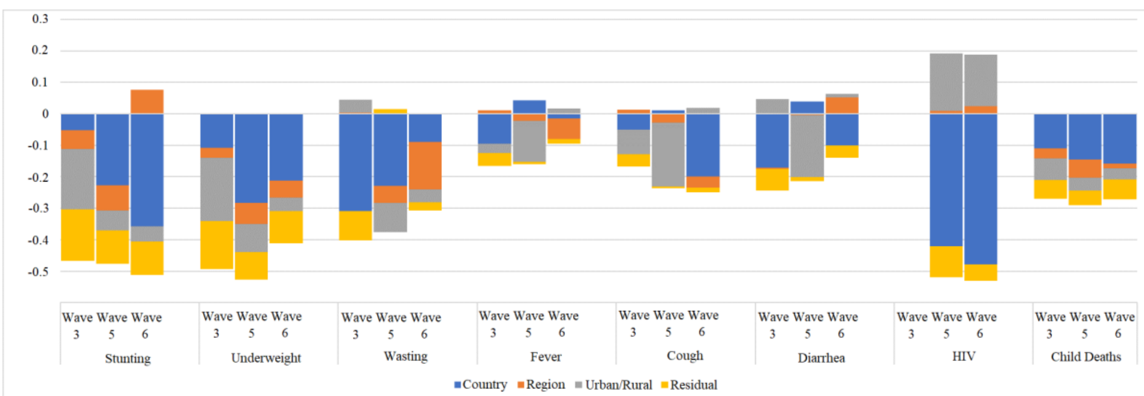


Panel 2. Concentration curves for child deaths and HIV status in wave three (top), wave five (middle), and wave six (bottom) for transnational sample, Haiti, and Dominican Republic



Concentration curves for both countries and for Hispaniola are presented for children's health outcomes in Panel 1, and women's health outcomes in Panel 2. For the transnational analysis, every outcome is disproportionately concentrated among the poor, with underweight, stunting, and wasting consistently being the most inequitably distributed outcomes, while fever, cough, and diarrhea are relatively more equitably distributed throughout the socioeconomic spectrum of Hispaniola. For example, in wave five more than 60% of underweight children were found within the poorest third of the population of Hispaniola and over 80% of underweight children were within the poorest half of the population. These wealth-related inequalities in child health outcomes worsened between waves three and five, but subsequently decreased in wave six. Among all these outcomes, there is one clear outlier – HIV status. In Haiti, HIV is more prevalent among the relatively more affluent, while in the Dominican Republic, it is more prevalent among the less affluent. As a result, the transnational concentration curve displays a pronounced rise in inequality at the middle of the SES spectrum, the effect of combining two of the hidden effects demonstrated in our simulated data.

Figure 5. Concentration index decompositions for every wave and outcome



Finally, the magnitude of the contributions of country, subregion, and urban-rural status to wealth-related inequalities in health are presented graphically in Figure 5.[21,22] Most of

[21] Distributional decompositions of each concentration index are presented in Appendix Tables 10-12.
[22] Wealth itself is not included in the decomposition because household asset index values have no meaningful scale.

the systematic variation in wealth-related inequalities can be explained by the three location-based variables in every wave and for every outcome, leaving little variation in the residual. Stunting and wasting inequality were mainly driven by urban-rural status in wave three, after which country status became the primary driver of inequality. Wasting displays a different trend in which country of residence was the primary driver of inequality in waves three and five, while subregions have become the primary cause of inequality in wave six. This may be due to the low prevalence of the outcome, or due to the slow, but steady rise in prevalence in the Dominican Republic over each wave. Fever, cough, and diarrhea display no such systematic variation from wave to wave. Interestingly, wealth-related inequalities in HIV status are consistently made more concentrated among the poor by country of residence, but urban-rural status significantly reduces these inequalities. This is driven by increased prevalence in cities, and further elucidates the results seen in Panel 2. Finally, inequalities in child deaths are primarily driven by country of residence in every wave, with lesser contributions of subregions and urban-rural status. These previously hidden trends in the geographic distribution of adverse health outcomes in Hispaniola have significant implications for health inequality research.

Discussion

The empirical results of this first transnational wealth-related health inequality analysis demonstrate that the distribution of wealth and of health outcomes across countries affects the estimation of health inequalities in country-by-country comparisons and that these limitations can be overcome using the same sources of data currently used in the literature. The transnational wealth index analysis confirms a large and increasing divergence in household wealth between Haiti and the Dominican Republic over time. However, poorer Dominican respondents living primarily in rural areas are still not as wealthy as the far fewer relatively wealthy Haitian respondents living primarily in urban areas. Acute child health outcomes of fever, cough, and diarrhea are common throughout the island, and decomposition results do not identify a consistent geographic driver of inequality among these outcomes. In contrast, the long-term child health outcomes of underweight, stunting, and wasting were all much more prevalent in Haiti.[23] It appears that this is not attributable to differential incidence of short-term disease, rather, the extremely high concentration index values point to long-term wealth-associated determinants such as nutrition, living conditions, and healthcare access. The ratio of child deaths follows the same mould as these long-term health outcomes, albeit at slightly lower levels of wealth-related inequality.[24] In contrast to these long-term health outcomes, HIV status exhibits a very different distribution. The magnitude of wealth-related inequality is just as large as child deaths, but the decomposition identifies country of residence to be a major driver of inequality, with urban/rural status reducing this

[23] This may be partially attributed to recall bias since these outcomes are not directly measured, but the relative rate at which parents recalled their children falling ill within the last two weeks of being surveyed was fairly consistent from wave to wave.
[24] The impact of the devastating 2010 earthquake can certainly not be overlooked, and the health outcome one might have most expected to be affected would be child deaths. Nonetheless, the ratio of child deaths observed in the sample falls continuously from waves three to five to six for both countries, and the Port-au-Prince area does not appear to have a markedly higher child death ratio than surrounding areas in Haiti.

inequality significantly. This is because HIV status is the only health outcome which is more prevalent in urban areas, which are relatively wealthier than rural areas in both countries. Looking at the wealth-related inequalities in health over time, it is encouraging that following increases from waves three to five, a decrease in wealth-related inequality for every health outcome has started to take hold.

Researchers investigating global health inequalities should take note of several aspects of these empirical results. First, limiting analysis of health inequalities to country-by-country comparisons effectively ignores the influence of shifting levels of national disease prevalence, absolute wealth, and inequalities in both wealth and health. A researcher could conclude, for example, that wealth-related inequalities in wasting had gone from very low levels in wave three to non-existent in waves five and six using country-by-country comparisons. However, using a transnational sample, the large inequalities primarily driven by country of residence and subregion become clear. Complex distributions of disease can also be made clear, as demonstrated by HIV prevalence in waves five and six. Rather than simply finding that richer Haitians and poorer Dominicans are more likely to be HIV prevalent, a picture emerges of relatively "middle class" urban residents of Hispaniola having an elevated risk of infection. Even attempting to consider the relative distribution of wealth seen in Figure 1 would be impossible if country-by-country methods were used.

Examining the change in health inequalities from wave to wave clearly reveals the hidden effects we hypothesized in our simulated data. Changes in wasting inequalities from wave five to wave six, for example, would lead a researcher believe that since wealth-related inequalities had increased in both countries, the overall inequality must have increased using country-by-country methods. In spite of this, there was actually a substantial decrease in transnational inequality primarily due to error #1 identified in the simulated survey data. Just as significantly, changes in stunting, underweight, and wasting from wave three to five would have led a country-by-country researcher to a somewhat mixed conclusion. Wealth-related inequalities had decreased significantly in the Dominican Republic for each outcome, while there was either a decrease, an increase, or no change in inequalities in Haiti. This would have led a researcher to the uncertain but tempting country-by-country conclusion that inequality had probably been reduced overall. Despite this appearance, the transnational approach reveals that overall inequality had actually increased due to a combination of factors, including larger between-country income inequality and larger reductions in absolute prevalence in the richer country. When considering the overall picture of changes in the distribution of health and wealth over time in Hispaniola, these findings are unsurprising, however had a country-by-country approach been undertaken, they would have been completely overlooked.

The limitations of these findings mostly relate to survey data methods and difficulties in comparing data across national boundaries. Some health outcomes may be affected by recall or other biases inherent in survey methodology, but half of the outcomes presented are physically measured or lab tested, allowing for apples-to-apples comparisons between countries. It is possible that household assets are valued differently or are of different quality between Haiti and the Dominican Republic, meaning that direct comparisons of these assets would not be appropriate. Wealth indices, whether they are calculated using

PCA or not, are not equivalent to household expenditure or income (Howe et al., 2009). This does not mean that the indices are any less valid, but rather that a separate dimension of SES is being measured. In fact, the greater stability over time, potential causal pathways from assets to health outcomes, and direct comparability between countries give wealth indices several advantages over measures based on national currencies or purchasing power parity equivalents. These advantages have even led to promising research assigning an estimated national income distribution according to each household's relative asset index ranking, developed at least in part to address transnational SES measurement issues (Harttgen and Vollmer, 2013; Joseph et al., 2018). The effect of divergent country-level wealth and disease prevalence is large due to the extreme case selection method used in this study, however, there are many other countries which would likely produce similar results. The results should not be taken to be generalizable to any other contexts due to the case selection method, therefore, and further study should be conducted to reveal whether these trends are echoed in other regions of the world. Although the methods described are theoretically applicable in any country, household asset data are not routinely collected in more wealthy regions such as Europe, meaning that our findings are most applicable to low- and middle-income countries.

The transnational approach is informed by the rapidly growing field of global income and wealth inequality measurement, which primarily utilizes internationally standardized household surveys as data sources and inequality measures such as the Gini index and generalized entropy measures – tools and data sources which have direct analogues in the field of health. Although it has been a topic of theoretical discussion for well over a century, the first published empirical estimation of global income distribution (Milanovic, 2002) was only possible after the widespread implementation of household surveys in the developing world. Global income distribution estimates have since become more comprehensive, both in terms of population and years covered, and have been reinforced through the use of different methodologies and data sources (Darvas, 2016; Lakner and Milanovic, 2013). This research has begun to provide evidence that the within- and between- country composition of inequality changes over time and is sensitive to policy change and technological change. Additionally, research into the political geography of wealth inequality has begun to produce insights into the complex political and economic determinants of inequalities at different scales of analysis (Beramendi, 2012).

Building upon these theoretical foundations, the results of this empirical demonstration of transnational wealth-related health inequality analysis demonstrate the utility and validity of the approach in hopes of inspiring further research at this new scale. Transnational health inequality composition effects such as the divergent child death ratio and HIV status decompositions may point to new hypotheses regarding the determinants of these outcomes at a level not restricted by national boundaries, and clearly have implications for policies meant to address these disparities. Policymakers deciding how to allocate scarce resources at both national and international levels should be informed by empirical research to know which administrative levels to target with health interventions in order to have the greatest impact. In addition, decomposition of the geographic distribution of health outcomes is only one possible use of this approach. Analysis of specific infectious diseases which are endemic to a transnational region could benefit from pooling of data, and groupings of subregions according to primary economic activity or ecologic characteristics offer yet another avenue of research. The many possible applications of transnational health inequality analysis should be of interest to global health researchers, multilateral agencies, and all parties involved in measuring progress in achieving the SDG.

Measuring inequality is not a mere quantitative exercise – it is an actualization of normative judgements. Decisions on whether to use relative versus absolute differences in wealth and which population to use as a reference point all imply normative judgements – whether they are acknowledged or not (Harper et al., 2010). By ignoring the transnational dimensions of wealth-related health inequalities using a country-by-country approach, the normative position has been to essentially to ignore these differences, or at least place them outside of the scope of policy. This effect is the result of a well-known process within political science by which the act of measuring itself creates political communities and heavily influences which issues reach the governmental agenda of policymakers (Kingdon, 2003; Stone, 2012). If transnational inequalities in health outcomes targeted by the SDG are politically determined – a hypothesis for which there is much supporting evidence (Ottersen et al., 2014) – then a first step towards a recognition of this pathway is rigorous analysis of the best available data to ensure that we are overlooking hidden dimensions of global health inequalities through inadequate methodology.

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Appendix

Appendix Table 1. Concentration indices for simulated survey data

Variable modified	Direction of modification	Poorer country concentration index	Richer country concentration index	Country-by-country conclusion	Transnational concentration index
None (reference concentration index)		-0.087	-0.132	-0.109	-0.160
Health inequality between countries	Convergence (poor reduces disease prevalence more than rich country)	-0.095	-0.132	-0.113	-0.147
	Divergence (rich reduces disease prevalence more than poor country)	-0.087	-0.151	-0.119	-0.191
Income inequality between countries	Convergence (poor catches up to rich)	-0.087	-0.132	-0.109	-0.150
	Divergence (rich becomes even wealthier than poor)	-0.087	-0.132	-0.109	-0.157
Health inequality within countries	Decrease in richer country	-0.087	-0.045	-0.066	-0.106
	Increase in richer country	-0.087	-0.356	-0.222	-0.268
	Decrease in poorer country	-0.039	-0.132	-0.085	-0.119
	Increase in poorer country	-0.149	-0.132	-0.140	-0.218
Income inequality within countries	Decrease in richer country	-0.087	-0.121	-0.104	-0.156
	Increase in richer country	-0.087	-0.132	-0.109	-0.157
	Decrease in poorer country	-0.080	-0.132	-0.106	-0.156
	Increase in poorer country	-0.087	-0.132	-0.109	-0.157

Appendix Table 2. Description of DHS variables used for child health outcomes[25]

Dataset Used	Variables	Variable Descriptions	Notes
Children's Recode	h22	Has child had a fever in the last two weeks?	
Children's Recode	h31	Has child had a cough in the last two weeks?	
Children's Recode	h11	Has child had diarrhea in the last two weeks?	
Children's Recode	hw8	Weight-for-age Z-score (WAZ)	WAZ < -2 SD* = Underweight
Children's Recode	hw5	Height-for-age Z-score (HAZ)	HAZ < -2 SD* = Stunting
Children's Recode	hw11	Weight-for-height Z-score (WHZ)	WHZ < -2 SD* = Wasting
HIV Dataset	hiv03	Blood test result	Available for waves 5 and 6 only
Individual's Recode	v201, v206, v207	Total children ever born, sons who have died, daughters who have died	(v206 +v207)/v201 = Ratio of child deaths to live births

Appendix Table 3. Spearman's rho for all wealth indices

Wave 6					
		Polychoric PCA	PCA	DHS Haiti Score	DHS DR Score
Polychoric PCA	rho	1			
	obs	24252			
PCA	rho	0.9728	1		
	obs	23587	23621		
DHS Haiti Score	rho	0.8771	0.9001	1	
	obs	13157	13178	13181	
DHS DR Score	rho	0.9022	0.9203		1
	obs	11095	10443		11464
Wave 5					
		Polychoric PCA	PCA	DHS Haiti Score	DHS DR Score
Polychoric PCA	rho	1			
	obs	39849			
PCA	rho	0.9745	1		
	obs	39849	39988		
DHS Haiti Score	rho	0.8965	0.8069	1	
	obs	9915	9953	9997	
DHS DR Score	rho	0.9462	0.9003		1
	obs	29934	30035		32431
Wave 3					
rho	0.9701				
obs	12882				

[25] SD = Standard Deviations

Appendix Table 4. Wave Three Children's Summary Statistics

Dominican Republic	Age (months)	Stunting	Wasting	Underweight	Diarrhea	Cough	Fever	PCA	Polychoric PCA
mean	29.4	0.131	0.016	0.078	0.170	0.417	0.298	0.385	0.105
se(mean)	0.26	0.006	0.002	0.004	0.006	0.008	0.007	0.029	0.020
N	4413	3739	3740	3739	4288	4288	4285	4219	4219
min	0	0	0	0	0	0	0	-3.976	-3.452
max	59	1	1	1	1	1	1	4.764	3.230
Haiti	**Age (months)**	**Stunting**	**Wasting**	**Underweight**	**Diarrhea**	**Cough**	**Fever**	**PCA**	**Polychoric PCA**
mean	29.3	0.316	0.078	0.274	0.282	0.526	0.411	-1.693	-1.286
se(mean)	0.31	0.009	0.005	0.009	0.008	0.009	0.009	0.026	0.016
N	3208	2740	2753	2740	3113	3099	3099	3542	3542
min	0	0	0	0	0	0	0	-4.259	-3.150
max	59	1	1	1	1	1	1	4.336	2.777
Total	**Age (months)**	**Stunting**	**Wasting**	**Underweight**	**Diarrhea**	**Cough**	**Fever**	**PCA**	**Polychoric PCA**
mean	29.4	0.209	0.042	0.161	0.217	0.463	0.346	-0.563	-0.530
se(mean)	0.20	0.005	0.002	0.005	0.005	0.006	0.006	0.023	0.015
N	7621	6479	6493	6479	7401	7387	7384	7761	7761
min	0	0	0	0	0	0	0	-4.259	-3.452
max	59	1	1	1	1	1	1	4.764	3.230

Appendix Table 5. Wave Three Individual's Summary Statistics

Dominican Republic	Age	Death Ratio	PCA	Polychoric PCA
mean	28.8	0.064	1.039	0.584
se(mean)	0.10	0.002	0.021	0.014
N	8422	5942	7925	7925
min	15	0	-3.976	-3.452
max	49	1	4.884	3.230
Haiti	**Age**	**Death Ratio**	**PCA**	**Polychoric PCA**
mean	28.0	0.147	-1.061	-0.854
se(mean)	0.13	0.004	0.025	0.016
N	5356	3288	5335	5335
min	15	0	-4.259	-3.150
max	49	1	4.681	2.854

Total	Age	Death Ratio	PCA	Polychoric PCA
mean	28.5	0.094	0.194	0.005
se(mean)	0.08	0.002	0.018	0.012
N	13778	9230	13260	13260
min	15	0	-4.259	-3.452
max	49	1	4.884	3.230

Appendix Table 6. Wave Five Children's Summary Statistics

Dominican Republic	Age (months)	Stunting	Wasting	Under weight	Diarrhea	Cough	Fever	PCA	Polychoric PCA
mean	29.8	0.083	0.017	0.047	0.167	0.287	0.224	0.795	0.256
se(mean)	0.17	0.003	0.001	0.002	0.004	0.004	0.004	0.018	0.013
N	10038	9255	9264	9255	10587	10606	10570	10276	10236
min	0	0	0	0	0	0	0	-7.158	-4.782
max	59	1	1	1	1	1	1	3.907	3.256
Haiti	**Age (months)**	**Stunting**	**Wasting**	**Under weight**	**Diarrhea**	**Cough**	**Fever**	**PCA**	**Polychoric PCA**
mean	27.7	0.245	0.083	0.216	0.222	0.462	0.262	-3.405	-2.629
se(mean)	0.34	0.009	0.005	0.008	0.006	0.007	0.006	0.029	0.019
N	2620	2536	2538	2536	5470	5477	5468	5985	5964
min	0	0	0	0	0	0	0	-7.899	-5.285
max	59	1	1	1	1	1	1	3.773	2.864
Total	**Age (months)**	**Stunting**	**Wasting**	**Under weight**	**Diarrhea**	**Cough**	**Fever**	**PCA**	**Polychoric PCA**
mean	29.3	0.118	0.031	0.083	0.186	0.347	0.237	-0.751	-0.806
se(mean)	0.16	0.003	0.002	0.003	0.003	0.004	0.003	0.022	0.015
N	12658	11791	11802	11791	16057	16083	16038	16261	16200
min	0	0	0	0	0	0	0	-7.899	-5.285
max	59	1	1	1	1	1	1	3.907	3.256

Appendix Table 7. Wave Five Individual's Summary Statistics

Dominican Republic	Age	Death Ratio	HIV Positive	PCA	Polychoric PCA
mean	29.7	0.041	0.008	1.237	0.666
se(mean)	0.06	0.001	0.001	0.011	0.008
N	27195	19541	25452	25771	25676
min	15	0	0	-7.158	-4.782
max	49	1	1	3.987	3.413

Haiti	Age	Death Ratio	HIV Positive	PCA	Polychoric PCA
mean	28.2	0.101	0.025	-2.708	-2.075
se(mean)	0.10	0.002	0.002	0.024	0.016
N	10757	6547	5224	10709	10651
min	15	0	0	-7.899	-5.285
max	49	1	1	3.828	2.969
Total	**Age**	**Death Ratio**	**HIV Positive**	**PCA**	**Polychoric PCA**
mean	29.2	0.056	0.011	0.079	-0.138
se(mean)	0.05	0.001	0.001	0.014	0.010
N	37952	26088	30676	36480	36327
min	15	0	0	-7.899	-5.285
max	49	1	1	3.987	3.413

Appendix Table 8. Wave Six Children's Summary Statistics

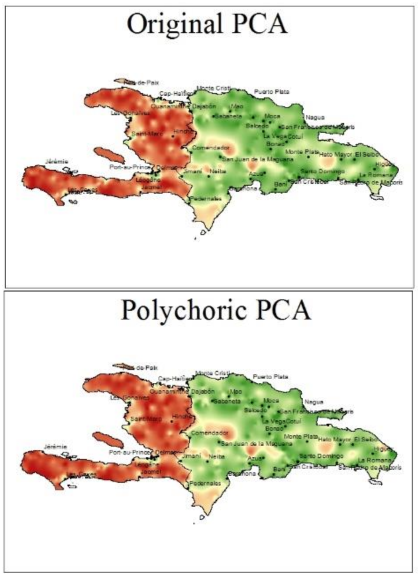
Dominican Republic	Age (months)	Stunting	Wasting	Under weight	Diarrhea	Cough	Fever	PCA	Polychoric PCA
mean	29.2	0.053	0.019	0.051	0.179	0.280	0.233	2.131	1.196
se(mean)	0.3	0.004	0.002	0.004	0.006	0.008	0.007	0.027	0.018
N	3387	3090	3188	3188	3560	3568	3570	3337	3580
min	0	0	0	0	0	0	0	-3.634	-3.348
max	59	1	1	1	1	1	1	4.966	3.961
Haiti	**Age (months)**	**Stunting**	**Wasting**	**Under weight**	**Diarrhea**	**Cough**	**Fever**	**PCA**	**Polychoric PCA**
mean	27.4	0.179	0.045	0.150	0.214	0.526	0.284	-2.181	-1.639
se(mean)	0.3	0.006	0.003	0.006	0.005	0.006	0.006	0.022	0.014
N	4074	3967	3968	3968	6598	6596	6617	7247	7240
min	0	0	0	0	0	0	0	-5.822	-4.221
max	59	1	1	1	1	1	1	4.824	3.465
Transnational	**Age (months)**	**Stunting**	**Wasting**	**Under weight**	**Diarrhea**	**Cough**	**Fever**	**PCA**	**Polychoric PCA**
mean	28.2	0.124	0.034	0.106	0.202	0.440	0.266	-0.822	-0.701
se(mean)	0.2	0.004	0.002	0.004	0.004	0.005	0.004	0.026	0.017
N	7461	7057	7156	7156	10158	10164	10187	10584	10820
min	0	0	0	0	0	0	0	-5.822	-4.221
max	59	1	1	1	1	1	1	4.966	3.961

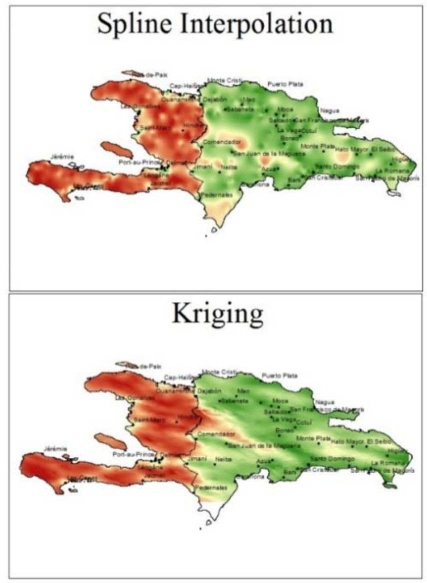
Appendix Table 9. Wave Six Individual's Summary Statistics

Dominican Republic	**Age**	**Death Ratio**	**HIV**	**PCA**	**Polychoric PCA**
mean	29.8	0.039	0.009	2.458	1.435
se(mean)	0.10	0.002	0.001	0.015	0.011
N	9372	6687	8897	8804	9180
min	15	0	0	-4.258	-3.348
max	49	1	1	5.039	3.961
Haiti	**Age**	**Death Ratio**	**HIV**	**PCA**	**Polychoric PCA**
mean	28.1	0.089	0.027	-1.602	-1.276
se(mean)	0.08	0.002	0.002	0.017	0.011
N	14287	8671	9326	14286	14249
min	15	0	0	-5.860	-4.221
max	49	1	1	5.495	3.465
Total	**Age**	**Death Ratio**	**HIV**	**PCA**	**Polychoric PCA**
mean	28.8	0.067	0.018	-0.054	-0.214
se(mean)	0.06	0.001	0.001	0.018	0.012
N	23659	15358	18223	23090	23429
min	15	0	0	-5.860	-4.221
max	49	1	1	5.495	3.961

Appendix Figure 1. Original PCA and Polychoric PCA Comparison

Appendix Figure 2. Spline Interpolation and Kriging Comparison





Appendix Table 10. Decomposition of concentration indices for wave six[26]

	Stunting	Underweight	Wasting	Fever	Cough	Diarrhea	Death Ratio	HIV
Country elasticity	-0.805	-0.483	-0.215	-0.021	-0.241	-0.166	-0.358	-1.301
Country concentration index	0.444	0.438	0.411	0.652	0.824	0.608	0.442	0.367
Country contribution	**-0.357**	**-0.212**	**-0.088**	**-0.014**	**-0.199**	**-0.101**	**-0.158**	**-0.478**
Country percentage contribution	0.911	0.514	0.289	0.179	0.857	1.332	0.581	1.394
Urban/Rural elasticity	0.388	0.352	0.352	-0.115	-0.096	-0.077	0.134	-0.247
Urban/Rural concentration index	-0.123	-0.122	-0.114	-0.150	-0.190	-0.141	-0.110	-0.099
Urban/Rural contribution	**-0.048**	**-0.043**	**-0.040**	**0.017**	**0.018**	**0.011**	**-0.015**	**0.024**
Urban/Rural percentage contribution	0.122	0.104	0.131	-0.222	-0.079	-0.143	0.054	-0.071
Contribution of regional fixed effects	**0.077**	**-0.055**	**-0.152**	**-0.066**	**-0.036**	**0.052**	**-0.035**	**0.165**
percentage contribution of regional fixed effects	-0.178	0.133	0.495	0.844	0.153	-0.693	0.128	-0.481
residual	**-0.107**	**-0.103**	**-0.026**	**-0.016**	**-0.016**	**-0.038**	**-0.065**	**-0.054**

[26] Bolded numbers are the primary outcomes, representing each variable's contribution to the concentration index. Elasticity, variable-specific concentration index, and percentage contribution are presented for as supporting information.

Appendix Table 11. Decomposition of concentration indices for wave five[27]

	Stunting	Underweight	Wasting	Fever	Cough	Diarrhea	Death Ratio	HIV
Country elasticity	-0.600	-0.766	-0.663	0.070	0.015	0.069	-0.343	-1.508
Country concentration index	0.379	0.370	0.345	0.622	0.761	0.581	0.423	0.279
Country contribution	**-0.227**	**-0.283**	**-0.229**	**0.043**	**0.012**	**0.040**	**-0.145**	**-0.421**
Country percentage contribution	0.477	0.538	0.635	-0.374	-0.052	-0.230	0.499	1.283
Urban/Rural elasticity	0.627	0.536	0.463	0.140	0.154	0.030	0.476	-0.087
Urban/Rural concentration index	-0.128	-0.124	-0.116	-0.152	-0.186	-0.142	-0.119	-0.106
Urban/Rural contribution	**-0.080**	**-0.067**	**-0.054**	**-0.021**	**-0.029**	**-0.004**	**-0.057**	**0.009**
Urban/Rural percentage contribution	0.168	0.127	0.149	0.184	0.128	0.025	0.196	-0.028
Contribution of regional fixed effects	**-0.063**	**-0.090**	**-0.093**	**-0.132**	**-0.203**	**-0.197**	**-0.042**	**0.182**
percentage contribution of regional fixed effects	0.132	0.171	0.257	1.137	0.902	1.137	0.144	-0.556
residual	**-0.107**	**-0.087**	**0.015**	**-0.006**	**-0.005**	**-0.012**	**-0.047**	**-0.099**

Appendix Table 12. Decomposition of concentration indices for wave three[28]

	Stunting	Underweight	Wasting	Fever	Cough	Diarrhea	Death Ratio
Country elasticity	-0.104	-0.225	-0.744	-0.156	-0.069	-0.337	-0.291
Country concentration index	0.505	0.477	0.414	0.611	0.737	0.506	0.378
Country contribution	**-0.052**	**-0.107**	**-0.308**	**-0.095**	**-0.051**	**-0.171**	**-0.110**
Country percentage contribution	0.112	0.217	0.862	0.619	0.326	0.864	0.409
Urban/Rural elasticity	0.474	0.272	-0.034	-0.069	-0.069	0.027	0.266
Urban/Rural concentration index	-0.125	-0.118	-0.102	-0.156	-0.188	-0.130	-0.118
Urban/Rural contribution	**-0.059**	**-0.032**	**0.003**	**0.011**	**0.013**	**-0.004**	**-0.031**
Urban/Rural percentage contribution	0.127	0.065	-0.010	-0.070	-0.084	0.018	0.116
Contribution of regional fixed effects	**-0.192**	**-0.201**	**0.041**	**-0.030**	**-0.078**	**0.047**	**-0.070**
percentage contribution of regional fixed effects	0.411	0.407	-0.115	0.194	0.505	-0.238	0.260
residual	**-0.164**	**-0.154**	**-0.094**	**-0.040**	**-0.039**	**-0.070**	**-0.058**

[27] Bolded numbers are the primary outcomes, representing each variable's contribution to the concentration index. Elasticity, variable-specific concentration index, and percentage contribution are presented for as supporting information.
[28] Bolded numbers are the primary outcomes, representing each variable's contribution to the concentration index. Elasticity, variable-specific concentration index, and percentage contribution are presented for as supporting information.

Chapter 5. Conclusions

This chapter concludes with the principal findings, opportunities for future research, strengths and limitations, and policy implications for the measurement of international and transnational health inequalities using household survey data. Taken as a whole, the substantive and methodological findings of this thesis all support two primary theoretical contributions. First, asset wealth, consumption, and income measure different dimensions of household socioeconomic status (SES), and these differences should inform the proper use of each measure in the field and inspire research into the specific pathways that lead from SES to health outcomes. Second, international and transnational health inequalities are measuring separate and equally informative dimensions of global health inequalities, and the difference between the two is only likely to grow larger in the future. The first theoretical contribution is supported by the quantitative evidence synthesized in Chapter 2 demonstrating a moderate association between asset wealth, income, and consumption, but more importantly, qualitative evidence mapping the use of asset indices to conceptual frameworks of SES. The first theoretical contribution is also supported by the substantive empirical findings of Chapter 3 pointing to systematic variation in the magnitude of health inequality depending on the SES measure used to rank households (these various dimensions of SES affect health and health inequality differently, suggesting different pathways). The second theoretical contribution is supported by the thorough methodological accounting of the new transnational method in Chapter 4 and reinforced by the suggestive trends in international inequality identified in Chapter 3. In sum, despite limitations to the measurement of household SES using asset indices, this thesis provides justification for their use in measuring SES-related health inequalities, in calculating transnational inequalities, and for the importance of findings generated using the transnational approach.

The findings of this thesis have significant implications for the practice of measuring health inequalities for global health researchers and multilateral organizations, and policymakers will eventually have to understand and respond to the findings uncovered by transnational health inequality measurement. Lastly, the many gaps in knowledge identified in this thesis, from the need to understand causal pathways from the various dimensions of SES to health, to further demonstrating the utility of transnational health inequality measurement methods in new contexts, to translating results to policymakers responsible for achieving the Sustainable Development Goals (SDGs) promise to spur ongoing research for many years to come.

Income, Consumption, and Asset Wealth

The substantive findings contained in each chapter are critical to understanding and lending support to the primary theoretical and methodological contributions of this thesis. The evidence establishing asset wealth as a distinct measure of SES goes well beyond the moderate mean Spearman rank correlation coefficient of 0.42 between wealth indices and household income and of 0.55 between wealth indices and household consumption presented in Chapter 2. These quantitative findings echo similar results by previously published studies that have systematically investigated these associations

(Ferguson et al., 2003; Filmer and Scott, 2012; Howe et al., 2009; Sahn and Stifel, 2003), but the critical interpretive synthesis (CIS) methodology implemented also allowed for the synthesis of a wealth of supporting qualitative information: for instance, the CIS showed that the correlation between asset wealth and consumption was stronger in middle-income than in low-income countries, suggesting that asset wealth captures a dimension of poverty that consumption cannot capture in environments where food-expenditures use a large share of household budgets. Also, asset indices capture more urban-rural inequalities than consumption measures, suggesting that measures such as consumption have different meanings and implications across the urban-rural divide. Lastly, the CIS showed that the correlation depended on the number and variety of assets included in the index, suggesting that not all asset indices are created alike and that care must be taken in comparing and interpreting results derived from different indices. Even more quantitative evidence for the real difference between these separate dimensions of household SES is documented by the suggestive findings of Chapter 3 that asset indices, as well as the predicted income measures based on them, result in the largest magnitudes of health inequality for 11 out of the 12 health outcomes tested. Although meta-analysis results do not meet the threshold of significance at the 95% level, the evidence points in the same suggestive direction – that asset wealth, household income, and household consumption measure three distinct dimensions of household SES and that asset wealth may be more strongly associated with social health inequalities.

Examining these suggestive differences from a pragmatic and theoretical perspective offers even more context for why these differences matter. The advent of using asset wealth as a method of quantifying household SES was not a process that flowed from theory to practice, but the reverse – a stockpile of pre-existing household asset data was harnessed to meet a growing desire to measure household SES in LMICs using the previously underused method of principal components analysis in the field of global health (Filmer and Pritchett, 2001; Howe et al., 2012; Rutstein and Johnson, 2004). As a result of the widespread and rapid uptake of this pragmatic solution, many asset indices simply recreate previous methods with little discussion of the conceptual implications of the composition and nature of the set of assets considered or the statistical methods used to weight and aggregate these assets into an index. While there have been moments of realization that these choices matter – such as when asset wealth contradicted national accounts data in evaluating the social welfare of African countries in the 1990s (Johnston and Abreu, 2016) – a concerted effort to come to terms with what asset wealth is truly measuring has yet to come about in the global health literature. This is not to say that a theory supporting the fundamental difference between these different SES measures cannot be generated. Gendered effects of primarily male-headed households in LMICs choosing the proportion of income and expenditure to devote to household assets may be one factor driving these differences. Households needing to spend money obtaining reliable electricity, clean water, and many other goods and services that can be provided more efficiently and at higher quality through public financing and provision may also be an important dimension of household welfare that is captured using asset indices. Understanding these theoretical differences between the primary measures of household SES used in measuring health inequalities using household surveys will be critical to advancing the field.

Having identified substantive and theoretical differences between income, consumption, and asset wealth, as well as across methods of generating asset indices, there are several gaps in knowledge and emerging areas of innovation that will need more research. Many questions remain about the competing methods of calculating asset indices, although some insights from this thesis give light to promising first avenues for research. The Chapter 2 review of primary methods used to calculate indices based on a set list of assets (i.e, methods to aggregate and weight the possession of assets into one synthetic value) identified multiple correspondence analysis and polychoric PCA as two wealth index quantification methods with evidence-based advantages to the standard DHS PCA method (Booysen et al., 2008; Filmer and Pritchett, 2001; Kolenikov and Angeles, 2009). The use of polychoric PCA in subsequent chapters proved to be easier to calculate, produced less clumping at the lower end of the SES spectrum, and resulted in little reordering in comparison to the standard PCA approach. Likewise, the predicted income method (Fink, 2016; Fink et al., 2017; Harttgen and Vollmer, 2013) identified in the CIS as a promising approach for scale dependent measures proved useful for calculating slope indices of inequality and relative indices of inequality in Chapter 3. Even more interesting however, was the finding that much like the asset indices they are based on, the predicted income method resulted in larger magnitudes of social health inequality than either household consumption or household income. These promising results should encourage other researchers to employ these emerging methods in new contexts, in addition to researching the potential limitations to widespread adoption. Other alternative methods such as item response theory and Mokken scale analysis may not yet have the same amount of published supporting evidence, but new research supporting their use may arise in the future.

The next research frontier of asset wealth measurement will likely come from emerging technologies used to proxy directly measured, rather than self-reported, asset wealth using household surveys. While these technologies offer much promise – of cell phone metadata offering a unified repository of rich SES and mobility data, of satellite imagery rendering expensive in-person data collection unnecessary, or of machine learning algorithms becoming more efficient and accurate than human analysts at calculating complex indices – these emerging technologies need much more research before being accepted as superior or even complementary to existing methods. There are real advantages to current methods that may be lost in each of these scenarios, including decades of existing survey data with comparable measures and rich in-person health and household data that must be collected from local surveyors. Researchers advancing these methods will still have to overcome hurdles identified in published articles of limitations in recreating successful findings from one country to another for both machine learning of satellite imagery data and cell phone metadata. Recognizing these existing advantages and challenges will not prevent the likely rapid expansion in research of these methods from occurring, nor will it prevent the difficulties of the major survey implementing organizations from incorporating evidence-based innovations into international survey instruments.

A separate line of methodological research should delve into ways of addressing other well-publicized limitations of the standard wealth index. Many possibilities exist for researching changes to the asset mix and addressing urban-rural concerns further. The dangers of changes in the asset mix rendering wealth indices less effective at measuring household SES over time (Lindelow, 2006; Wittenberg and Leibbrandt, 2017) were not observed in Chapter 3 or Chapter 4, with effective ranking of households uncovering gradients of health achievement from the 1980s up to recent years. Nevertheless, further research into the specific impact of the rise of cell phones as significant indicators of relative SES in every country of the world is warranted. Similarly, the urban-rural divide often observed in wealth indices proved to be informative rather than confounding to the identification of inequalities in HIV prevalence in Hispaniola in Chapter 4, replicating the experience of other research teams (Balen et al., 2010; Ngo and Christiaensen, 2018; Ward, 2014). These informative differences may echo the experience of disparities between asset wealth and national accounts data in measuring national development progress (Johnston and Abreu, 2016), indicating that the differences between measures are not due to measurement error, but should be reconciled through a theoretical rather than methodological lens.

Yet another direction for future research should examine whether household asset wealth affects health inequalities through different pathways than consumption or income. The evidence uncovered in support of the fundamental differences between the primary SES measures, coupled with evidence generated in Chapter 3 that magnitudes of health inequalities may systematically vary according to the measure used, may indicate that each measure is associated with health outcomes through separate pathways. If a survey results in larger magnitudes of health inequalities using a wealth index than household income, it may be due to confounding factors such as endogenous health-linked variables, increasing affordability of household durables, a rural population-biased disease distribution, or an artifact of how the index was calculated; or it may be attributable to causal mechanisms such as long-term (vs. short term) disease progression, access to healthcare systems, specific social determinants of health, or some other context-specific pathway. These questions should be posed not to find an error that should be addressed or because they cause results to fall short of a "gold standard" of SES measurement, but because the pathway from SES to health can elucidate why health inequities arise and how policy should be designed to address them.

Transnational and International Health Inequalities

The second primary theoretical contribution of this thesis surrounds the utility and importance of measuring transnational health inequalities as a supplementary approach to international health inequalities. There are several complementary reasons why the transnational approach offers information that cannot be captured using the international approach. Chapter 4 is entirely focused on laying out these justifications, detailing the challenges and methodological steps for any researcher wanting to recreate the method using microdata, and generating evidence of impactful findings that could only have been uncovered using the transnational approach. It is important to note, however, that much of the inspiration for this approach comes from global income and wealth inequality measurement (Darvas, 2016; Lakner and Milanovic, 2013; Milanovic, 2002). Not only is the transnational approach to health inequalities echoing research advances in other fields, but the socially and epidemiologically significant interactions between absolute differences in SES and inequalities both between and within countries has been recognized as an issue worth studying within the field of international health inequality measurement in the exact same country context as those selected for Chapter 4 (Wagstaff, 2002). Wagstaff's (2002) qualitative description of the tendency for health inequalities to increase as per capita incomes increase and gains in health outcomes begin to take root among those benefiting from economic growth demonstrates the ongoing importance of transnational composition effects, of which this thesis represents the first effort to generate a reproducible quantitative measure.

Building on previous research extending the use of asset indices across national boundaries identified in Chapter 2 (Córdova, 2008; Harttgen and Vollmer, 2013; Michelson, 2013; Smits and Steendijk, 2013), the empirical demonstration of the transnational approach across the island of Hispaniola uncovered hidden health inequalities and demonstrated conflicting conclusions between transnational and country-by-country approaches. Complex distributions of disease were also made clear, as demonstrated by the outcome of human immunodeficiency virus (HIV) prevalence in survey waves five and six. Rather than simply finding that richer Haitians and poorer Dominicans are more likely to be HIV prevalent, a picture emerges of relatively "middle class" urban residents of Hispaniola having an elevated risk of infection. This finding incidentally provides further evidence for the inverse equity hypothesis (Hargreaves et al., 2013) that had previously been identified in sub-Saharan Africa. This hypothesis, postulating that there is a level of human development at which new health interventions (including primary prevention) are taken up at faster rates by the relatively wealthy, even when they begin as the most severely affected by an epidemic, is certainly one that could benefit from transnational measurement to identify the point at which it begins to take hold.

Other hidden health inequalities uncovered in the chapter included secular and transnational health inequalities that would have been hidden using country-by-country methods. Instead of concluding that wealth-related inequalities in childhood wasting were small to non-existent by averaging both countries' national concentration indices, the transnational method revealed large inequalities primarily driven by country of residence and subregion. Relatedly, a researcher could have come to the uncertain but tempting country-by-country conclusion that inequality had probably been reduced over time by averaging national concentration indices. Despite this appearance, the transnational approach revealed that overall inequality had actually increased due to a combination of factors, including larger between-country income inequality and larger reductions in absolute prevalence in the richer country. These contrasting conclusions do not mean that measuring health inequalities at the national level is unnecessary, but rather that transnational and international health inequalities represent two independent measures of global health inequalities and that drawing conclusions from both measures results in a richer understanding of global health inequalities.

The importance of the theoretical and methodological advancement of transnational health inequalities developed in Chapter 4 is underscored by a secondary finding of this thesis. The general tendency of national health inequalities to increase as country incomes increase, which has been previously identified in multiple settings (Filmer and Scott, 2012; Harper et al., 2010; Howe et al., 2009), was independently confirmed using Living Standards Measurement Study (LSMS) data in Chapter 3. This general tendency, which appears to be even stronger when measured using household assets instead of income or consumption, is also observed in Chapter 4 with the difference in health inequalities between Haiti and the Dominican Republic becoming even larger as the large wealth disparity between the two countries increased over time. The theoretical implication of this repeated tendency is that as countries become more unequal within their borders, simple comparisons of country-by-country summary measures will become more misleading as LMICs become wealthier due to the analytical errors identified in Chapter 4's simulated data analysis. This means that international and transnational health inequalities are not only different, but the difference between the two is only likely to grow more significant in the future.

The implication that measuring both transnational and international health inequalities will become increasingly informative as time goes on makes the importance of continuing this line of research clear. As a first step, some of the potential analytical errors identified in Chapter 4's simulated transnational composition effects that were not present in the empirical demonstration in Hispaniola would benefit from empirical demonstration in other settings to establish the reality of these distortions and to highlight how significant these errors can be. These potential country-by-country analytical errors were not present because the most-different (i.e. extreme case) case selection approach using the Dominican Republic and Haiti compared high to low SES levels and high to low wealth inequality levels. A different case selection approach could compare countries of approximately equal SES, but very different levels of wealth inequality. This example would identify why populations may have very different levels of health inequalities even at the same average level of development – a hidden determinant of health which would not be immediately apparent in LMICs lacking data.

As critical as these findings will be to advance the method, possibilities for more research are far more extensive than simple extensions of these thesis chapters. Even more promising avenues for future research involve continuing to develop transnational health inequality measurement methods and applying these methods to new regions and research questions. For global health research specifically, the transnational threats to health, such as the vector-borne disease that played a major role in inspiring this research can be studied across national boundaries using the methods detailed in Chapter 4. Other transnational populations such as indigenous groups that span across international boundaries or populations inhabiting areas with devolved or loosely enforced national governance can also be studied for health inequalities with the same methods. Collaborations with researchers in other fields will be critical to uncovering mechanisms determining transnational health inequalities and to translating findings to policy and practice. The field of global income inequality measurement (Darvas, 2016; Lakner and Milanovic, 2013; Milanovic, 2012, 2002) which inspired many of the methods employed in this thesis offers one clear opportunity for interdisciplinary research and collaboration. Research uncovering the political determinants of these global inequalities can be extended to health to create a political economy of health on a new scale, not bound by either cross-country comparisons or extrapolations of intra-country results to the international scale. Finally, empirically demonstrating global equity in the progress of achieving the SDGs is a constant and overriding objective of that will continue to inspire research using an interdisciplinary political approach.

Strengths and Limitations

Despite the numerous theoretical, methodological, and substantive contributions of this thesis, several limitations must be acknowledged relating to data availability, gaps in academic literature, and for the use of asset wealth in measuring international and transnational health inequalities. The primary limitations for Chapter 2 can be attributed to the highly variable and sometimes inconsistent definitions of key concepts, which were only compounded by the lack of research designed to answer methodological issues specifically rather than as secondary research questions dispersed throughout many fields. While a paucity of dedicated research for a method used by a large proportion of global health equity researchers is concerning, the work of identifying which priority areas are in need of more research can also be seen as a strength of this thesis. For example, although innovations to the calculation and proxying of asset wealth using emerging technologies are exciting, these advances must first be demonstrated to offer evidence-based advantages in comparison to the use of the current incarnation of wealth indices that remain the primary SES measure for global health researchers in LMICs. Another consequence of the diffuse nature of the underlying literature regarding asset indices was the limitation of methods that could be used to synthesize the information. A systematic review involving several coders or a quantitative meta-analysis would not have been feasible for this study because the logistical and financial requirements to produce a meaningful qualitative synthesis of the specialized topic area and expansive literature would have been exceedingly large, and a meta-analysis of the small number of comparable quantitative outcomes updating the one compiled in 2009 (Howe et al., 2009) would not have produced novel results. Because of these pragmatic limitations, critical interpretive synthesis was the most appropriate choice to present the debates surrounding this methodology in all its complexity using both qualitative and quantitative information. By presenting the key concepts, exploring the contradictions in the literature, and proposing lines-of-argument syntheses the thesis was able to include and synthesize more studies than any prior work on creating wealth indices from household survey data.

The systematic comparison of income, consumption, and asset wealth in Chapter 3 could have taken an even more comprehensive approach by comparing many health and healthcare utilization outcomes from a larger number of international household surveys. Although this would have increased the probability of finding significant effects and improving the generalizability of the findings, the threats to the internal validity of the research were determined to be too great. This led to the decision to limit the sample to directly comparable household surveys containing income, consumption, assets, child anthropometrics, and fertility data, which decreased the size of the compiled dataset. It is possible that if more surveys were included for analysis, either by obtaining non-public surveys or by analyzing surveys that did not contain household income or consumption modules, the suggestive differences observed may have become statistically significant. Nevertheless, by strictly limiting the inclusion of potential surveys, the study ensured that all health outcomes were directly comparable, survey methodologies were similar, and the variation observed between SES variables was due to the inherent differences in the constructs they measure, rather than due to the methods that were used to calculate them. The relatively small number of households reporting income in some survey waves did limit the effective sample size for analysis, but this limitation represents a persistent and real challenge in the collection of income data from low-income countries which has motivated many researchers to use consumption or asset measures rather than income data. Finally, the choice to use LSMS surveys for the sake of direct comparability of all three SES measures is a strength of the study, but it is possible that the countries sampled by the World Bank or the countries that chose to include health modules may be systematically different than countries sampled for DHS or MICS surveys. Despite these limits to generalizability, the study represents the first ever systematic comparison of income, consumption, and asset indices on magnitudes of directly measured and comparable health inequalities using the same microdata for several countries.

As a study describing a methodological innovation, Chapter 4 is clearly limited by the amount of independently-produced supporting studies, but by demonstrating the need for innovation using simulated data and the real-world utility of the method using

Demographic and Health Survey (DHS) microdata, we aimed to establish the need to continue studying and further developing the transnational method. The extreme case selection design using the example of Haiti and the Dominican Republic succeeded in demonstrating several of the simulated composition effects and uncovering hidden transnational inequalities, however there are trade-offs to this study design. This is because the large and divergent country-level wealth and disease prevalence levels uncovered should not be assumed to be generalizable to any other contexts, and some transnational composition effects could never have been observed by selecting these most-different country cases. Similarly, the results are not necessarily generalizable to health inequalities quantified using consumption or income, or to high-income countries that have limited data supporting the use of asset indices as measures of SES. Besides study design, issues relating to cross-country asset index comparisons underlie many of the remaining limitations. Although health outcomes are very likely to be exactly comparable because of direct measurement using standardized methods, it is possible that household assets are valued differently or are of different quality between Haiti and the Dominican Republic. The degree to which these differences impacted SES measurement is unlikely to significantly affect the results of the chapter, however, as the countries of study were specifically chosen for their shared historical and geographical context. In addition, asset indices offer advantages of relative stability over time, can identify potential causal pathways from assets to health outcomes, and can be directly compared between countries.

Viewed as a whole, the strengths of this thesis lie in the creative deployment of several quantitative and qualitative methods in support of its primary theoretical contributions. Demonstrating the intrinsic differences between the primary measures used to quantify global health inequalities using household survey data is an inherently theoretical exercise, and therefore had to be supported by a synthesis of existing qualitative data. In comparison to the rich qualitative data compiled in chapter two, the relative paucity of existing quantitative studies was revealed to be a limiting factor. By identifying this neglected research area, the decision was made to systematically analyze the largest existing quantitative data source on this topic in the form of LSMS data. Taken together, the qualitative data synthesized in Chapter 2 coupled with suggestive quantitative data from Chapters 2 and 3 together form a compelling case for much more work in this understudied research area.

Limitations that arose in support of the second primary theoretical contribution made clear that the transnational approach cannot be applied to every country-context or research question. The transnational method will not and should not replace country-specific health inequality measurement, and its implementation must be done with appropriate knowledge of contextual factors and the limitations of the method itself. There are clearly limitations in comparing disparate cultural contexts or extremes in country-development status that push the boundaries of what asset indices can appropriately measure. Although the limits to international comparisons may not be as strict as commonly assumed (Córdova, 2008; Harttgen and Vollmer, 2013; Michelson, 2013; Smits and Steendijk, 2013), a precautionary principle of involving researchers with knowledge of the populations and contexts under study should generally be followed before more research has examined the limitations to the transnational approach of measuring health inequalities. Despite these limitations inherent in research on methodological innovations, Chapter 4 built on the knowledge gained in each of the previous chapters and produced strong evidence in support of the idea that transnational health inequalities are measuring a new dimension of global health inequality. While recognizing the real limitations of the research undertaken in this thesis, it is still possible that by quantifying health inequalities in new ways, this research can be used to inform policy changes in health funding and international cooperation so that no one is left behind in the pursuit of meeting the global goals.

Implications for Policy and Practice

The substantive, theoretical, and methodological contributions of this thesis all lead to important implications for policy and practice. In the global effort to achieve the SDGs, the measurement of household SES is one necessary input into the monitoring and evaluation of progress towards achieving equity for every objective. In order to adequately measure progress in achieving these goals, we must therefore continually research the challenges in developing reproducible, rigorous, and easily implemented methodologies for constructing asset indices using household surveys around the world. The impetus for this research agenda can be shared, but ultimate responsibility must be taken by the funders and organizers of the largest international household survey instruments used by the global health community. These organizations, including USAID, UNICEF, and the World Bank must take the lead on efforts to research the nuances, limitations, and opportunities for their wealth indices and continually work with country partners and researchers to update these findings.

Global health researchers, in turn, should recognize that their choice of SES measure will affect their research, since choosing a wealth index over household income may represent the choice to measure a more permanent indicator of household SES, and as demonstrated in Chapter 3, may result in larger magnitudes of health inequality. As wealth indices have become the dominant method to measure SES in LMICs across many fields, the tendency to institutionalize past decisions can lead to complacency in re-evaluating hegemonic methodologies (Pierson, 2000, 1993). Researchers employing wealth indices in their research – whether they are developing surveys, analyzing data, or interpreting data for policymakers – must understand the strengths, limitations, and normative choices associated with the measurement of international health inequalities using household surveys. Wealth indices have matured from being a technical solution for making use of DHS household asset data where data on income or consumption were not available or reliable (Filmer and Pritchett, 2001; Rutstein and Johnson, 2004) into being the most commonly employed method of quantifying household SES using household surveys in LMICs, even where data on income and consumption are reliably collected. The importance of the method for the field of global health therefore demands renewed cooperation to standardize asset information collection, generating research into which calculation methods are appropriate across country contexts, acknowledging real differences between the use of different SES measures, and beginning proactive research into the implications of emerging technologies

Lastly, findings uncovered by the transnational approach to measuring health inequalities will lead to sometimes difficult policy choices. For example, the slight decrease in wealth-related inequality for every health outcome uncovered in Hispaniola in Chapter 4 is encouraging, but the trend is neither representative of other regions around the world, nor guaranteed to continue. If transnational health inequalities are demonstrated to worsen, even in the face of improving health inequalities within nations, the tendency towards political inaction (Beland, 2010; Hacker, 2004; Ottersen et al., 2014) will be difficult to overcome. The decisions of how best to allocate scarce resources at national and international levels are complex and rarely undertaken based on research evidence alone (Lavis et al., 2002; Lewis, 2007). Nevertheless, ignoring the transnational dimensions of wealth-related health inequalities has led to the normative decision to render these inequalities as outside of the scope of policy.

Although by no means the only factor involved, the act of measuring these inequalities can create political communities and influence the issues that reach the governmental agenda of policymakers (Kingdon, 2003; Stone, 2012). Researchers have found that the economic and social welfare of citizens of the same country matters more than that of populations of other countries (Ravallion, 2019), but this effect is not universally applicable because uneven globalization has created political communities that can affect policies through a number of pathways (Beland, 2010; Gautier et al., 2018; Hacker, 1998; Sabatier, 2007; Stone, 2008). In much the same way as comparisons between Canada and the United States are inescapable, the relative transnational inequalities between Haiti and the Dominican Republic are not inequalities of an anonymous foreign population - comparisons between these two countries are an inescapable product of their shared cultural, economic, geographic, and historical linkages. Because of these ties, policy changes in response to the relative prosperity or deprivation of each country have occurred frequently, and the findings of transnational inequality measurement of Hispaniola is also more likely to impact the governmental health agenda than comparisons with more distant regional comparators. There are examples of country-pairs and transnational populations throughout the world that share this experience, and this is precisely where transnational health inequality measurement can have the greatest impact in promoting policies that can accelerate progress in achieving the SDGs for populations that would otherwise be left behind.

The theoretical, methodological, and substantive contributions of this thesis do not obviate the need for continuing research using established methods. The use of income and consumption as measures of personal and household SES remain informative and high-quality income and consumption data will likely become more readily available as LMICs continue to develop. National-level health inequality measurement will also continue to be a critical measure of population health to inform both national and international policymaking. Notwithstanding these facts, rigorous measurement of asset wealth and transnational health inequalities will form a critical part of a larger ecosystem of knowledge in the global effort to address hidden dimensions of health inequalities. Studies of the specific pathways that lead from SES to health outcomes will be informed by the different dimensions of household SES being measured by asset wealth, consumption, and income; and research into the separate and equally informative dimensions of global health inequalities being measured by international and transnational health can lead to accelerating progress in achieving the SDGs through transnational political communities.

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