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Health And Nutrition In The Context Of Developing Countries

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Abstract

This dissertation examines three different aspects of population health and nutrition in low- and middle-income countries. Chapter 1 is methodological in nature and investigates the implications of using self-reported anthropometrics as proxies for measured ones. I analyze misreporting patterns of height and weight (and resulting body mass index, or BMI) in China, India, Russia, and South Africa, and find heterogeneity of reporting patterns both between these countries and high-income countries, as well as heterogeneity among these countries themselves. Adjustments of self-reported heights and weights are investigated, and the use of measured, self-reported, and adjusted BMI are compared in various applications. Chapters 2 and 3 study more substantive topics. Less-developed countries have traditionally dealt with issues of stunting, wasting, and underweight, and most resources have been put toward rectifying these. But as these countries continue to work on problems of under-nutrition, over-nutrition has been rising rapidly at rates not historically witnessed before, resulting in a double burden of malnutrition. Chapter 2 examines the population-level double burden by analyzing within- and between-country nutritional disparities among older adults in China, Ghana, India, Mexico, Russia, and South Africa. Using both country-specific and pooled partial proportional odds models, I analyze patterns of BMI categories along various socioeconomic dimensions. I conclude that economic development and the nutrition transition are intertwining processes, and progression through these processes results in shifts of the population segments affected by the two nutritional extremes. In Chapter 3, I use a birth cohort study from Guatemala to study changes in nutritional status over the life course, the double burden at an individual level. With an analysis of transitions, multiple regressions, and structural equation modeling, I find that while early anthropometrics are generally not associated with adulthood BMI, there are direct relationships between childhood nutritional status and growth with some chronic disease indicators, such as triglycerides and fasting blood glucose. Furthermore, these relationships are not mediated by BMI. When taken together, these three chapters have both significant research and policy implications for population health in the developing context.

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HEALTH AND NUTRITION IN THE CONTEXT OF DEVELOPING COUNTRIES

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ABSTRACT

HEALTH AND NUTRITION IN THE CONTEXT OF DEVELOPING COUNTRIES

Carmen Doris Ng

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This dissertation examines three different aspects of population health and nutrition in low- and middle-income countries. Chapter 1 is methodological in nature and investigates the implications of using self-reported anthropometrics as proxies for measured ones. I analyze misreporting patterns of height and weight (and resulting body mass index, or BMI) in China, India, Russia, and South Africa, and find heterogeneity of reporting patterns both between these countries and high-income countries, as well as heterogeneity among these countries themselves. Adjustments of self-reported heights and weights are investigated, and the use of measured, self-reported, and adjusted BMI are compared in various applications. Chapters 2 and 3 study more substantive topics. Less-developed countries have traditionally dealt with issues of stunting, wasting, and underweight, and most resources have been put toward rectifying these. But as these countries continue to work on problems of under-nutrition, over-nutrition has been rising rapidly at rates not historically witnessed before, resulting in a double burden of malnutrition. Chapter 2 examines the population-level double burden by analyzing within- and between- country nutritional disparities among older adults in China, Ghana, India, Mexico, Russia, and South Africa. Using both country-specific and pooled partial proportional odds models, I analyze patterns of BMI categories along various socioeconomic dimensions. I conclude that economic development and the nutrition transition are intertwining processes, and progression through these processes results in

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PREFACE

The overarching goal of this dissertation is to explore developing-context phenomena in the realm of population health and contrast them with what have been observed in developed countries. Much of what is known about population health is based on studies of the United States and other high-income countries. To what extent are high-income results generalizable to less prosperous contexts? More specifically, the focus of this dissertation is on anthropometrics, as they are a good indicator of one's overall health and nutritional status.

I first begin with a methodological study. Self-reported anthropometrics are often used as proxies for measured anthropometrics, but research has shown that heights and weights are often misreported in high-income countries – on average, height is over-reported and weight is under-reported (Krul, Daanen, and Choi 2010). Using the Study on global AGEing and adult health (SAGE), a study of health and well-being that focuses on older adults (WHO 2017b), I analyze misreporting patterns of height and weight (and resulting body mass index, or BMI) in China, India, Russia, and South Africa, and investigate whether the biases in reporting patterns in these four countries match what has been observed in developed countries.

In deciding whether to use measured or self-reported anthropometrics, there is a trade-off between accuracy and resource constraints. Data that are often considered unreliable for one purpose might be "good enough" for another, rendering the choice of a metric dependent on the research question at hand. With my data on measured and self-reported anthropometrics, I adjust my height and weight data, and test how adjusted metrics compare with measured and self-reported ones in various applications – studying the distribution of heights, weights, and BMI within a population, as covariates in models of chronic disease-related health outcomes, and for individual-level prediction of health outcomes.

The next two chapters are more substantive in nature. Less-developed countries have traditionally been burdened by their under-nourished population, and assistance from governments and international organizations has been provided to alleviate this problem. But as these countries continue to work on under-nutrition, over-nutrition has been rising rapidly at rates not historically witnessed before. As a result, both ends of the nutritional spectrum are now significant problems in many low- and middle-income countries, leading to a so-called "double burden" of malnutrition (Shrimpton and Rokx 2012).

I examine within- and between- country nutritional disparities among older adults using SAGE data again, but with the addition of Ghana and Mexico. Using country-specific partial proportional odds models, I analyze the patterns of BMI categories along various dimensions of development – place of residence, educational attainment, and wealth. This investigates within-country differences and casts light on how country-specific interventions could be used to address nutritional problems. I then use a pooled partial proportional odds model which merges all the countries' datasets and includes gross domestic product per capita interactions to make the case for intertwining processes of development and the nutrition transition. Here, the focus is on between-country differences and how development might be associated with patterns of nutritional stratification. An important consideration that policy-makers need to keep in mind in their attempt to counter the two nutritional extremes is that resources need to target appropriate population segments, and that such targeted segments might change over time.

Finally, I move on to a discussion of the double burden at the micro level, which require a different set of policy considerations. Besides being a population problem, the double burden can also manifest itself at the individual level, as people could be under- and over-nourished at different stages of life. If children start off as under-nourished, it might seem like a good sign if they end up catching up by adulthood. However, how and when these children get to a higher nutritional status should not be overlooked. When children lack nutrients in early life, biological mechanisms come into play and attempt to compensate for these shortcomings. As a result, nutritional improvements later in life could actually have unintended long-term health implications (Barker 2004; Caballero 2005).

There is not much in the literature on nutritional status transitions over the life course because of the dearth of longitudinal studies that cover a long period of time. Moreover, such studies are even rarer in countries that are not high-income. Using the Institute of Nutrition of Central America and Panama (INCAP) Nutrition Trial Cohort Study, I am able to study nutritional status over the life course in four Guatemalan villages with an analysis of transitions, multiple regressions, and structural equation modeling, in a context that has not been well studied. The results from this study shed light on the relationship between nutritional status, growth, and chronic disease risks throughout the life course, and point to the delicate and precarious nature of policy implementation.

These chapters highlight some of the trends and shifts in population health that are occurring in low- and middle-income countries. These findings are especially salient as such countries continue to develop, become more prosperous, and progress through the nutrition transition over the next few decades. It is my hope that this dissertation could act as a catalyst for future research and offer insights into policy implementation.

BIASES IN SELF-REPORTED HEIGHT AND WEIGHT MEASUREMENTS AND THEIR EFFECTS ON MODELING HEALTH OUTCOMES

Introduction

Self-reported measures are often solicited in questionnaires, and subjects are expected to provide reasonably accurate responses. However, it has been found that self-reported measurements are often not reliable, perhaps due to lack of recall or a desire to conform to aspired norms. Regardless of the reason, misreporting could be detrimental, as it could render the results derived from these measurements also unreliable. Height and weight are both components that go into body mass index (BMI), which is an important metric associated with one's overall health. A low BMI would suggest under-nourishment, which is associated with, among other ailments, infectious diseases. On the other end, a high BMI would suggest over-nourishment, which is associated with chronic diseases, including diabetes, cardiovascular disease, and cancer (WHO 2017a).

Biases in self-reported heights and weights have been found in several high-income countries, but they have not been as extensively studied in the context of countries that are not as developed. With data from the World Health Organization (WHO) Study on global AGEing and adult health (SAGE), I examine the biases in self-reported heights and weights in China, India, Russia, and South Africa, and their effects on the estimation of BMI. In particular, I study the direction and magnitude of misreporting, and investigate whether similar misreporting holds across different countries and population segments.

Slight misreporting might not be problematic if substantive results thence derived are not severely distorted. If so, it would make sense to use self-reported data, as they are not as administratively onerous or costly to collect. Otherwise, actual measures might be needed. A compromise would be to devise an adjustment methodology to convert self-reported information into reasonably reliable data. In this paper, attempts are made to adjust self-reported heights and weights so that BMI values derived therefrom are more reliable. These different values, measured, self-reported, and adjusted, are then used to evaluate the relationships between BMI and chronic disease-related health outcomes, and to predict such health outcomes for individuals. The purpose of this is to ascertain to what extent self-reported data or adjusted self-reported data can take the place of measured data in studying health outcomes.

This study could have implications for many of the analyses in the health arena that rely on self-reported anthropometric measurements. The conclusions from these analyses are important, as policies are often recommended and decided based on them.

Background

BMI, a function of height and weight, is a major risk factor for many diseases. There are numerous studies on factors associated with underweight (low BMI, typically in a lower-income context) or overweight (high BMI, typically in a higher-income context), as well as studies on how BMI is related to various morbidity or mortality outcomes. Many surveys ask for self-reported height and weight, as it is much easier to solicit than to measure them for each subject. Since BMI derived from actually measured height and weight is often not available, is BMI derived from self-reported height and weight a reliable proxy? Throughout this paper, the following terminology will be used. Measured/self-reported BMI is the value derived from measured/self-reported height and weight, respectively. The term objective data refers to data actually measured and other quantities derived therefrom, and the term subjective data refers to self-reported data and other quantities thus derived.

BMI is defined as the ratio of weight (in kg) to height squared (in m^2). An incorrect height or weight would result in an incorrect BMI. While misreporting of both height and weight in the same direction could reduce the error in BMI, misreporting of both in opposite directions, such as over-estimating height and under-estimating weight, would magnify the error. Furthermore, BMI classification is conventionally based on strict cut-points. Thus even if the numerical discrepancy in BMI is not too blatant, it could cause a person to be classified into another BMI category.

It has been found in the Oxford cohort of the European Prospective Investigation into Cancer and Nutrition National Health (EPIC-Oxford) and National Health and Nutrition Examination Survey (NHANES) that despite the high and positive correlation between measured and self-reported BMI, there is disagreement in BMI categorization between the two measures for about 20% of the sample (Spencer et al. 2001; Preston, Fishman, and Stokes 2015). How could this affect other outcomes? Preston et al. find that hazard ratios (for risk of mortality) are similar for objective and subjective measures when BMI is used as a continuous variable, but this is not the case when BMI is used as a categorical variable (Preston, Fishman, and Stokes 2015).

For this reason, it is important to determine whether there are significant differences between objective and subjective anthropometric measures, and if so, where these biases are most prevalent. Krul et al. study absolute differences between measured height/weight and self-reported height/weight with representative samples from Italy, the Netherlands, and North America. They find that in general, height is over-estimated and weight is under-estimated, leading to an overall under-estimation of BMI. However, there are substantial differences between population sub-groups. Height is over-estimated more by males than by females, more by those who are short than by those who are tall, more by young and old people than by those who are middle-aged, and more by Italians than by Dutch and North Americans. Weight is under-estimated more by females than by males, more by those who are heavy than by those who are light, more by middle-aged and old people than by those who are young, and more by Dutch than by Italians and North Americans (Krul, Daanen, and Choi 2010).

The SAGE data focus on older adults, 50 years of age or older. Do older people have different reporting biases? As referred to earlier, Krul et al. find differences in reporting by age (Krul, Daanen, and Choi 2010). An age-related bias has also been found in a longitudinal study of Swedes. Differences are found between self-reported and assessed height, but not weight, and these differences increase significantly as subjects age (Dahl et al. 2010). Reasons for the greater discrepancies in old age could include declines in stature or poor memory (Kuczmarski, Kuczmarski, and Najjar 2001; Dahl et al. 2010).

It is clear that there are differences by population segments, and that the differences between objective and subjective measures are not consistent across sex, age, and height/weight sub-groups. How about other personal characteristics, such as place of residence, educational attainment, or marital status? An analysis on Eastern Finland finds that, upon controlling for BMI category and age, women with higher education and women in urban areas have greater errors in self-reported weight, though these results do not hold for men (Jalkanen et al. 1987). For both men and women in a French cohort, higher levels of education are associated with a smaller over-estimation of height, the opposite of what is found in Jalkanen et al. In this same French cohort, there are no significantly different patterns in height and weight misreporting by marital status (Niedhammer et al. 2000).

Niedhammer et al. also find in this French cohort that self-reported height and weight values ending in zero and five appear more than what would be expected from a uniform distribution of last digits. As a result, they use a dichotomous variable to distinguish between values ending with zero or five, and those ending with other digits. Both men and women who report heights ending with zero or five tend to over-estimate their heights, and women who report weights ending with zero or five are more likely to under-estimate them. Perhaps it is not surprising that numbers are rounded to convenient digits as it could be difficult to remember one's exact height or weight to the nearest unit. What is interesting is that rounding across individuals does not cancel out, and there is a noticeable direction in which it occurs – upward for height and downward for weight (Niedhammer et al. 2000). Heaping is found in many other studies, both in anthropometric measures (Palloni, Soldo, and Wong 2004; Heineck 2006) and in other variables such as age and cigarette consumption (A'Hearn, Baten, and Crayen 2009; Wang et al. 2012).

Perhaps people overstate their heights and understate their weights because they want to present what they consider to be more desirable versions of themselves. Would the results be different if people knew that their information would be verified? In an experiment on patients in Australia, participants reported their heights and weights as part of a questionnaire. They were randomized to informed and uniformed groups – informed participants knew that their heights and weights would be measured afterwards, whereas uninformed participants were asked for consent to measure their heights and weights only after they had completed the questionnaire. Classification into underweight, normal weight, overweight, and obese using BMI with self-reported versus measured heights and weights agreed 80% of the time for both groups. Informing patients prior to measurement does not seem to greatly affect the accuracy of their self-reported heights or weights (Yoong et al. 2013).

All of these studies give some indication as to the directions and magnitudes of height and weight reporting biases. However, all populations in the studies discussed above are in high-income contexts, and not much has been published on this topic in other geographic, economic, and development settings. The patterns that have been seen in the high-income context might not be generalizable to low- and middle-income countries. As a result, continuing the investigation of measurement biases in under-studied contexts is interesting and worthwhile.

What are known about countries in the SAGE dataset? Zhou et al., using a cross-sectional study of adolescents in Xian, China, conclude that self-reported height and weight are not sufficiently accurate to screen for overweight. They also find that misreporting errors are associated with place of residence, age, and actual BMI (Zhou et al. 2010). Gildner et al. actually use the SAGE dataset to look at the distinctions between objective and subjective measures of BMI and find significant differences. However, the discrepancies vary by country, demonstrating the heterogeneity of these countries. They then use multiple regression models to determine the contribution of measured height, measured weight, and other demographic and health behavior variables to differences between measured and self-reported BMI (Gildner et al. 2015). In this paper, I study China, India, Russia, and South Africa, with additional variables that have been found to be significant in other analyses.

In addition to simply studying the biases overall and by sub-groups, the analysis in this paper takes three extra steps – adjusting self-reported values, studying the differences in objective, subjective, and adjusted measures, and investigating whether these adjusted values could be used when measured data are not at a researcher's disposal. Attempts have been made to adjust self-reported measures using data from an Oxford cohort in the United Kingdom and a sample from ten Canadian provinces by regressing measured anthropometrics on self-reported anthropometrics and other characteristics on a training sample of the cohort and predicting height and weight values on a testing sample (Spencer et al. 2001; Dutton and McLaren 2014). Spencer et al. are able to decrease the propensity of BMI misclassification by making adjustments to self-reports (Spencer et al. 2001). Dutton and McLaren conclude that while an adjustment is useful for modeling a population distribution of BMI or estimating obesity prevalence, adjusted BMI does not fix the biases of self-reported BMI in models on various health outcomes; in fact, self-reported data are still sometimes better (Dutton and McLaren 2014). Both papers on adjustment study high-income countries and present the results from one random split of the dataset into training and testing datasets. Consequently, the results pertain to only that particular random sample. In this paper, proposed models will be subject to multiple validations to check their reliability.

Data and Methods

For my analyses, I use the first wave of SAGE, which was implemented between 2007 and 2010. SAGE is an ongoing longitudinal study (though data from later waves have yet to be released) of health and well-being that focuses mostly on people aged 50 years or over in China, Ghana, India, Mexico, Russia, and South Africa (WHO 2017b). To ensure good-sized samples for statistical reliability, I restrict my analyses to China, India, Russia, and South Africa. Additionally, even though there are smaller samples of younger adults, I focus on those who are at least 50 years of age since the propensity for chronic disease is higher at older ages.

Sample sizes for China, India, Russia, and South Africa are 9122, 1487, 3396, and 645, respectively, after excluding observations with missing data by listwise deletion. Self-reported height and weight, as well as measured height and weight, are mostly available.[1] Missing values are usually self-reported height or weight.[2] The availability of this information allows investigation of whether measured height, weight, and BMI are significantly different from self-reported height, weight, and BMI. If two-sided paired t-

[1] Height is measured in centimeters and weight is measured in kilograms.
[2] Survey weights are not used for these analyses. While these SAGE surveys are nationally representative with the use of household- and individual-level weights, the amount of missing data for the self-reported variables renders it such that even the use of weights would not necessarily make the samples representative after removal of observations without appropriate data. While country-level analyses are run and implications are presented, this is a caution for interpretation.

tests are significant, is the direction of the bias similar to that of the countries that have already been studied? Are biases systematic across different population segments, such as sex, place of residence, educational attainment, marital status, and age, within a country?

Regressions in the health literature are commonly run with self-reported measures (Kristensen et al. 2005; Jeffery et al. 2006; Narayan et al. 2007), and the results are usually accepted. But if self-reported measures are inaccurate, there is a possibility that conclusions drawn therefrom are as well. While slightly different coefficients might not be problematic, changes in significance could result in flawed conclusions. Due to the availability of both self-reported and measured information in SAGE, there is a unique opportunity here to investigate whether adjustments could be made to self-reported measures to make them more reliable.

Measured height and weight are predicted as follows:

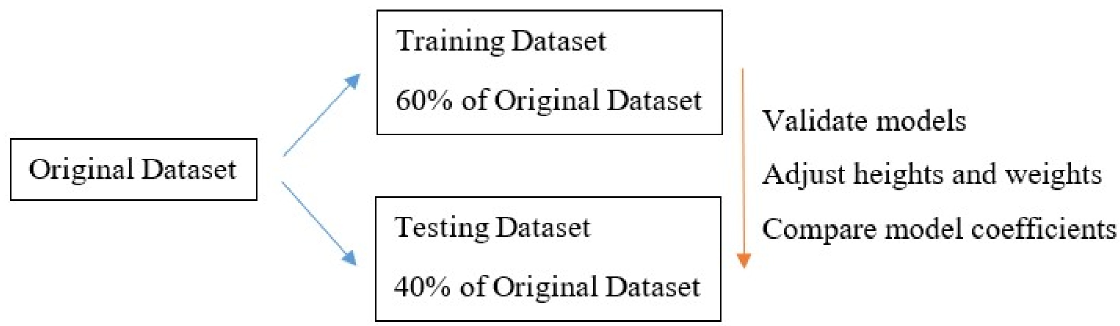
$$
\begin{aligned}
(1)\text{:}\ \mathit{Measured\ height} \\
&= \beta_0 + \beta_1 * \mathit{sex} + \beta_2 * \mathit{place\ of\ residence} + \beta_3 \\
&* \mathit{educational\ attainment} + \beta_4 * \mathit{marital\ status} + \beta_5 * \mathit{age} \\
&+ \beta_6 * 0/5\ \mathit{digit\ indicator\ for\ self\text{-}reported\ height} \\
&+ \beta_7 * \mathit{self\text{-}reported\ weight} \\
&+ \beta_8 * \mathit{self\text{-}reported\ height} + \mathit{error}
\end{aligned}
$$

$$
\begin{aligned}
(2)\text{: } Measured\ weight \\
&= \gamma_0 + \gamma_1 * sex + \gamma_2 * place\ of\ residence + \gamma_3 \\
&* educational\ attainment + \gamma_4 * marital\ status + \gamma_5 * age \\
&+ \gamma_6 * 0/5\ digit\ indicator\ for\ self\text{-}reported\ weight \\
&+ \gamma_7 * self\text{-}reported\ height \\
&+ \gamma_8 * self\text{-}reported\ weight + error
\end{aligned}
$$

For the categorical variables, the reference groups are male for sex, urban for place of residence, less than high school for educational attainment, never married for marital status, and not 0/5 for the digit indicator. The rest of the variables are continuous. Interactions have also been tested in these measured height and weight models, but the models with interactions are not significantly distinguishable from the models without interactions, as determined by Vuong tests for model comparison.

I validate the models using repeated holdout cross-validation. For each country sample, I partition it into a training set with 60% of the data and a testing set with the remaining 40% of the data, as illustrated in Figure 1.1. Partitions are stratified by self-reported BMI categorization. Stratified random sampling ensures that each of the self-reported BMI categories is properly represented in the sub-datasets.

Figure 1.1: Stage one of dataset splitting



With these regression models estimated using data in the training set, self-reported heights and weights are adjusted for each observation in the testing set, with a resulting adjusted BMI. This partition and modeling process is repeated 100 times. Two-sided paired t-tests are performed between measured and self-reported height/weight/BMI, and between measured and adjusted height/weight/BMI, in each of the 100 runs. If the models are any good, it would be reasonable to expect that the latter tests are less likely to be significant than the former.

In addition to height and weight, I run logistic regression models on several health outcomes – having been diagnosed with stroke, having been diagnosed with diabetes, and having been diagnosed with hypertension.[3] Such logistic regressions study the log odds of having stroke/diabetes/hypertension.

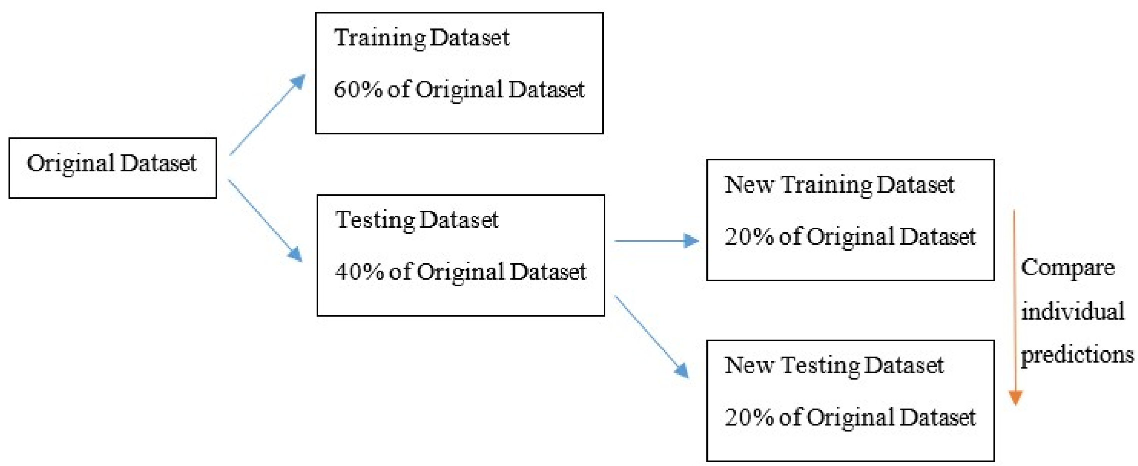
[3] Subjects were asked if they had ever been diagnosed with these outcomes. A positive diagnosis is treated as a proxy for actually having the outcome. However, there are certainly issues with diagnosis reports. Recall bias might occur if people do not remember whether they have been diagnosed with the outcome. Selection bias might occur if only a non-random subset of the sample has access to medical care, which is a prerequisite for receiving a diagnosis.

$$(3): \log\left(\frac{P(health\ outcome)}{1 - P(health\ outcome)}\right)$$
$$= \delta_0 + \delta_1 * sex + \delta_2 * place\ of\ residence + \delta_3 * educational\ attainment + \delta_4 * marital\ status + \delta_5 * age + \delta_6 * BMI\ + error$$

As described above, the height and weight models estimated from each training set are used to adjust self-reported height and weight in the complementary testing set. This testing dataset is then used to estimate the health-outcome logistic models, with measured, self-reported, or adjusted BMI as covariates. It should be noted that there are cases of quasi-complete separation in some of the logistic regression runs. Quasi-complete separation tends to happen with small samples or with "extreme splits on the frequency distribution of either the dependent or independent variables" (Allison 2008). For example, since occurrences of stroke are not that common, it is not unthinkable that at least one level of an independent categorical variable would have few observations with a diagnosis in at least one run. To resolve the problem of possible non-existence of maximum likelihood estimates, methods of median bias reduction are used (Pagui, Salvan, and Sartori 2017). The median of the coefficient estimates for each independent variable is taken over the 100 runs and significance at the five-percent level is determined using the 2.5% and 97.5% quantiles of the empirical distribution of the coefficient estimates. The reported McFadden R^2 values are the median over the 100 runs.

Moving from the aggregate to the individual level, I investigate how the rate of correct individual prediction within a sample changes depending on which BMI metric is used. This is where my testing set is further split into two – a new training set (consisting of half of the original testing set) and a new testing set (consisting of the other half of the original testing set), again using stratified random sampling. Figure 1.2 shows the second stage of this dataset splitting.

Figure 1.2: Stage two of dataset splitting



The health-outcome models presented above are estimated from the training dataset using measured BMI and are treated as the “correct” models. These models are then applied to the testing dataset using measured/self-reported/adjusted BMI. The predicted probabilities in the new training set are used to determine a threshold, based on Youden’s J statistic to maximize the sum of sensitivity (true positive rate) and specificity (true negative rate) (Youden 1950; Lalkhen and McCluskey 2008). This chosen threshold is then applied to the new testing set to evaluate the accuracy of the resulting predictions. A predicted probability above this threshold is classified as having the condition and a predicted probability below is classified as not. Choosing a threshold probability to maximize the true positive and true negative rates for each training set is an attempt to better predict the existence of a health condition than a fixed constant, such as 0.5, might do.

Finally, these health-outcome and individual prediction analyses are re-run, but with BMI as a categorical variable instead of as a continuous one. How do results derived from categorical BMI compare to those derived from continuous BMI? Categorical BMI is split into two levels, overweight and not overweight (i.e., normal and underweight combined), since only overweight is a risk factor for chronic conditions such as stroke, diabetes, and hypertension.

All analyses are run using the statistical software R (version 3.4.1) (R Core Team 2017). The R package brglm2 is used for median bias reduction in generalized linear models (Kosmidis 2017). When discussing the results, the term "significant" means significant at the level of five percent.

Results

Self-reported vs. measured height and weight:

I first illustrate how measured height and weight differ from self-reported height and weight. Figures 1.3 and 1.4 show height and weight density curves, respectively. The red curves are for objective measures and the blue curves are for subjective measures.

Figure 1.3: Density curves of measured and self-reported height (in cm) for China, Russia, India, and South Africa

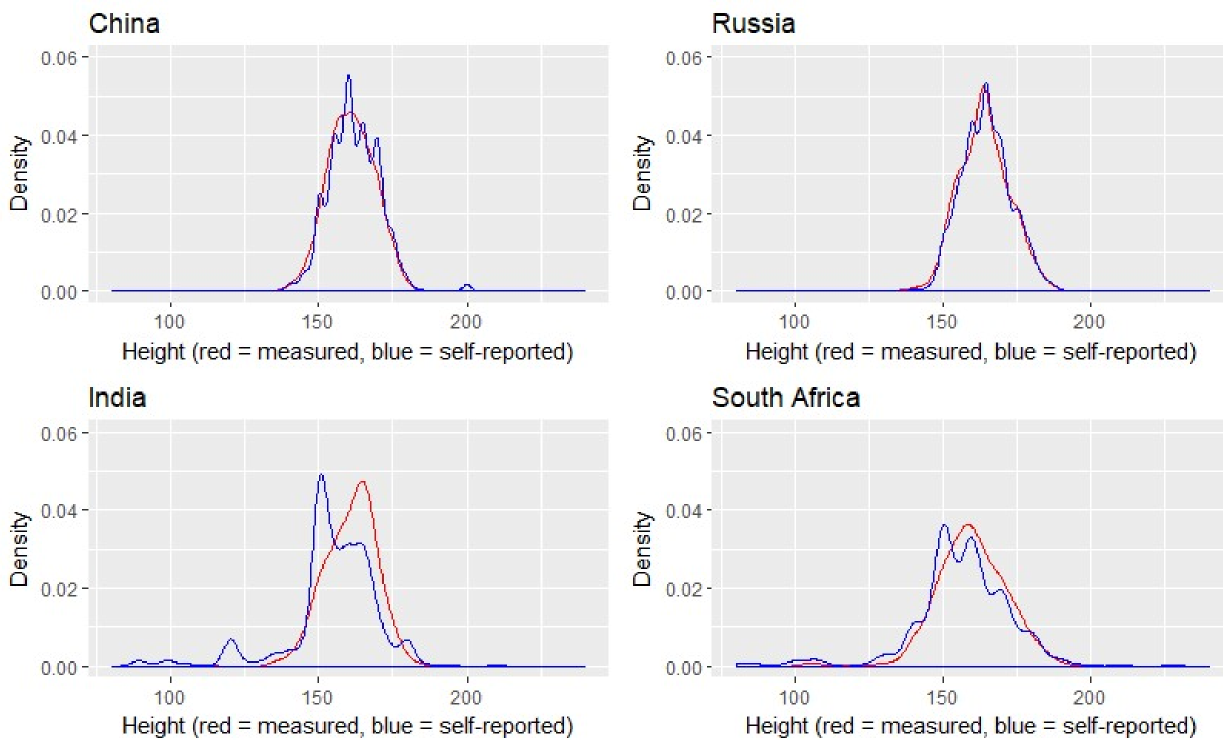
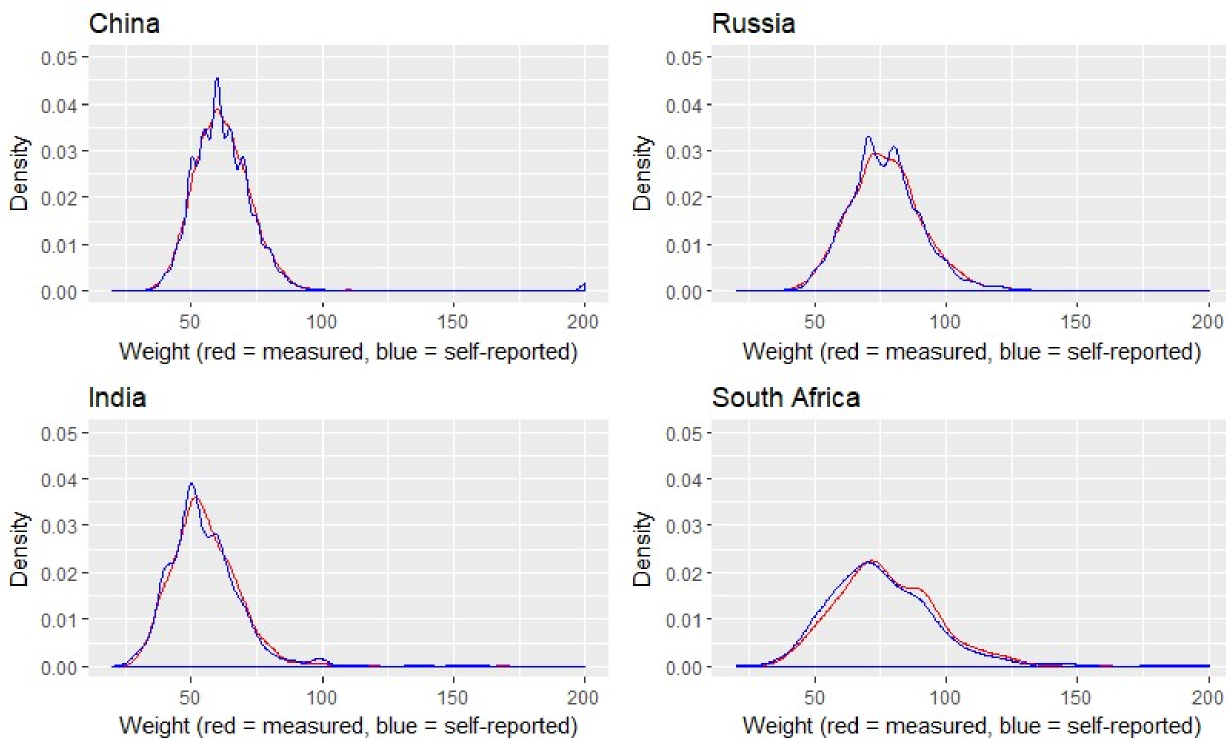


Figure 1.4: Density curves of measured and self-reported weight (in kg) for China, India, Russia, and South Africa



In both Figures 1.3 and 1.4, there is distinctive heaping at certain numbers in self-reported height and weight. The most frequently reported heights and weights tend to end with the more "convenient" unit digits of zero and five. This is consistent with the finding that people in France self-reported values with convenient end digits (Niedhammer et al. 2000). Corresponding figures for BMI are not shown, since BMI is derived from information on height and weight – it is implied and not actually reported by the survey participants themselves.

To determine whether individuals' mean self-reported heights and weights are significantly different from their mean measured heights and weights for each of the four countries, two-sided paired t-tests are used. Tables 1.1, 1.2, and 1.3 below show these results for height, weight, and BMI, both overall and by various population sub-groups. In the tables, each cell shows the mean difference of (self-reported heights/weights/BMIs – measured heights/weights/BMIs), and whether the difference is significantly non-zero.

Table 1.1: Mean differences between self-reported height and measured height (in cm) for China, India, Russia, and South Africa

	China	India	Russia	South Africa
Overall	0.93 ***	–5.88 ***	0.42 ***	–3.24 ***
Male	0.79 ***	–5.73 ***	0.30 ***	–4.33 ***
Female	1.09 ***	–6.42 ***	0.49 ***	–2.42 ***
Urban	1.24 ***	–4.42 ***	0.46 ***	–3.18 ***
Rural	0.56 ***	–6.61 ***	0.32 *	–3.62 *
Less than high school	0.91 ***	–6.63 ***	0.57 ***	–3.72 ***
Completed high school	1.02 ***	–4.62 ***	0.44 ***	–0.29
Completed college	1.04 ***	–3.82 ***	0.16	–3.55 *
Never married	1.81 **	–9.84 *	0.98 ***	–2.59
Cohabiting or currently married	0.89 ***	–5.80 ***	0.31 ***	–3.51 ***
Previously married	1.22 ***	–6.01 ***	0.56 ***	–3.09 ***
Age [50, 65)	0.72 ***	–6.06 ***	0.15	–3.85 ***
Age [65, 80)	1.19 ***	–5.55 ***	0.63 ***	–2.19 **
Age [80, max]	2.99 ***	–4.93 *	1.16 ***	–2.26

In this table and all tables hereinafter, * denotes significance at the 0.05 level, ** at the 0.01 level, and *** at the 0.001 level.

Table 1.2: Mean differences between self-reported weight and measured weight (in kg) for China, India, Russia, and South Africa

	China	India	Russia	South Africa
Overall	0.72 ***	–0.50	–0.63 ***	–1.42 *
Male	0.66 ***	–0.50	–0.51 ***	–1.22 *
Female	0.78 ***	–0.52	–0.69 ***	–1.56
Urban	1.35 ***	–1.08 *	–0.63 ***	–1.41 *
Rural	–0.05	–0.21	–0.63 ***	–1.47
Less than high school	0.64 ***	–0.07	–0.46 *	–1.52 *
Completed high school	1.03 **	–1.03	–0.67 ***	–0.78
Completed college	0.92	–1.97 *	–0.76 ***	–1.45
Never married	3.07	–3.97 *	–0.56	–0.28
Cohabiting or currently married	0.56 ***	–0.41	–0.68 ***	–2.04 **
Previously married	1.80 **	–0.73	–0.56 ***	–0.92
Age [50, 65)	0.23	–0.74 *	–0.92 ***	–2.96 ***
Age [65, 80)	1.09 ***	0.01	–0.33 **	1.43
Age [80, max]	7.56 ***	0.17	–0.22	–0.66

Table 1.3: Mean differences between self-reported BMI and measured BMI (in kg/m^2) for China, India, Russia, and South Africa

	China	India	Russia	South Africa
Overall	–0.05	2.33 ***	–0.37 ***	1.69 **
Male	–0.02	2.05 ***	–0.26 ***	2.10 **
Female	–0.08	3.30 ***	–0.43***	1.38 *
Urban	0.02	1.33 **	–0.39 ***	1.43 **
Rural	–0.13 *	2.83 ***	–0.30 **	3.19
Less than high school	–0.07	2.91 ***	–0.35 **	2.04 **
Completed high school	0.03	1.41 ***	–0.39 ***	–0.20
Completed college	0.01	0.70	–0.34 ***	1.58
Never married	0.25	2.09	–0.53 **	2.81
Cohabiting or currently married	–0.09	2.31 ***	–0.33 ***	1.47 *
Previously married	0.25	2.54 **	–0.42 ***	1.55 *
Age [50, 65)	–0.12 *	2.43 ***	–0.36 ***	1.37 *
Age [65, 80)	–0.03	2.18 ***	–0.35 ***	2.39 *
Age [80, max]	1.41 **	1.46	–0.48 *	0.91

For the overall population, the mean height differences are significantly non-zero for all countries. Individuals in China and Russia, on average, report being taller than they actually are. Individuals in India and South Africa, on average, report being shorter than they actually are. The mean weight differences are significantly non-zero for China, Russia, and South Africa. On average, individuals in China report being heavier than they actually are, while individuals in Russia and South Africa report being lighter than they actually are.

For a country where the mean weight difference is not significantly different from zero, if the mean height difference is significantly non-zero and negative, then one would expect the mean BMI difference, ceteris paribus, to be significantly non-zero and positive. This is the case of India overall. If the mean height difference is significantly non-zero and positive, and the mean weight difference is significantly non-zero and negative, then one would expect the mean BMI difference to be significantly non-zero and negative. This is the case in Russia overall. In China and South Africa overall, the signs are the same for height difference and weight difference. On average, people in China think that they are taller and heavier than they actually are, whereas people in South Africa think that they are shorter and lighter than they actually are. In China, the effects of misreported height and weight might have canceled each other to make the measured BMI and self-reported BMI about the same. However, it is interesting to note that South Africa does not exhibit this cancellation effect and the mean BMI difference is significant non-zero and positive, a possible reason being that the height-squared difference is more significantly negative than the weight difference.

The paired t-tests are run again by sub-groups – male, female, urban, rural, less than high school, completed high school, completed college, never married, cohabiting or currently married, previously married, and three different age groups. In these countries, sub-group height and weight misreporting is usually in the same direction as the overall sample, though the misreporting direction differs among countries. Are there certain sub-groups that, on average, report differently from the overall pattern? For China, Russia, and South Africa, the insignificant results (that is, no significant misreporting) tend to be for the more educated and not married sub-groups. However, the case of weight in India is a very interesting exception. In India, those in urban areas, those who have completed college, those who have never been married, and those in the [50, 65) age group have significant negative differences between self-reported weight and measured weight, whereas the overall sample does not. These are also the sub-groups that tend to misreport less in other contexts.

The results from Tables 1.1 through 1.3 demonstrate whether there are significant differences between measured and self-reported anthropometrics, both overall and by sub-group, but they do not control for the other covariates. Table 1.4 shows the results from multiple regressions of (self-reported height – measured height) on these same covariates, as well as the height 0/5 indicator. Table 1.5 is the corresponding table for weight. Age is treated as a continuous variable in these multiple regressions.

Table 1.4: Multiple regressions of the difference between self-reported height and measured height (in cm) on demographic, socioeconomic, and anthropometric covariates for China, India, Russia, and South Africa

	China	India	Russia	South Africa
Intercept	–0.89	–11.43 **	–1.37 *	–10.58 **
Female	0.30 **	–0.56	0.12	2.31 *
Rural	–0.56 ***	–1.70 *	–0.00	–0.24
Completed high school	–0.04	1.76 *	0.17	4.18 **
Completed college	–0.31	2.22 *	–0.09	1.00
Cohabiting or currently married	–0.98	4.10	–0.73	–1.18
Previously married	–1.05	4.20	–0.78 *	–1.66
Age	0.05 ***	0.04	0.04 ***	0.10
Height 0/5 indicator	0.07	–0.13	–0.57 ***	0.49
Adjusted R^2	0.010	0.009	0.016	0.009

In China, the coefficient for female is significant and positive. That is, females tend to have a greater difference between self-reported height and measured height than males, i.e., greater over-reporting or smaller under-reporting. Since height is over-reported in China, this suggests that females over-report their heights more than males. The coefficient for female is significant and positive for South Africa as well, but since height is under-reported in South Africa, this suggests that females under-report their heights less than males. In both China and India, the coefficient for rural is significant and negative. In China, where height is over-reported overall, rural dwellers over-report their heights less than urban dwellers. In India though, height is under-reported overall. Therefore, a negative coefficient for rural suggests that rural dwellers under-report more than urban dwellers. Relative to the baseline of less than high school, completed college and completed high school are both significant and positive for India, and the coefficient for completed college is more positive than the coefficient for completed high school. Completed high school, but not college, is also significant and positive for South Africa. These are both countries in which height is under-reported overall, so it seems that people with more education tend to under-report their heights less. For marital status, there is only one significant result. Previously married is significant and negative for Russia, relative to the baseline of never married. In Russia, where height is over-reported, this means that those who have previously been married over-report their heights less than those who have never been married. Age is significant and positive for China and Russia, meaning that height is over-reported more for those who are older. The last digit indicator is significant and negative for Russia, so those who use the convenient digits of 0 and 5 actually over-report less, conditional on all of the other covariates. The adjusted

R^2 values are quite low, ranging from 0.009 to 0.016. Similar adjusted R^2 values are found in Gildner et al. (Gildner et al. 2015).

Table 1.5: Multiple regressions of the difference between self-reported weight and measured weight (in kg) on demographic, socioeconomic, and anthropometric covariates for China, India, Russia, and South Africa

	China	India	Russia	South Africa
Intercept	–4.20 *	–4.80	–1.58	–10.77 *
Female	0.14	0.52	–0.27	–0.74
Rural	–1.20 ***	0.74	0.03	–0.20
Completed high school	0.15	–0.92	0.01	1.36
Completed college	–0.72	–2.22 *	–0.07	0.31
Cohabiting or currently married	–2.50	3.21	–0.25	–2.73
Previously married	–2.12	2.78	–0.23	–1.81
Age	0.12 ***	0.04	0.03 **	0.19 **
Weight 0/5 indicator	1.18 ***	–2.18 ***	–0.81 ***	–0.26
Adjusted R^2	0.010	0.008	0.007	0.004

Sex is not significantly associated with weight misreporting for any of these countries. Rural is again significant and negative for China. Since weight is also over-reported in China overall, the conclusion is the same here as it is for height misreporting – rural dwellers over-report less than urban dwellers. Relative to the baseline of less than high school, completed college is significant and negative for India. There is no significant weight misreporting in India overall, suggesting that those who completed college under-report their weights more or over-report their weights less than their less educated peers. Age is significant and positive for all countries except for India. Russia and South Africa both have under-reporting of weight overall, so the positive coefficient is interpreted as less under-reporting with increasing age, whereas the positive coefficient is interpreted as more over-reporting with increasing age in China. For weight differences, the last digit indicator is significant in China, India, and Russia. However, the sign is positive for China and negative for India and Russia. Those who report a convenient last digit in China over-report their weights more, and those who report a convenient last digit in India and Russia under-report their weights more. For weight differences, South Africa has the lowest adjusted R^2 value at 0.004 and China has the highest one at 0.010.

Table 1.6 shows how self-reported BMI categorization (using self-reported height and weight) compares with measured BMI categorization (using measured height and weight).[4] The agreement proportion is the sum along the main diagonal.

[4] Adult underweight is defined as having a body mass index (BMI) under 18.5 kg/m^2, overweight is defined as having a BMI of 25 kg/m^2 or above, and the normal range falls in between (WHO 2006).

Table 1.6: Agreement on self-reported and measured BMI categorization for China, India, Russia, and South Africa

China	Measured BMI categorization			
Self-reported BMI categorization		Underweight	Normal	Overweight
	Underweight	0.025	0.019	0.001
	Normal	0.012	0.572	0.075
	Overweight	0.001	0.031	0.264

Agreement proportion = 0.861

India	Measured BMI categorization			
Self-reported BMI categorization		Underweight	Normal	Overweight
	Underweight	0.122	0.063	0.006
	Normal	0.110	0.397	0.042
	Overweight	0.026	0.111	0.123

Agreement proportion = 0.642

Russia	Measured BMI categorization			
Self-reported BMI categorization		Underweight	Normal	Overweight
	Underweight	0.006	0.003	0.000
	Normal	0.003	0.207	0.042
	Overweight	0.001	0.020	0.719

Agreement proportion = 0.932

South Africa	Measured BMI categorization			
Self-reported BMI categorization		Underweight	Normal	Overweight
	Underweight	0.019	0.008	0.005
	Normal	0.012	0.135	0.084
	Overweight	0.005	0.062	0.671

Agreement proportion = 0.825

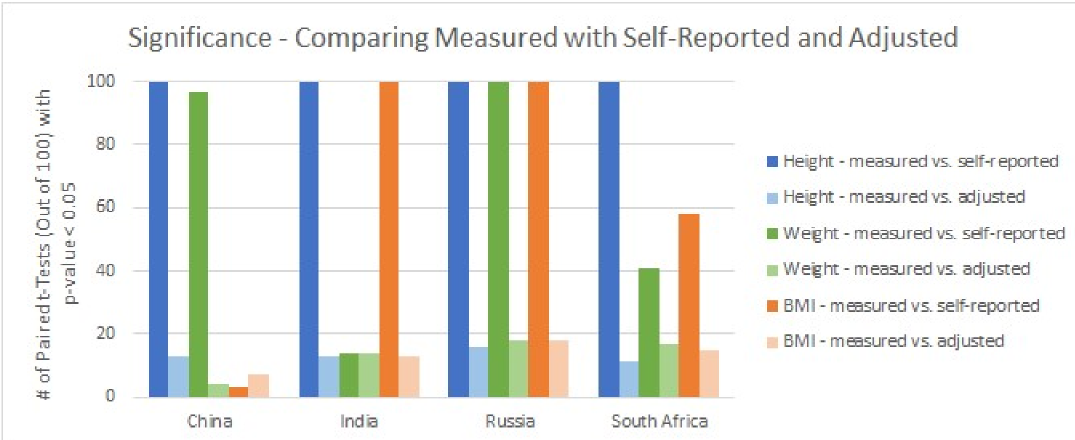
The agreement is highest for Russia (0.932), followed by China (0.861), South Africa (0.825), and India (0.642). The agreement in India is noticeably worse than that in the other three countries. In India, almost half of the people who are underweight when using objective measures actually report being in the normal category and about 20% of the people who are normal weight using objective measures actually report being in the overweight category. That is, there is a tendency in India to over-report BMI category.

Might it be that being overweight, like beauty or wealth, is something that people in India tend to aspire to? Research has shown that there is a desire to be thin among Indian adolescent girls (Dixit et al. 2011; Zimik 2016), but perhaps there might be a difference between the young and old in this generation.

Adjustments to self-reported height and weight:

Models of measured height and weight are run on a 60% training set 100 times. Over 100 runs, the measured height model has average McFadden R^2 values of 0.74, 0.57, 0.85, and 0.48 while the measured weight model has average McFadden R^2 values of 0.41, 0.46, 0.88, and 0.59 for China, India, Russia, and South Africa, respectively. The resulting models are then used to adjust heights and weights for the observations in the testing set. To analyze how well these adjustments perform, I use two-sided paired t-tests to determine, among 100 holdout validations, how often the measured and self-reported means are significantly different, and how often the measured and adjusted means are significantly different. Having measured BMI is the best-case scenario, so in testing measured versus self-reported and measured versus adjusted, I am comparing measured versus the two potential alternatives. These results are shown in Figure 1.5 for height, weight, and BMI for each of the four countries.

Figure 1.5: Frequency of significance when comparing measured values with self-reported values and with adjusted values in China, India, Russia, and South Africa



From Figure 1.5, it is evident that, whenever Tables 1.1 and 1.2 show significant misreporting in height or weight (which is so in all cases, except for weight in India), the frequency of significance in the holdout validations decreases drastically from measured versus self-reported height/weight to measured versus adjusted height/weight. That is, measured heights and weights tend to be closer to adjusted heights and weights than they are to self-reported heights and weights. What does this mean for BMI? Although the height and weight adjustments do appear to be beneficial for China, the misreporting in height and misreporting in weight seem to have canceled out in the calculation of BMI, rendering BMI adjustment to be not useful. Nevertheless, BMI is not significantly misreported in China anyway. In the other three countries, there is a drop in frequency of significant results when going from measured versus self-reported to measured versus adjusted BMI, and so adjustment appears to be beneficial.

Using measured, self-reported, and adjusted BMI as continuous covariates:

There are three health outcomes of interest in this study – having ever been diagnosed with stroke, diabetes, and hypertension. Logistic regressions are run on these health outcomes for each of the four countries. Table 1.7 shows the resulting log odds. For each health outcome and country, three sets of results are shown – measured (M), self-reported (S), and A (adjusted). The results show the median coefficient estimates from 100 runs on the testing sets and whether zero does not fall within the empirical 95% confidence interval, i.e. significance at five percent.

Table 1.7: Logistic regressions of health outcomes on continuous BMI (measured, self-reported, and adjusted) and other demographic and socioeconomic covariates for China, India, Russia, and South Africa

China	Stroke			Diabetes			Hypertension		
	M	S	A	M	S	A	M	S	A
Intercept	–9.75 ~	–9.50 ~	–10.01 ~	–6.94 ~	–6.21 ~	–7.41 ~	–6.77 ~	–5.62 ~	–7.45 ~
Female	–0.26	–0.26	–0.27	0.17	0.17	0.13	0.14 ~	0.18 ~	0.13 ~
Rural	–0.43 ~	–0.44 ~	–0.42 ~	–1.11 ~	–1.14 ~	–1.10 ~	–0.51 ~	–0.54 ~	–0.49 ~
High school	0.22	0.21	0.21	0.01	0.00	0.01	0.09	0.08	0.10
College	0.16	0.15	0.15	0.01	0.01	0.00	0.18	0.19	0.17
Cohabiting or currently married	1.48	1.49	1.45	0.57	0.64	0.59	0.07	0.14	0.05
Previously married	1.27	1.25	1.21	0.32	0.36	0.35	–0.01	–0.00	–0.05
Age	0.07 ~	0.07 ~	0.07 ~	0.04 ~	0.04 ~	0.04 ~	0.06 ~	0.05 ~	0.06 ~
BMI	0.04 ~	0.02 ~	0.05 ~	0.05 ~	0.03 ~	0.08 ~	0.10 ~	0.05 ~	0.13 ~
McFadden R^2	0.069	0.070	0.066	0.070	0.068	0.066	0.081	0.071	0.070

In this table and all tables hereinafter, ~ denotes a case when zero falls outside the 95% empirical confidence interval.

India	Stroke			Diabetes			Hypertension		
	M	S	A	M	S	A	M	S	A
Intercept	–5.43 ~	–5.78 ~	–5.70 ~	–6.68 ~	–5.16 ~	–7.83 ~	–6.41 ~	–4.95 ~	–7.01 ~
Female	–0.37	–0.41	–0.41	0.22	0.30	0.14	0.78 ~	0.84 ~	0.76 ~
Rural	–0.35	–0.34	–0.28	–0.79 ~	–0.86 ~	–0.68 ~	–0.14	–0.23	–0.14
High school	0.17	0.17	0.13	0.16	0.22	0.07	0.41	0.47	0.38
College	0.73	0.69	0.71	0.48	0.70 ~	0.35	0.60 ~	0.75 ~	0.51
Cohabiting or currently married	0.17	0.17	0.15	1.68 ~	1.52 ~	1.62 ~	0.01	–0.01	–0.03
Previously married	0.70	0.74	0.75	1.63 ~	1.50 ~	1.53 ~	–0.05	–0.13	–0.08
Age	0.04 ~	0.04 ~	0.04 ~	0.03 ~	0.03	0.03 ~	0.05 ~	0.05 ~	0.05 ~
BMI	0.00	0.01	0.01	0.07 ~	0.01	0.13 ~	0.07 ~	0.01 ~	0.10 ~
McFadden R^2	0.016	0.028	–0.016	0.063	0.059	0.041	0.079	0.067	0.068

Russia	Stroke			Diabetes			Hypertension		
	M	S	A	M	S	A	M	S	A
Intercept	–7.83 ~	–7.69 ~	–7.78 ~	–6.19 ~	–6.23 ~	–6.55 ~	–6.36 ~	–6.32 ~	–6.53 ~
Female	–0.21	–0.21	–0.22	0.50 ~	0.50 ~	0.46 ~	0.68 ~	0.70 ~	0.66 ~
Rural	0.03	0.04	0.04	–0.39 ~	–0.39 ~	–0.41 ~	–0.21	–0.20	–0.20
High school	0.04	0.04	0.03	–0.11	–0.11	–0.12	–0.04	–0.03	–0.03
College	0.09	0.08	0.08	0.03	0.04	0.03	–0.15	–0.14	–0.13
Cohabiting or currently married	0.40	0.41	0.41	0.37	0.35	0.34	–0.06	–0.08	–0.08
Previously married	0.34	0.35	0.35	0.36	0.35	0.36	–0.09	–0.12	–0.11
Age	0.06 ~	0.06 ~	0.06 ~	0.02 ~	0.02 ~	0.02 ~	0.06 ~	0.06 ~	0.06 ~
BMI	0.02	0.02	0.03	0.06 ~	0.06 ~	0.07 ~	0.09 ~	0.09 ~	0.10 ~
McFadden R^2	0.040	0.039	0.039	0.049	0.048	0.051	0.115	0.112	0.113

South Africa	Stroke			Diabetes			Hypertension		
	M	S	A	M	S	A	M	S	A
Intercept	–1.47	–2.24	–1.91	–3.43 ~	–2.97 ~	–4.07 ~	–2.07 ~	–1.51	–1.50
Female	0.37	0.41	0.37	0.22	0.27	0.14	0.35	0.41	0.43
Rural	0.28	0.21	0.24	–0.22	–0.22	–0.29	–0.20	–0.13	–0.14
High school	0.25	0.22	0.23	–0.25	–0.22	–0.26	–0.18	–0.15	–0.15
College	–1.73 ~	–1.80 ~	–1.80 ~	–0.17	–0.16	–0.19	–0.70	–0.70	–0.70
Cohabiting or currently married	0.37	0.31	0.33	–0.14	–0.14	–0.10	–0.07	–0.08	–0.08
Previously married	0.90	0.81	0.87	0.28	0.30	0.30	–0.06	–0.04	–0.05
Age	–0.03	–0.03	–0.03	0.02	0.01	0.02	0.02	0.01	0.01
BMI	–0.01	0.01	0.00	0.02	0.01	0.04 ~	0.02	–0.00	–0.00
McFadden R^2	0.083	0.088	0.084	0.044	0.039	0.050	0.036	0.034	0.034

First, I look at the overarching results from Table 1.7. How is BMI associated with stroke, diabetes, and hypertension? In South Africa, BMI is never a significant covariate in any of these health-outcome models, regardless of which BMI metric is used, with one exception – the adjusted BMI model for diabetes. South Africa has the smallest sample size of the four countries, which might explain the lack of significance. Besides the case of South Africa, BMI is generally a significant covariate in models of diabetes and hypertension. However, BMI is significant for stroke only in China.

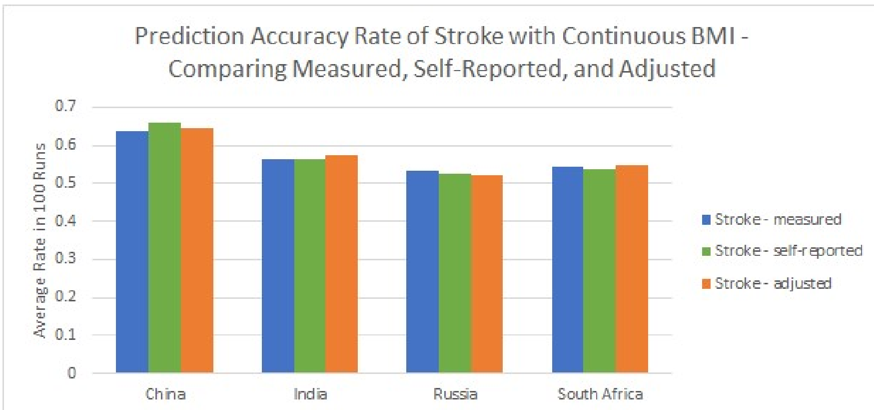
I then compare the models using measured and self-reported BMI. For the same country and health outcome, the coefficient estimate for measured BMI is usually greater than that of self-reported BMI, meaning that measured BMI predicts a higher probability of the health outcome than self-reported BMI does. Since self-reported BMI has reporting errors, that its coefficient estimates tend to bias downward toward zero is not unexpected. Of special note is the variable BMI in the diabetes model for India. Measured BMI is a significant variable for diabetes, but self-reported BMI is not. Not only might the BMI variable itself change in significance, but the choice of metric might also affect the significance of other variables in the model. The results show that substantive conclusions might change depending on whether measured or self-reported BMI is used as a covariate. However, discrepancies between significance and non-significance occur in very few cases.

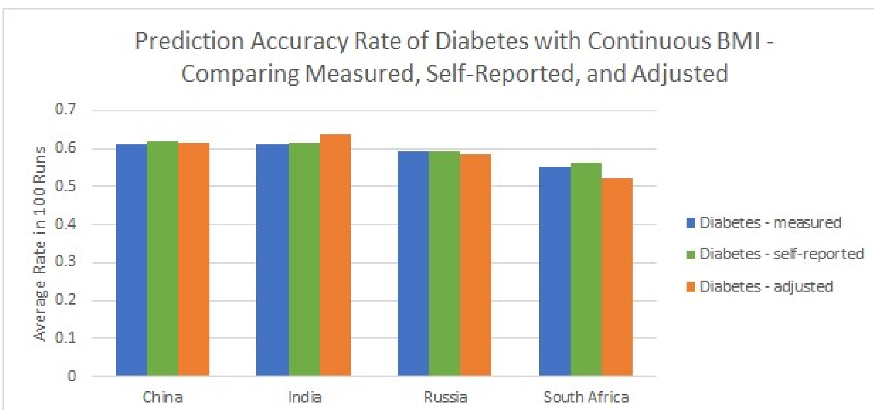
The results from the adjusted BMI models are similar. When a variable is significant using adjusted BMI, the coefficient estimate matches up pretty closely with the corresponding coefficient estimates from the measured and self-reported models. While the coefficient estimate for self-reported BMI is typically lower than that of measured BMI, the coefficient estimate for adjusted BMI is typically greater than that of measured BMI. That is, if the assumption is that the model with measured BMI is the correct model, the adjustment overcorrects the association of BMI with these health outcomes. This is potentially due to certain variables being used as covariates in the measured height/weight models and again in the health-outcome models. There is only one discrepancy between the significance of BMI in models using measured BMI and models using adjusted BMI (diabetes for South Africa). However, these cases are exceptions rather than the norm. Generally, the measured, self-reported, and adjusted models actually perform quite similarly.

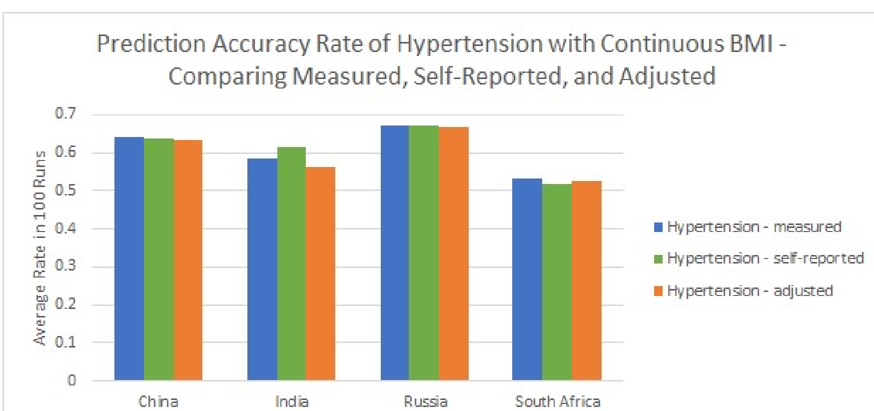
Modeling health outcomes at the individual level with BMI as a continuous covariate:

How well can measured/self-reported/adjusted BMI for an individual predict that person's predisposition to stroke/diabetes/hypertension? Each of the health-outcome models estimated from the training set is applied to the testing set, with measured/self-reported/adjusted BMI as a covariate, to determine a predicted probability of having the health outcome. With such predicted probabilities for half of the testing set (referred to earlier as the new training set), a threshold is chosen to maximize the sum of sensitivity and specificity in classifying the observations as having or not having the health outcome. This threshold is then applied to the other half of the testing set (referred to earlier as the new testing set) to predict whether an observation has or has not been diagnosed with a health outcome. With both the actual outcome and the predicted outcome, a prediction accuracy rate can be calculated. Figure 1.6 compares the average prediction accuracy rate over 100 runs for each health outcome, country, and BMI metric.

Figure 1.6: Comparison of prediction accuracy rates using measured, self-reported, and adjusted continuous BMI in China, India, Russia, and South Africa







The prediction accuracy rates in these health outcome, country, and BMI metric combinations range from about 0.5 to 0.7. Visually, there does not appear to be any substantial difference in prediction accuracy rates, or a pattern along any of these variables. Among the twelve two-sided paired t-tests comparing prediction accuracy rates with measured BMI and prediction accuracy rates with self-reported BMI, only the tests for stroke in China and hypertension in India are significant. In both of these significant cases, the average prediction accuracy rate is higher using self-reported BMI. There could be a possibility that the errors in self-reported BMI and diagnosis reports are correlated. Among the twelve two-sided paired t-tests comparing prediction accuracy rates with measured BMI and prediction accuracy rates with adjusted BMI, only the tests for hypertension in China, diabetes in India, hypertension in India, and diabetes in South Africa are significant. In these four significant cases, the average prediction accuracy rate is higher using measured BMI three times. These results seem to say that self-reported BMI might actually have an edge over measured BMI, and measured BMI over adjusted BMI. However, it should be noted that the measured prediction accuracy rates and self-reported/adjusted prediction accuracy rates are not significantly different 18 out of 24 times. This indicates that the prediction accuracy rate might not necessarily be better using a certain BMI metric as opposed to another BMI metric. The resources expended in securing measured data might not be worthwhile.

Using continuous vs. categorical BMI:

The modeling and prediction analyses above have been performed using BMI as a continuous variable. Preston et al. have found that there is not much difference in predicting the risk of mortality when using measured or self-reported BMI as continuous variables, but there is a difference between measured and self-reported BMI as categorical variables (Preston, Fishman, and Stokes 2015). I repeat the above analyses, but I categorize measured, self-reported, and adjusted BMI into overweight and not overweight, where not overweight is the reference category. The results using categorical BMI are exhibited in Table 1.8.

Table 1.8: Logistic regressions of health outcomes on categorical BMI (measured, self-reported, and adjusted) and other demographic and socioeconomic covariates for China, India, Russia, and South Africa

China	Stroke			Diabetes			Hypertension		
	M	S	A	M	S	A	M	S	A
Intercept	–8.97 ~	–9.00 ~	–9.06 ~	–5.63 ~	–5.57 ~	–5.62 ~	–4.55 ~	–4.50 ~	–4.56 ~
Female	–0.26	–0.25	–0.29	0.15	0.16	0.11	0.14 ~	0.17 ~	0.11
Rural	–0.46 ~	–0.43 ~	–0.42 ~	–1.14 ~	–1.13 ~	–1.11 ~	–0.55 ~	–0.54 ~	–0.50 ~
High school	0.21	0.21	0.21	0.01	0.02	0.04	0.08	0.07	0.11
College	0.15	0.14	0.15	–0.02	–0.01	–0.00	0.16	0.17	0.18
Cohabiting or currently married	1.51	1.50	1.47	0.57	0.58	0.59	0.09	0.09	0.08
Previously married	1.28	1.24	1.24	0.33	0.33	0.32	–0.01	–0.03	–0.03
Age	0.07 ~	0.07 ~	0.07 ~	0.04 ~	0.04 ~	0.04 ~	0.05 ~	0.05 ~	0.06 ~
Overweight	0.30	0.45 ~	0.42	0.61 ~	0.63 ~	0.55 ~	0.79 ~	0.75 ~	0.72 ~
McFadden R^2	0.069	0.072	0.070	0.072	0.072	0.069	0.080	0.076	0.071

India	Stroke			Diabetes			Hypertension		
	M	S	A	M	S	A	M	S	A
Intercept	–5.50 ~	–5.69 ~	–5.60 ~	–5.13 ~	–4.91 ~	–5.03 ~	–4.86 ~	–4.82 ~	–4.68 ~
Female	–0.32	–0.45	–0.34	0.23	0.24	0.21	0.80 ~	0.79 ~	0.83 ~
Rural	–0.34	–0.32	–0.34	–0.81 ~	–0.84 ~	–0.82 ~	–0.18	–0.21	–0.22
High school	0.17	0.14	0.18	0.18	0.22	0.16	0.45	0.47	0.46
College	0.78	0.70	0.77	0.63	0.70 ~	0.55	0.69 ~	0.73 ~	0.72 ~
Cohabiting or currently married	0.17	0.17	0.21	1.57 ~	1.53 ~	1.62 ~	0.01	0.00	0.00
Previously married	0.75	0.75	0.70	1.51 ~	1.46 ~	1.59 ~	–0.08	–0.15	–0.12
Age	0.04	0.04	0.04	0.03	0.03	0.03	0.05 ~	0.05 ~	0.05 ~
Overweight	–0.23	0.39	–0.18	0.62 ~	0.42	0.60	0.57 ~	0.67 ~	0.27
McFadden R^2	0.017	0.022	0.020	0.062	0.061	0.058	0.071	0.078	0.066

Russia	Stroke			Diabetes			Hypertension		
	M	S	A	M	S	A	M	S	A
Intercept	–7.47 ~	–7.41 ~	–7.46 ~	–5.08 ~	–4.93 ~	–4.97 ~	–4.21 ~	–4.21 ~	–4.20 ~
Female	–0.19	–0.18	–0.20	0.61 ~	0.61 ~	0.60 ~	0.83 ~	0.82 ~	0.80 ~
Rural	0.05	0.05	0.05	–0.33 ~	–0.33 ~	–0.33	–0.12	–0.13	–0.12
High school	0.03	0.03	0.02	–0.13	–0.14	–0.14	–0.04	–0.05	–0.05
College	0.08	0.08	0.08	–0.03	–0.03	–0.03	–0.18	–0.19	–0.18
Cohabiting or currently married	0.41	0.40	0.39	0.33	0.35	0.40	–0.02	–0.03	0.01
Previously married	0.34	0.35	0.36	0.33	0.36	0.42	–0.07	–0.07	–0.04
Age	0.06 ~	0.06 ~	0.06 ~	0.02 ~	0.02 ~	0.02 ~	0.06 ~	0.05 ~	0.05 ~
Overweight	0.34	0.28	0.37	0.95 ~	0.85 ~	0.82 ~	0.77 ~	0.78 ~	0.76 ~
McFadden R^2	0.042	0.042	0.042	0.044	0.041	0.038	0.096	0.098	0.094

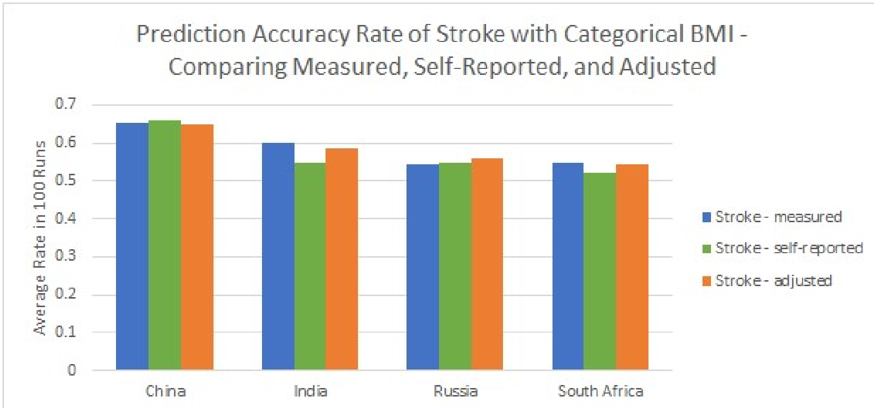
South Africa	Stroke			Diabetes			Hypertension		
	M	S	A	M	S	A	M	S	A
Intercept	–1.49	–2.12	–1.23	–3.18 ~	–2.90 ~	–3.56 ~	–2.04 ~	–1.59	–1.43
Female	0.43	0.33	0.45	0.22	0.27	0.22	0.36	0.40	0.41
Rural	0.32	0.22	0.22	–0.21	–0.19	–0.20	–0.17	–0.17	–0.15
High school	0.29	0.22	0.30	–0.25	–0.23	–0.26	–0.17	–0.14	–0.14
College	–1.72 ~	–1.79 ~	–1.67 ~	–0.19	–0.16	–0.22	–0.68	–0.69	–0.69
Cohabiting or currently married	0.38	0.37	0.36	–0.17	–0.14	–0.13	–0.09	–0.07	–0.06
Previously married	0.85	0.80	0.90	0.25	0.29	0.25	–0.06	–0.04	–0.02
Age	–0.03	–0.03	–0.03	0.02	0.01	0.02	0.02	0.01	0.01
Overweight	–0.65	0.04	–0.69	0.53	0.26	0.82	0.47 ~	0.02	0.03
McFadden R^2	0.072	0.057	0.054	0.048	0.040	0.043	0.040	0.033	0.034

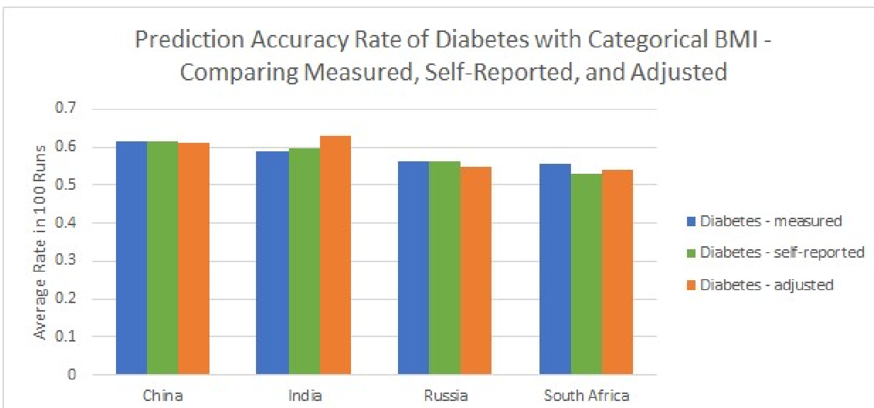
When overweight is significant, its median coefficient estimate is always positive. That is, those who are overweight are more at risk of these health outcomes compared to those who are not overweight. This is an expected result as having a higher BMI is a known risk factor for chronic conditions. As with the health-outcome models using continuous BMI, the health-outcome models using categorical BMI for South Africa and stroke have the fewest significant relationships.

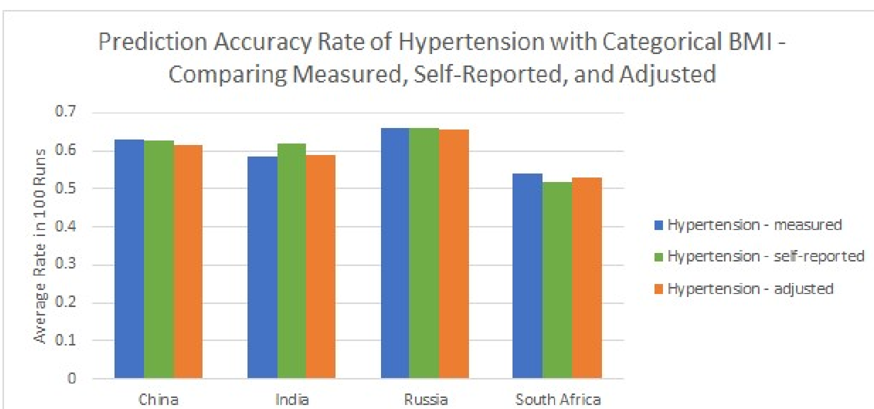
There appear to be more discrepancies between models when BMI is categorical instead of continuous. These discrepancies are more apparent in the overweight variable than in the other variables. There are three changes in significance in the overweight variable between measured and self-reported categorical BMI – stroke in China, diabetes in India, and hypertension in South Africa. For diabetes in India and hypertension in South Africa, overweight is significant only when classified by measured BMI, while for stroke in China, overweight is significant only when classified by self-reported BMI. When comparing measured and adjusted, there are three changes in significance in the overweight variable – diabetes and hypertension in India, and hypertension in South Africa. In all these cases, overweight is significant only when classified by measured BMI. The argument for using self-reported BMI or adjusting self-reported BMI appears weaker with categorical BMI.

I then look at prediction accuracy using categorical BMI.

Figure 1.7: Comparison of prediction accuracy rates using measured, self-reported, and adjusted categorical BMI in China, India, Russia, and South Africa







Again, there does not appear to be any substantial visual difference in prediction accuracy rates, or a pattern along health outcomes, country, or BMI metric. Among the twelve two-sided paired t-tests comparing prediction accuracy rates with measured BMI and prediction accuracy rates with self-reported BMI, stroke in India, hypertension in India, and hypertension in South Africa are significant. Among the twelve two-sided paired t-tests comparing prediction accuracy rates with measured BMI and prediction accuracy rates with adjusted BMI, hypertension in China, diabetes in India, stroke in Russia, and hypertension in Russia are significant. In these seven significant cases, the average prediction accuracy rates are higher for measured BMI than for self-reported/adjusted BMI in four cases, but there is no clear pattern as to which combinations of health outcome, country, and BMI metric are more likely to be in which direction. Again though, differences between prediction accuracy rates using measured BMI and prediction accuracy rates using self-reported/adjusted BMI are not significant in the majority of cases (17 out of 24). As in the case for continuous BMI, this again indicates that the prediction accuracy rate might not necessarily be better using a certain categorical BMI metric as opposed to another categorical BMI metric.

Discussion

There are significant differences between measured and self-reported height and weight, but such differences vary by country. Most research in high-income countries has shown that height is typically over-reported. While this is true in China and Russia, height tends to be significantly under-reported in India and South Africa. Most research in high-income countries has also shown that weight is typically under-reported (at least at older ages). In my study, weight is significantly under-reported in Russia and South Africa, significantly over-reported in China, but not significantly misreported in India.

The reporting patterns in Russia are closest to those of the higher-income countries that have previously been studied. In terms of the Human Development Index (HDI), Russia (height over-reported and weight under-reported) is ranked the highest, followed by China (height over-reported, but weight also over-reported), South Africa (weight under-reported, but height also under-reported), and India (height under-reported and weight not significantly misreported) (UNDP 2016). The different patterns of height and weight misreporting among these four countries indicate the heterogeneity among low- and middle-income countries, and that there might be a relationship between reporting patterns and level of development. Understanding the unique processes of misreporting in these and other countries would be an interesting path for further research. Perhaps height and weight aspirations shift as countries develop, leading to misreporting in different directions for countries at different stages of development. This might be most evident in the case of India. As mentioned before, a large proportion of these older adults tend to over-report their BMI categories, despite research showing that younger people in India aspire to have thinner figures. Perhaps this difference could be attributed to their having grown up in periods belonging to different stages of development in India.

What is similar among my four study countries is that sub-groups in a country tend to report their heights and weights in a way that matches the country's overall pattern. When a country has significant overall misreporting, significant differences within country sub-groups usually point in the same direction as that of the country overall. However, not all sub-groups show significant misreporting, even when a country has significant overall misreporting. Typically, the insignificant results tend to be for the more educated and not married sub-groups. If there are constraints to collecting measured height and weight, perhaps there are certain sub-groups in which self-reported data are reliable enough. However, caution is in order, and the specific situation of a country should be considered. For example, the case of weight in India does not follow the usual pattern, since the same sub-groups that tend not to misreport in other contexts significantly misreport their weights, even when an overall pattern of weight misreporting is not found.

Another way to avoid collecting measured data altogether would be to adjust self-reported height and weight based on the measured height and weight models in this paper. This would be a way to save time, money, and other resources. In this paper, the measured height and weight models are run 100 times on a random training set and applied to a random testing set for verification purposes. In actual applications, all the data in a population or a subset thereof could be used to estimate a model, and these coefficient estimates could then be used to adjust heights and weights in another population. However, researchers are cautioned that the models for one country should not be indiscriminately used for another country. These models might be more suited for the same country, or perhaps even countries at similar levels of development or with similar demographics.

So how well do these adjustments do? In these four countries, adjusted heights/weights tend to be closer to measured heights/weights than self-reported heights/weights are to measured heights/weights. For India, Russia, and South Africa, adjusted BMIs are closer to measured BMIs than self-reported BMIs are. For China, the adjustment in BMI actually performs slightly worse in my 100 runs, likely because the height and weight misreporting go in opposite directions and cancel each other in the BMI determination. If the goal is to look at distributions of height, weight, or BMI, adjusting self-reported measures could be beneficial. The same conclusion has been reached in higher-income contexts as well (Spencer et al. 2001; Dutton and McLaren 2014).

BMI is often used as a covariate in models to predict various health outcomes, since it is a major risk factor for chronic diseases. While there are some differences among models using continuous measured, self-reported, and adjusted BMI in terms of level of significance, they are usually not actually that different. There are a couple of exceptions – measured and adjusted BMI, but not self-reported BMI, are significant covariates for diabetes in India, while adjusted BMI, but not measured or self-reported BMI, is a significant covariate for diabetes in South Africa. When using categorical BMI, there are more discrepancies in the magnitude of coefficient estimates and even their significance when different BMI metrics are used, results consistent with previous research on the United States (Preston, Fishman, and Stokes 2015). It appears that, with a couple of exceptions, choice of BMI metric is not too important when using BMI as a continuous variable, and so the simplest option of using self-reported data is acceptable.

However, its tendency to understate the association should be kept in mind. Collecting measured data would be more crucial when using BMI as a categorical variable.

From an individual perspective, prediction accuracy rates are more important than coefficient estimates. Models using the three BMI metrics result in similar prediction accuracy rates. Regardless of whether BMI is used as a continuous or as a categorical variable and whether BMI is calculated using measured, self-reported, or adjusted heights and weights, the prediction accuracy rates range from about 0.5 to 0.7. More often than not, the results using measured and self-reported BMI, and the results using measured and adjusted BMI, are not statistically different, suggesting that using self-reported data or adjusted self-reported data are acceptable alternatives to using measured data.

While I randomly split my data into training and testing sets 100 times to confirm validity, further testing with additional data, such as future waves of SAGE, would seem to be a good next step. It should also be noted that only older populations in four countries are studied. Researchers are cautioned against using or not using self-reported data in health-outcome models for other populations without further investigation. Nevertheless, this study does appear promising. China, India, Russia, and South Africa are very diverse countries with varying height and weight reporting patterns and varying degrees of BMI classification agreement. Despite these differences, the general substantive conclusions are similar. Self-reported data could be sufficient for certain purposes. If deemed necessary, adjustments could be made to self-reported data to improve the reliability of conclusions derived therefrom. However, there are applications for which measured data are still superior, and if resources are available, it would be preferable to have the most accurate data at the researcher's disposal.

Conclusion

There is significant height misreporting in China, India, Russia, and South Africa, and significant weight misreporting in China and Russia, which in turn often lead to significant differences between measured and self-reported BMI. While using misreported heights and weights might matter from the standpoint of understanding the distribution of anthropometrics in a population, their use might or might not have dire consequences for other applications.

Using measured, self-reported, and adjusted BMI as continuous covariates in models of stroke, diabetes, and hypertension typically result in similar overall conclusions, though exceptions to the pattern should not be ignored. BMI, however, is often classified based on thresholds related to health risk. Using measured, self-reported, and adjusted BMI as categorical covariates brings about noticeably different results in terms of coefficients and significance. The conclusions using measured, self-reported, or adjusted data for individual predictions are relatively similar for both continuous and categorical BMI.

The implication here is that measured data on anthropometrics are not always absolutely needed, depending on what the research question at hand is. For some questions, obtaining and using actual BMI is important. But for other questions, self-reported data might be sufficient, despite their shortcomings. There is a trade-off between accuracy and resource constraints, and data that are often considered unreliable for one purpose might be “good enough" for another.

STRATIFICATION OF NUTRITIONAL EXPERIENCES AMONG OLDER ADULTS WITHIN AND ACROSS COUNTRIES

Introduction

Much research has been conducted on the prevalence of under-nutrition and its consequences in less developed countries, but nutritional problems in these countries have actually become more complicated, as the improvements made in reducing under-nutrition have been accompanied by the even more rapidly increasing prevalence of over-nutrition. From population health and economic standpoints, the double burden of malnutrition, or the co-existence of under- and over-nutrition at relatively high levels, is problematic. Both ends of the nutritional spectrum are significant problems in many low- and middle-income countries (Shrimpton and Rokx 2012). As a result, these diametrically opposing problems warrant further study, especially in conjunction with each other.

Additionally, under- and over-nutrition, as measured by body mass index (BMI), usually affect different segments of the population. In India, for example, "the distribution of underweight and overweight … remains socially segregated," where the segregation is along dimensions of socioeconomic status (Subramanian, Perkins, and Khan 2009). With the heterogeneity among low- and middle-income countries, a natural question is whether the relationship of such characteristics with these nutritional extremes are consistent across these countries. To efficiently target available resources, it would be valuable to know which population segments within a country suffer from which nutritional extreme, as it would provide some insight as to where appropriate interventions should be directed.

I use the World Health Organization (WHO) Study on global AGEing and adult health (SAGE) to examine within-country nutritional disparities among older adults in six different countries – China, Ghana, India, Mexico, Russia, and South Africa. These six countries vary drastically in terms of geography, history, and culture, and should give insight as to how similar or different these disparities are across countries. I analyze the patterns of nutritional status along various dimensions of development – place of residence, educational attainment, and wealth. Here, nutritional status, as measured by BMI, is classified as underweight, normal, overweight (but not obese), and obese.[5] I then analyze how these associations vary depending on a country's level of development.

The first of these analyses looks into within-country differences and how country-specific interventions could be used to address nutritional problems within a population. The second of these analyses investigates between-country differences and how development might be associated with these patterns of nutritional stratification. Taken together, these analyses attempt to examine the stratification of nutritional experiences along the development spectrum, with an ultimate goal of hopefully being able to contribute to policy decisions and disparity reduction.

[5] Adult underweight is defined as having a body mass index (BMI) under 18.5 kg/m^2, normal is defined as having a BMI of at least 18.5 kg/m^2 but under 25 kg/m^2, overweight (but not obese) is defined as having a BMI of at least 25 kg/m^2 but under 30 kg/m^2, and obese is defined as having a BMI of 30 kg/m^2 or above (WHO 2006).

Background

As countries develop, transformations take place in many aspects of society. "As incomes rise and populations become more urban, societies enter different stages of what has been called the nutrition transition. Generally, diets high in complex carbohydrates and fiber give way to more varied diets with a higher proportion of fats, saturated fats, and sugars" (Drewnowski and Popkin 1997). At some point during the nutrition transition, the prevalence of under-nutrition remains stable or starts to decline, while the prevalence of over-nutrition increases.

Progress has been made in reducing underweight prevalence, though it still is at worrisome levels in many developing countries. But at the same time, overweight prevalence is increasing dramatically, making the issue of overweight grow in both absolute and relative importance. Of 36 developing countries studied between 1992 and 2000, overweight prevalence for women actually exceeded underweight prevalence in more than half of these countries. Within these 36 countries, a high prevalence of overweight and a low prevalence of underweight is more common among countries with relatively higher levels of urbanization and higher per capita gross national incomes, proxies of greater economic development, as in Mexico, South Africa, and Turkey (Mendez, Monteiro, and Popkin 2005).

The above study compares countries, but underweight and overweight prevalences are not distributed evenly within countries. It would be worthwhile to determine which segments of the population have higher concentrations of underweight or overweight, and whether this is consistent across countries at different stages of the nutrition transition, as this could have important implications for policy interventions.

What kinds of patterns have been found with regard to development-related characteristics?

In developing countries, underweight and overweight prevalences are generally problems of rural and urban areas, respectively. In Gambia, the prevalence of adult under-nutrition is still higher than that of adult obesity. And while under-nutrition seems to affect all layers of society, over-nutrition is "mainly confined to urban women 35 years or older" (van der Sande et al. 2001). The increase in overweight prevalence in China is driven by urban dwellers, while the overall decline in underweight prevalence is not observed among male rural residents (Popkin et al. 1995). Potential reasons for these patterns include more access to unhealthy foods and more sedentary lifestyles in urban areas (Caballero 2005).

Mendez et al. find in their between-country study that, while the overweight populations are generally larger than the underweight populations, the median ratio of overweight to underweight is 5.8 in urban areas and 2.1 in rural areas. In the more developed of these countries, the urban-rural differences diminish (Mendez, Monteiro, and Popkin 2005). Urban-rural differentials in BMI are not found in overweight and obesity prevalence in ten European countries (Peytremann-Bridevaux, Faeh, and Santos-Eggimann 2007), though interestingly, in the United States, it has been found that adults living in rural areas are more obese than their counterparts in urban areas (Befort, Nazir, and Perri 2012). If these countries are lined up by increasing level of development, over-nutrition starts off as being a greater issue for the urban dwellers, and slowly shifts to becoming a greater issue for those in rural areas.

Such a shift has also been observed in the relationship between socioeconomic status and nutritional experiences as countries develop. The association between socioeconomic status and over-nutrition is negative in developed societies, but positive in developing societies (Sobal and Stunkard 1989; McLaren 2007). There are various dimensions of socioeconomic status, such as income, wealth, and education, that would be important to analyze.

Neuman et al. find in their study of 37 low- and middle-income countries that there was a consistently positive association between BMI and household wealth quintile between 1991 and 2003, and that this pattern still held for 36 out of 37 countries based on surveys conducted between 1998 and 2008 (Neuman et al. 2011). However, as countries develop, obesity prevalence extends to other segments of the population and is no longer a problem reserved for people of high socioeconomic status (Monteiro et al. 2004). In a study of 54 low- and middle-income countries, a monotonic pattern of decreasing overweight prevalence is generally observed among females as one goes down the wealth quartiles. But in the richer of these 54 countries, women in the wealthiest quartile are actually less likely to be overweight than those in the second- and third-richest quartiles (Subramanian et al. 2011). These patterns show that higher income and greater access to unhealthy foods might be counterbalanced with increased knowledge and better healthcare (Caballero 2005). While educational attainment and income are positively correlated, it could be that more education prevents people from being at either nutritional extreme due to knowledge on health and nutrition. Having a low level of education is positively associated with underweight prevalence in men, but not women, in

Iran. In this same sample, overweight and obesity are more common among both men and women with low educational attainment (Janghorbani et al. 2007).

These studies have documented shifts in patterns of nutritional status as countries develop. What mechanisms might there be for these shifts? As countries develop, occupations comprising the workforce tend to shift from those requiring more energy expenditure to those that are less physically demanding. That, combined with more leisure activities at home (e.g., watching television) and perhaps fewer opportunities for exercise in urban areas, leads to more sedentary lifestyles (Goryakin and Suhrcke 2014). In addition, globalization of low- and middle-income countries has led to the diffusion of nutritional habits from higher-income countries. Food consumption patterns have shown signs of convergence toward a more western diet, which is higher in calories, fats, refined carbohydrates, and processed foods (Popkin, Adair, and Ng 2012; Goryakin and Suhrcke 2014). Increased demand for these foods also gives rise to the spread of global supermarket chains and fast food restaurants, further perpetuating the problem (Pingali 2007).

The interrelation between under- and over-nutrition demonstrates why it is necessary to study these two nutritional extremes simultaneously, and which is what many previous studies fail to take into account. For each country, which population segments are important to target for each of the two nutritional extremes? It is certainly important to look at the stratification of nutritional experiences within each country to determine where efforts need to be directed toward ameliorating both under- and over-nutrition, but previous literature highlights why it might also be important to look at countries together. Can a one-size-fits-all policy work for different countries? If not, are there discernible patterns? The strong connection between development and the nutrition transition puts forward a reasonable hypothesis, that there is a continuum in the relationship between under-/over-nutrition and development-related characteristics. Studying countries together might help to isolate the points of development that might be associated with trend reversals in an effort to understand when shifts in priorities might be appropriate. Both these within- and between-country differences are important for aid allocations and interventions.

Data and Methods

For my analyses, I use the first wave of SAGE, which was implemented between 2007 and 2010. SAGE is an ongoing longitudinal study (though data from later waves have yet to be released) of health and well-being that focuses mostly on people aged 50 years or over (WHO 2017b).[6] The objective is to study the relationship of categorical and continuous BMI, calculated using measured height and weight, with various development-related (place of residence, educational attainment, and wealth) and demographic (sex and age) factors in China, Ghana, India, Mexico, Russia, and South Africa.[7]

There is a clear ordering of BMI categorizations (underweight, normal, overweight (but not obese), and obese), so performing a multinomial logistic regression

[6] Due to the age of survey participants in these analyses, pregnancy is unlikely to be an issue.
[7] Survey weights are not used for these analyses. While these SAGE surveys are nationally representative with the use of household- and individual-level weights, the amount of missing data for the asset variables renders it such that even the use of weights would not necessarily make the samples representative after removal of observations without appropriate data. While country-level analyses are run and implications are presented, this is a caution for interpretation.

would sacrifice parsimony and interpretability. On the other hand, while a conventional ordinal logistic model would take the ordering into account and simplify the analysis and its resulting interpretation, the proportional odds assumption has been tested and generally rejected. A partial proportional odds model for an ordinal dependent variable would provide an alternative that falls in between, by relaxing the proportional odds assumption for certain variables while being more parsimonious and interpretable than a multinomial logistic regression model (Williams 2006).

All of the independent variables, except age, are categorical. The reference group is male for sex, urban for place of residence, less than high school for educational attainment, and the first quartile for wealth. Respondents in the SAGE surveys are asked about asset ownership. I compile whether these respondents' households have the following – electricity, bicycle, car, mobile phone, computer, television, land, and jewelry. However, ownership of one asset is likely dependent on ownership of another asset. I create an asset index that linearly combines these binary variables together using principal components analysis (PCA) (Vyas and Kumaranayake 2006). For all six countries, the first principal component already explains about 95% of the variance among observations, so only this first one is used. This way, an index representing wealth is constructed without unnecessarily increasing the dimension of the problem. One of the issues with using PCA is interpretability, as a unit in the wealth index does not translate into the ownership of a certain asset. Thus, instead of using the principal component as a continuous variable, I convert it into a categorical variable of wealth quartiles, with the first and fourth quartiles representing the poorest and the richest, respectively.

While I am not using the longitudinal aspect of the SAGE survey,[8] there is still something to be said about development and the nutrition transition. The six countries in this study are at different stages of development. By suitably ordering these countries, it would be possible to overlay the process of development with the nutrition transition. To this end, I use national gross domestic product (at purchasing power parity) per capita (GDPpC) in the year 2010, measured in current international dollars, as a measure of development. According to GDPpC in 2010, the ordering of these six countries from least to most developed is Ghana (2998), India (4316), China (9333), South Africa (11,647), Mexico (14,765), and Russia (20,498) (The World Bank 2018). If development is indeed an important player in the landscape of nutritional experiences, the coefficients across countries for a specific variable should reflect the GDPpC rankings of these countries.

Differences between countries could be attributable to a myriad of factors, as these countries are so heterogeneous. I need a method to test my hypothesis that these differences are associated with level of development. Instead of studying each of the six countries separately, I combine the data from all six countries and use the same independent variables as before, along with the natural logarithm of GDPpC and interactions between log(GDPpC) and the development-related covariates. log(GDPpC) is used instead of GDPpC because it produces better models. These additional variables would help determine whether BMI category is associated, not only with an individual's characteristics, but also with the level of development of the country where the individual is. There are a few advantages to doing this – I have a simplified and unifying model,

[8] The second wave has not been released for all the countries yet.

quantifying the association of BMI with level of development (if one exists), and providing a way to make predictions for individuals in a country other than the six in SAGE.

All analyses so far treat BMI as a categorical variable. However, one might not be interested in the association of a specific category of nutritional status with other variables, but in the association of BMI with other variables. Thus, additional models are studied where BMI is used as a continuous dependent variable in multiple regressions. While the interpretations might be different, the stories are actually quite similar. These results can be found in the Appendix.

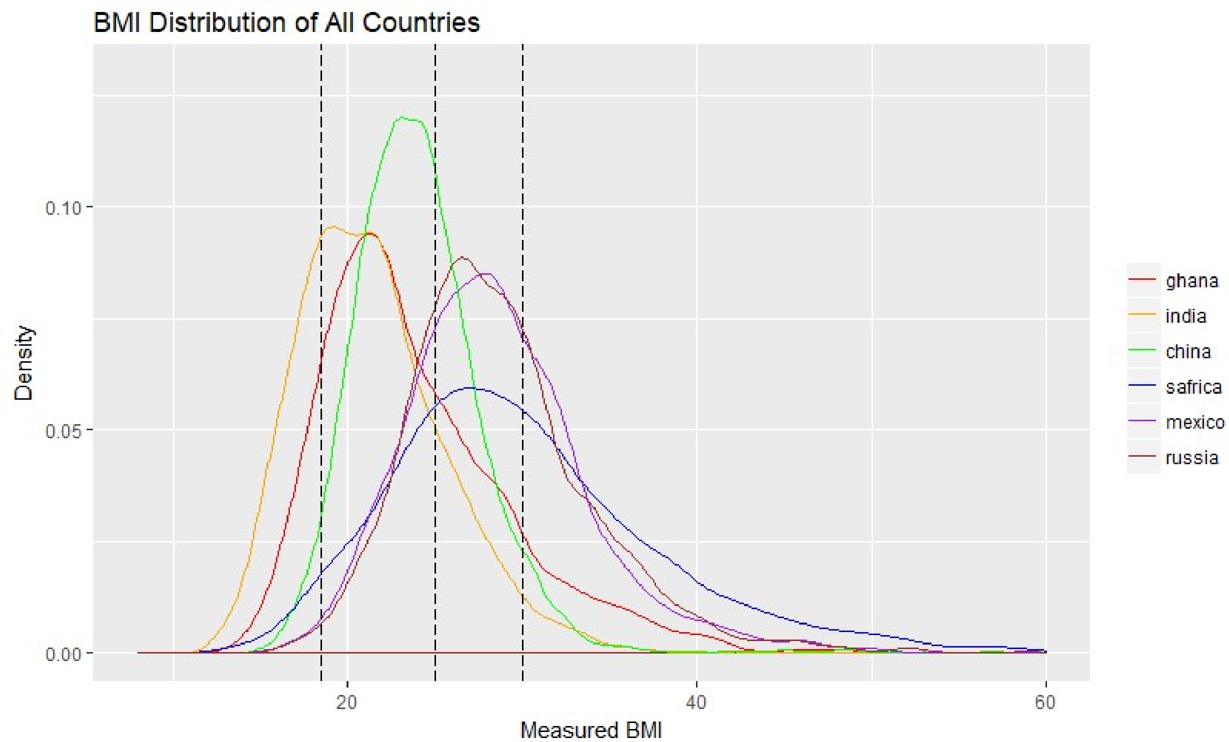
Most analyses are run in R (version 3.4.1) (R Core Team 2017). Partial proportional odds models are run in Stata using the gologit2 package (Williams 2006). When discussing the results, the term "significant" means significant at the level of five percent.

Results

Distribution of BMI and BMI categories:

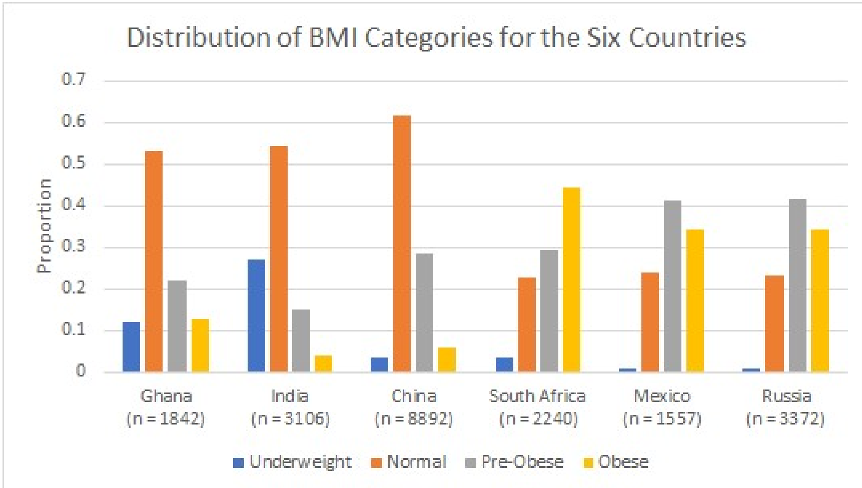
Figure 2.1 shows the BMI distribution for each of the six countries – China, Ghana, India, Mexico, Russia, and South Africa. Extreme BMI values (above 60 kg/m^2) have been removed. The left, middle, and right dotted vertical lines represent respectively the thresholds between underweight and normal (at 18.5 kg/m^2), between normal and overweight (at 25 kg/m^2), and between overweight (but not obese) and obese (at 30 kg/m^2). From here on out, I refer to these four categories as underweight, normal, pre-obese, and obese.

Figure 2.1: BMI density curves for the six countries



There appear to be two distinct groups of countries in Figure 2.1. India, Ghana, and China are at the lower end of the BMI distribution, while Russia, Mexico, and South Africa are at the higher end. These density curves are drawn with BMI as a continuous variable. Figure 2.2 shows the proportion of people in each BMI category (underweight, normal, pre-obese, and obese), along with the sample sizes for the six SAGE countries, arranged in ascending order of GDPpC. It describes how adult nutritional status varies across the six countries in this analysis.

Figure 2.2: Distribution of BMI categories for the six countries[9]



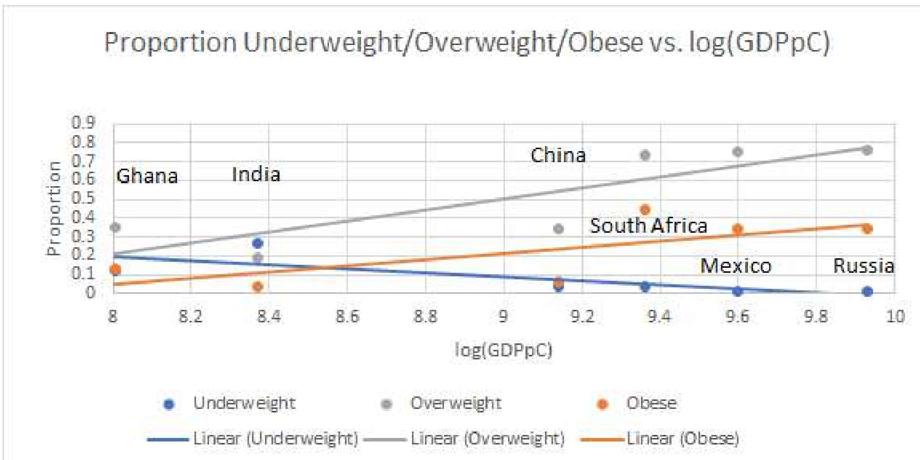
In Ghana, India, and China, more than half of the samples are in the normal category. In Ghana and China, pre-obese is the next largest group, followed by obese and underweight. In India, underweight is the second largest group, followed by pre-obese and obese. Of the six countries, India has the largest proportion of underweight at 27%. In South Africa, Mexico, and Russia, more than 70% of the sample populations are either pre-obese or obese, followed by normal, and then underweight. In Mexico and Russia, not even one percent is classified as underweight. While South Africa has a slightly more sizable proportion of underweight than Mexico and Russia, it is also the only country in which obese actually overtakes pre-obese. Besides India, which still shows a heavy underweight burden, the other five countries seem to have a greater over-nutrition problem that needs to be addressed.

To foreshadow the importance of development levels, I plot the proportions of underweight, overweight (pre-obese and obese), and obese in the country samples against

[9] These are the sample sizes after listwise deletion for missing data.

log(GDPpC) of each of the six SAGE countries in Figure 2.3 below. The least-squares line for each nutritional status is also illustrated.

Figure 2.3: Proportions of underweight, overweight, and obese versus log(GDPpC)

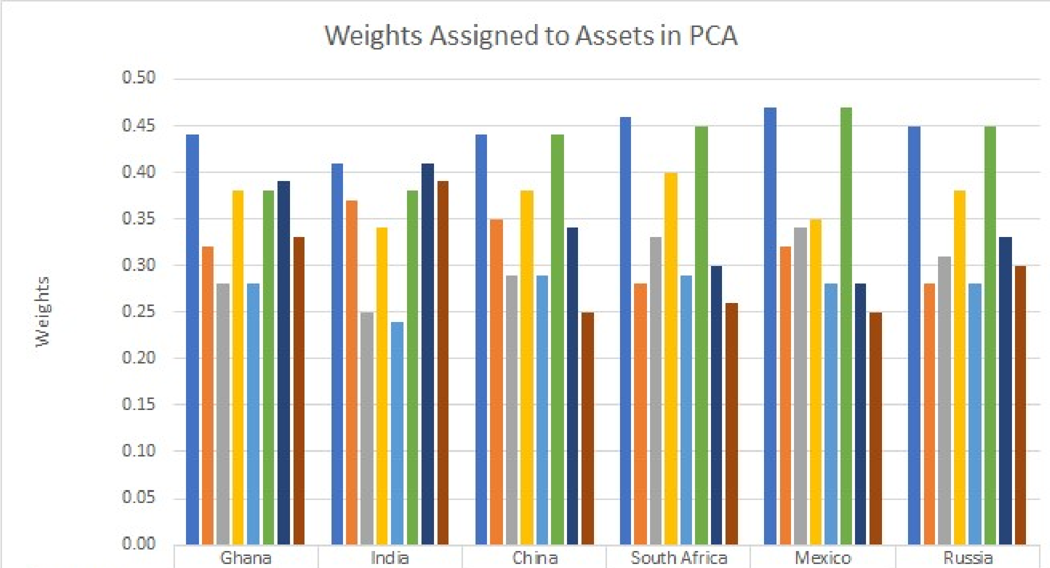


Generally, proportion of underweight is negatively associated with log(GDPpC), whereas proportions of overweight and obese are positively associated with log(GDPpC), in agreement with previous findings on nutritional status and development. The obese line is lower than the overweight line, which is expected, as obese is a subset of overweight. India is an interesting outlier here, with its underweight prevalence higher than its overweight prevalence.

Quantifying wealth:

Before running models, I perform PCA on the eight asset variables for each country. Figure 2.4 illustrates the weights assigned to the assets, both numerically and with a bar chart. These allow for comparison among assets and provide information on their relative importance.

Figure 2.4: Weights assigned to assets in PCA



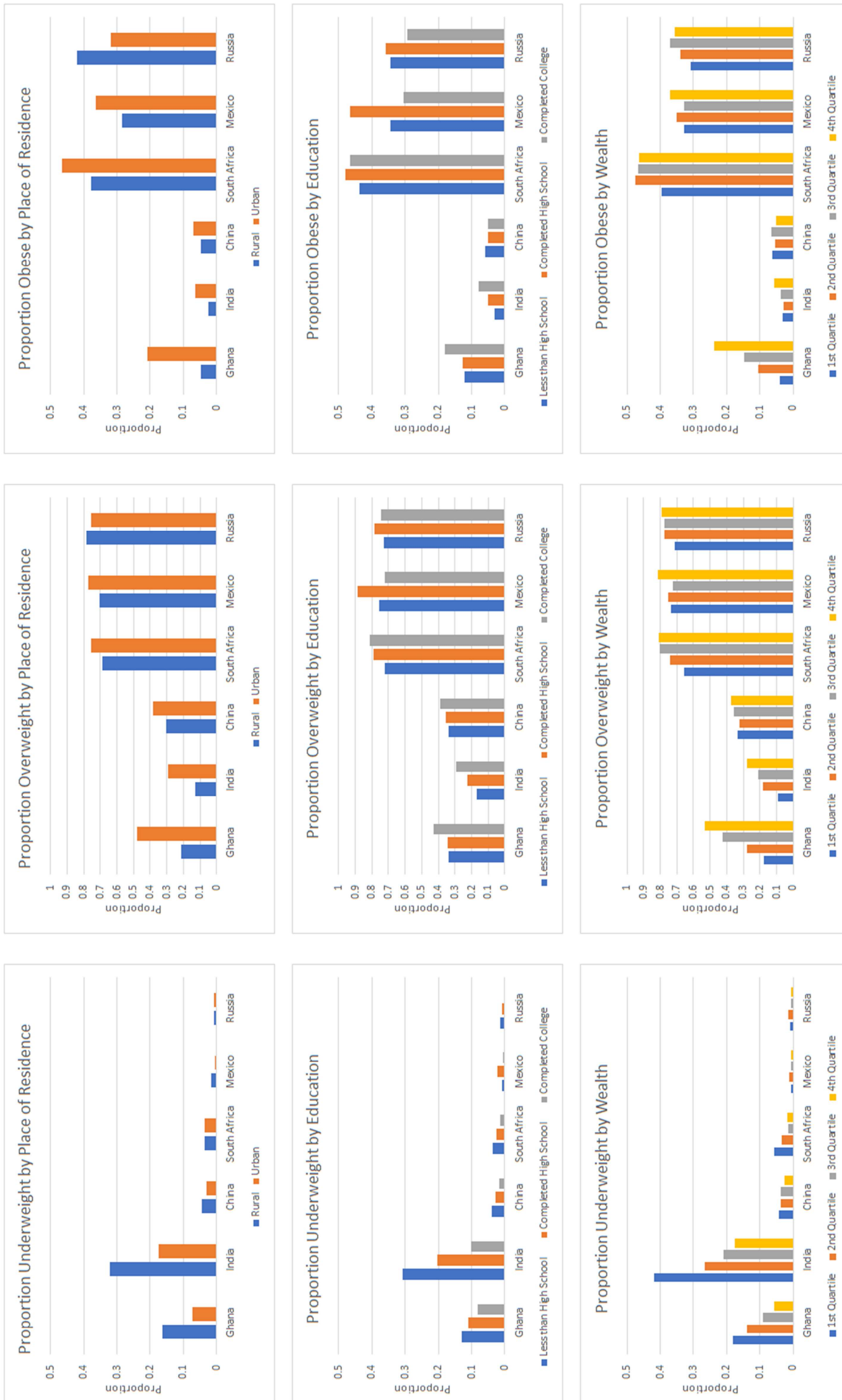
	Ghana	India	China	South Africa	Mexico	Russia
Electricity	0.44	0.41	0.44	0.46	0.47	0.45
Bicycle	0.32	0.37	0.35	0.28	0.32	0.28
Car	0.28	0.25	0.29	0.33	0.34	0.31
Mobile phone	0.38	0.34	0.38	0.40	0.35	0.38
Computer	0.28	0.24	0.29	0.29	0.28	0.28
Television	0.38	0.38	0.44	0.45	0.47	0.45
Land	0.39	0.41	0.34	0.30	0.28	0.33
Jewelry	0.33	0.39	0.25	0.26	0.25	0.30

All of the weights have the same sign, meaning that they all contribute to the wealth index. That is, having any of these assets is associated with wealth. Generally, it appears that electricity, mobile phone, and television have the greatest weights in the wealth index. In Ghana and India, land also seems to have a sizeable contribution. Since one of the issues with PCA is interpretability of the principal component, I categorize the observations into country-specific wealth quartiles. I use these wealth quartiles in the analyses below.

Associations between under- and over-nutrition with development-related factors:

Figure 2.5 has nine panels showing the bivariate relationships between the proportions of underweight, overweight (pre-obese and obese), and obese with the development-related characteristics. All of these variables will subsequently be studied in a multivariate framework.

Figure 2.5: Relationships between proportions of underweight, overweight, and obese with development-related characteristics



Consider first the panels on the left that show the relationships between proportion of underweight and place of residence, education, and wealth. Ghana and India show illustrative patterns. It is clear that the proportion of underweight in these two countries is higher among rural dwellers, the less educated, and the poor. Additionally, the bars for these two countries are monotonically decreasing in height. China and South Africa seem to exhibit similar patterns, although the proportion of underweight is relatively low. It appears that in the most developed country Russia, the bars level out to be around the same height.

Now consider the middle and right panels that illustrate the associations of the proportion of overweight and the proportion of obese with the development-related variables. In all countries except Russia, the proportion of overweight/obese is higher in urban areas. In Russia, the pattern is swapped – the proportion of overweight/obese is higher in rural areas. Support for the hypothesis that a shift would accompany development is evident here. There is a reversal in urban/rural gradients as level of development increases. In Ghana, the proportion of overweight/obese increases monotonically with educational attainment and wealth quartile, and the same general pattern can be seen in India. While this pattern holds for overweight by educational attainment in China and South Africa, it does not for obese. In China, the less than high school bar is the highest, though all three bars are relatively level. In South Africa, the proportion of obese is actually highest for those who have completed high school (the middle education category). These same finding is observed for overweight/obese in Mexico and Russia. Perhaps this population segment has enough resources for sustenance, but does not have the education to choose properly. The pattern is less clear for wealth quartile for the four more developed countries.

Proportional odds models with categorical BMI:

To quantify the relationship between BMI category and various social, economic, and demographic characteristics, I run partial proportional odds models for each of the six countries. Table 2.1 shows the coefficients in these partial proportional odds models. To facilitate the discussion, I rank the nutritional statuses, from low to high, as follows – underweight, normal, pre-obese, and obese. Since all of the covariates are categorical, the coefficients can be interpreted as follows – being in a specific category of an independent variable (relative to the baseline category) changes the log odds of being in a higher BMI category by the value of the coefficient, holding the other variables in the model constant. The first panel shows the logarithm of the odds of being normal, pre-obese, or obese versus being underweight, the second panel shows the logarithm of the odds of being pre-obese or obese versus being underweight or normal, and the third panel shows the logarithm of the odds of being obese versus being underweight, normal, or pre-obese. If the coefficients of a variable are the same in all three panels, the variable satisfies the proportional odds assumption.

Table 2.1: Log odds from partial proportional odds models with BMI as an ordinal variable in Russia, Mexico, China, South Africa, India, and Ghana

log(P(normal, pre-obese, or obese) / P(underweight))						
	Ghana	India	China	South Africa	Mexico	Russia
Intercept	3.28 ***	2.19 ***	6.04 ***	2.73 ***	7.43 ***	4.72 ***
Female	0.45 **	0.36 ***	–0.05	0.85 ***	–0.42	0.35
Age	–0.03 ***	–0.02 ***	–0.04 ***	–0.00	–0.03 ***	–0.00
Rural	–0.47 **	–0.61 ***	–0.35 ***	–0.17	–0.35 **	0.26
Completed high school	–0.10	0.37 ***	–0.05	0.18	–1.46	0.14
Completed college	–0.01	1.01 ***	0.11	0.22	–0.36 *	–0.12
Second quartile	0.31 *	0.53 ***	−0.01	0.32 **	0.04	–0.57
Third quartile	0.78 ***	0.75 ***	0.13 *	1.29 **	−0.08	0.36 ***
Fourth quartile	1.35 ***	0.86 ***	0.34 *	1.05 **	0.22	0.43 ***

In this table and all tables hereinafter, * denotes significance at the 0.05 level, ** at the 0.01 level, and *** at the 0.001 level.

log(P(pre-obese or obese) / P(underweight or normal))						
	Ghana	India	China	South Africa	Mexico	Russia
Intercept	0.26	–0.72 *	–0.57 **	0.46	3.04 ***	0.80 **
Female	1.08 ***	1.01 ***	0.34 ***	0.85 ***	0.48 ***	0.49 ***
Age	–0.03 ***	–0.02 ***	–0.00	–0.00	–0.03 ***	–0.00
Rural	–0.78 ***	–0.61 ***	–0.35 ***	–0.17	–0.35 **	0.21 *
Completed high school	–0.10	0.37 ***	–0.05	0.18	0.82	0.14
Completed college	–0.01	0.55 ***	0.11	0.22	–0.36 *	–0.12
Second quartile	0.31 *	0.53 ***	−0.01	0.32 **	0.04	0.35 **
Third quartile	0.78 ***	0.64 ***	0.13 *	0.66 **	−0.08	0.36 ***
Fourth quartile	1.35 ***	0.94 ***	0.22 *	0.73 **	0.22	0.43 ***

log(P(obese) / P(underweight, normal, or pre-obese))						
	Ghana	India	China	South Africa	Mexico	Russia
Intercept	–1.34 ***	–2.13 ***	–2.42 ***	–0.70 *	1.02 *	–1.53 ***
Female	1.44 ***	1.30 ***	0.62 ***	0.85 ***	0.77 ***	1.10 ***
Age	–0.03 ***	–0.02 ***	–0.01	–0.00	–0.03 ***	–0.00
Rural	–1.15 ***	–0.61 ***	–0.35 ***	–0.17	–0.35 **	0.56 ***
Completed high school	–0.10	0.37 ***	–0.05	0.18	0.41	0.14
Completed college	–0.01	0.98 ***	0.11	0.22	–0.36 *	–0.12
Second quartile	0.31 *	–0.33	−0.01	0.32 **	0.04	0.22 *
Third quartile	0.78 ***	–0.25	0.13 *	0.22	−0.08	0.36 ***
Fourth quartile	1.35 ***	0.13	−0.10	0.27 *	0.22	0.43 ***

With the exception of China, Mexico, and Russia in the first panel, female is always significant and positive, in all three panels. The three exceptions are all insignificant. The female variable only satisfies the proportional odds assumption in South Africa. In all other countries, the female coefficient is monotonically increasing, meaning that females are more likely to be in a higher category than males and the sex differential increases as one moves up the nutritional categories. Age is significant and negative for Ghana, India, and Mexico in all three panels, and it is also significant and negative for China when comparing normal, pre-obese, or obese versus underweight. That is, holding all else constant, older individuals are less likely to be in a higher category than those who are younger. In the case of China, this is only true when comparing everything above underweight with underweight. Age does not satisfy the proportional odds assumption in China, but it does for the other five countries.

The rural variable is significant for all countries and panels except South Africa in all three panels and Russia in the first. The coefficients are consistently negative for Ghana, India, China, and Mexico, meaning that rural dwellers are less likely to be in a higher category than urban dwellers. The coefficients are less negative for China and Mexico than for India and Ghana. In Ghana, the proportional odds assumption is not satisfied and the coefficients get more negative with each successive panel, meaning that the residential differential becomes greater for higher BMI categories. In Russia, the rural coefficients are positive. That is, rural dwellers tend to be in a higher category than urban dwellers. As with Ghana, the proportional odds assumption is not satisfied in Russia, though the coefficient becomes more positive from the second to the third panels. The differential gets larger here too, but in the opposite direction. Since Russia is the most developed among these six countries, this might not be surprising. The proportional odds assumption is satisfied in India, China, South Africa, and Mexico.

For educational attainment in all three panels, completed high school and completed college are significant and positive for India, and completed college is significant and negative for Mexico. In India, more education is associated with being in a higher category. Furthermore, the coefficient for completed college is more positive than the coefficient for completed high school, meaning that there is a greater propensity of being in a higher category with more education. The proportional odds assumption is not satisfied for completed college in India, but there is not a clear pattern in the coefficients. In Mexico, where the proportional odds assumption is not satisfied for completed high school, the opposite is true. Completed college, relative to less than high school, is negative, so the most educated in Mexico have a lower propensity of being a higher BMI category. The proportional odds assumption is satisfied in all other instances.

All of the significant results for the wealth variables are positive. While there tends to be an increase when climbing up the quartiles (that is, a greater likelihood of being in a higher category when in a higher wealth quartile), the patterns are not always consistent. None of the wealth quartiles is significant for Mexico in these partial proportional odds models, and they are also not significant for India in the third panel, when comparing obese versus underweight, normal, or pre-obese. In such cases, wealth quartile (relative to the first) does not have a significant relationship with a person's likelihood of being in a higher BMI category. The proportional odds assumption does not seem to show any patterns among these countries and panels.

There are statistically different coefficients between countries in Table 2.1, as tested by added variables for country and country interactions. (Such results are not shown in this paper for brevity.) But while level of development could play a role, it could also be argued that innate country characteristics, and not merely development itself, are the reason for the differences. As a result, I use the continuous variable log(GDPpC) to explicitly test the association of development. Interactions are included between log(GDPpC) and place of residence, educational attainment, and wealth quartiles, as previous research has provided evidence that there are shifts that accompany development. As a country moves from less developed to more developed, high BMI shifts from a problem of urban areas and high socioeconomic status to one of rural areas and low socioeconomic status. Table 2.2 shows these results. As opposed to three panels here, the results from each model are displayed side by side.

Table 2.2: Log odds of variables from partial proportional odds models with BMI as a categorical dependent variable and log(GDPpC) as an additional independent variable

	log(P(normal, pre-obese, or obese) / P(underweight))	log(P(pre-obese or obese) / P(underweight or normal))	log(P(obese) / P(underweight, normal, or pre-obese))
Intercept	–12.41 ***	–12.93 ***	–13.93 ***
Female	0.33 ***	0.57 ***	0.90 ***
Age	–0.03 ***	–0.00 *	–0.01 ***
Rural	–2.94 **	–4.88 ***	–10.30 ***
Completed high school	4.23 ***	1.08	3.07 ***
Completed college	0.10	1.78 *	4.96 ***
Second quartile	0.85	0.85	0.85
Third quartile	0.78	4.03 ***	2.23 *
Fourth quartile	0.60	5.10 ***	4.80 ***
log(GDPpC)	1.86 ***	1.39 ***	1.33 ***
Rural * log(GDPpC)	0.27 *	0.48 ***	1.06 ***
Completed high school * log(GDPpC)	–0.44 ***	–0.11	–0.33 ***
Completed college * log(GDPpC)	0.08	–0.17	–0.53 ***
Second quartile * log(GDPpC)	–0.08	–0.08	–0.08
Third quartile * log(GDPpC)	–0.04	–0.41 ***	–0.22 *
Fourth quartile * log(GDPpC)	–0.00	–0.51 ***	–0.48 ***

Although the coefficients are different, female is significant and positive in all three columns. Females are more likely to be in a higher BMI category than males, though the log odds are higher for pre-obese or obese versus underweight or normal, and even higher for obese versus underweight, normal, or pre-obese. Age is significant and negative for in all three columns. That is, being older decreases the log odds of being in a higher BMI category. Both of these findings are consistent with what have been presented in Table 2.1. log(GDPpC) is significant and positive in all three columns, so a higher log(GDPpC) is associated with a higher BMI category, though the coefficient becomes less positive from left to right. That is, higher GDPpC pulls people up from underweight more strongly than it pulls people up from normal or pre-obese.

Now, consider the development-related covariates, which have additional interaction terms in the models. Rural and its interactions are significant in all three columns. The negative coefficients of rural suggest that rural dwellers, on average, have a lower propensity of being in a higher BMI category than urban dwellers. However, the coefficients become increasingly negative across the three columns. Without the interactions, this would suggest that the average rural dweller is less likely to be in a higher BMI category than the average urban dweller, and this differential gets even more pronounced up the nutritional status spectrum. On the other hand, the coefficients of the interaction between rural and log(GDPpC) are significant and positive in all three columns, and they become increasingly positive across the three columns. With a high enough level of GDPpC, the pattern switches such that rural dwellers, on average, have a higher propensity of being in a higher BMI category than urban dwellers. Due to the largest magnitudes when comparing obese versus underweight, normal, and pre-obese, the residence differential of these log odds starts off the largest, but the rate at which this gap closes is the quickest as GDPpC goes up.

Completed high school has significant and positive coefficients in the first and third columns, and completed college has significant and positive coefficients in the second and third columns. Those who have higher levels of educational attainment, on average, are more likely to be in a higher BMI category. All of the corresponding interaction coefficients, except for completed college in the second column, are significant and negative. While more education is associated with a higher probability of being in a higher BMI category, the relationship changes in countries that are more developed, where eventually, more education is associated with a lower probability of being in a higher BMI category. The interesting comparisons for the wealth variables are the third and fourth quartiles in the second and third columns. Similar interpretations can be made here as with the education variables. While more wealth is associated with a higher probability of being in a higher BMI category, the relationship changes in countries that are more developed, where eventually, more wealth is associated with a lower probability of being in a higher BMI category. It is also interesting to note that the second quartile and its interaction are insignificant in each of the three columns, suggesting that the first and second wealth quartiles are not statistically different in their relationship with BMI category.

Discussion

Despite all six of these SAGE countries being low- and middle-income countries, there is a great deal of heterogeneity, with regard to nutritional experiences. The distribution of BMI, as well as the prevalence of underweight, normal, pre-obese, and obese, vary by country. Generally, development-related characteristics are related to BMI category. Typically, urban-living, educated, and wealthier individuals are more likely to be in a higher BMI category, which is what has been reported in the literature on less-developed countries.

While these results are certainly not directly causal in nature, they do reveal something about the relationship between nutritional experiences and development. In low- and middle-income countries, higher levels of education and wealth are associated with higher BMI category. In countries where underweight prevalence is still high, having a higher BMI than average or being in a higher BMI category is not necessarily bad, as being in either nutritional extreme is not ideal. In such cases, development might have positive implications with respect to nutrition status, as it (and processes intertwined with it) might be associated with pulling people out of the underweight category. In countries where over-nutrition is more dominant, backward development is certainly not suggested to pull people down to the normal category. However, the associations found in these analyses and the potential effect of development on nutritional status that has been reported in the literature suggest that programs could be initiated to counter the population health consequences.

Some of these countries might be at a level of development that is at the cusp of a trend reversal, as can be seen, for example, in the case of Russia with the place of residence variable. In the country-specific models for Russia, those who are in urban areas, on average, are less likely to be in a higher BMI category than their counterparts in rural areas. This is counter to the results from the five other countries in this study, but corroborates findings in more-developed countries. Of these six countries, Russia is the one with the highest level of economic development.

In countries where under-nutrition is more problematic than over-nutrition and the rural coefficient is negative (such as India), an emphasis on helping rural dwellers gain more access to nourishment might be needed. In countries where over-nutrition is more problematic than under-nutrition and the rural coefficient is negative (such as Ghana, South Africa, China, and Mexico), an emphasis on helping urban dwellers have healthier diets might be appropriate. In countries where over-nutrition is more problematic than under-nutrition and the rural coefficient is positive (such as Russia and other high-income countries), an emphasis on helping rural dwellers have healthier diets might be worth considering.

While this reversal in gradient is not as clear for the other development-related variables, the partial proportional odds model which merges all the country-specific datasets and includes log(GDPpC) interactions makes the case for intertwining processes of development and the nutrition transition, though perhaps at a higher level than these countries are at. The United States is more economically developed than these six countries and is a prime example of a nation that is facing the implications of over-nutrition. At all ages, minority groups and those with low socioeconomic status are disproportionately affected by this obesity epidemic (Wang and Beydoun 2007), as are those living in rural areas (Befort, Nazir, and Perri 2012). As these six SAGE countries become more developed, perspectives on which population segments to target for which nutritional problem might have to switch.

There are a few caveats to note. The development-related characteristics (place of residence, educational attainment, and wealth quartile) are not necessarily comparable across countries. For example, a survey participant in Russia with a college degree is different from a survey participant in Ghana with a college degree with respect to other socioeconomic and development-related factors, despite reaching the same level of education.

There is an additional issue with the wealth index. PCA is used to create this wealth index with assets. I avoid using incomes or expenditures, which suffer from recall bias and could be subject to cyclical fluctuations as a result of the economy, the seasons, etc. Additionally, survey participants in this sample are 50 years of age or older, and their incomes or expenditures might be different at the time of survey from those when they were working adults. Assets, on the other hand, take into account long-term household wealth. However, there is a disadvantage of using assets. Quality of assets is not considered and so there could be differences in the assets themselves (Vyas and Kumaranayake 2006).

I use GDPpC as a proxy for economic development, though development can also take place in non-economic spheres. Consideration has been given to using the Human Development Index (HDI). HDI is "a composite index measuring average achievement in three basic dimensions of human development—a long and healthy life, knowledge and a decent standard of living," takes into account life expectancy and education as well (UNDP 2016). However, using HDI could result in reverse causality, as the dependent variable BMI category can be a factor affecting mortality, a component of HDI, an independent variable. However, as a sensitivity analysis, these models are run with HDI in lieu of log(GDPpC), and similar results are produced.

Other sensitivity analyses are also performed. To test whether age associations might be non-linear, I use age as a categorical instead of a continuous variable in these models. Models perform similarly regardless of how age is quantified. Furthermore, while BMI category is the dependent variable in the above analyses, the continuous variable BMI is also tested as a dependent variable. The results are similar and can be found in the Appendix.

Finally, since there are only six countries in this analysis, there are also only six levels of GDPpC. As a result, interpretations from these models should be taken with caution. While there is variation in GDPpC among these six countries, more levels are needed to make credible interpretations. Added variation could come in the form of more countries or future waves of SAGE with these same countries. SAGE is a longitudinal study, though data from only one wave are available for these countries thus far. Future research could look at differences in nutritional status between multiple waves.

Conclusion

This line of research could be extremely relevant from a policy perspective. Traditionally, assistance from developed countries and international organizations has mainly been devoted to alleviating the under-nutrition problem. While the prevalence of under-nutrition has been reduced by such laudable efforts, the prevalence of over-nutrition is rising rapidly at the same time. Policy-makers need to adapt to this new nutritional landscape and create policies to counter both nutritional extremes (Shrimpton and Rokx 2012).

An important consideration that policy-makers need to keep in mind is that assistance needs to target appropriate population segments. This paper parses out the appropriate segments of the population that are likely to be more afflicted by one nutritional extreme or the other. For the most part, the six country-specific models produce similar findings, despite differences in magnitude. However, the exceptions in these country-specific models demonstrate that there is a potential shift in nutritional patterns working in tandem with the processes of development. The collective model with the addition of economic development and its interactions reveals that these shifts could in fact occur, and might be at levels of economic development beyond the scope of these six countries. Further research in this direction could prove fruitful.

Appendix

Multiple regression models with continuous BMI:

To quantify the relationship between BMI and various social, economic, and demographic characteristics, I run multiple regressions for each of the six countries. Table 2.3 shows the coefficients of the variables in multiple regressions, with BMI as a continuous dependent variable.

Table 2.3: Coefficients from multiple regressions with BMI as a continuous dependent variable in Russia, Mexico, China, South Africa, India, and Ghana

	Ghana	India	China	South Africa	Mexico	Russia
Intercept	26.03 ***	23.36 ***	26.31 ***	28.58 ***	33.13 ***	27.06 ***
Female	2.94 ***	1.78 ***	0.53 ***	3.86 ***	1.91 ***	2.53 ***
Age	−0.05 ***	−0.05 ***	−0.03 ***	−0.01	−0.08 ***	−0.01
Rural	−2.28 ***	−1.44 ***	−1.06 ***	−0.87 *	−1.02 **	1.30 ***
Completed high school	−0.17	0.82 ***	−0.28 *	1.13	0.89	0.23
Completed college	0.14	1.93 ***	−0.13	0.71	−0.93 *	−0.57
Second quartile	0.52	0.78 ***	−0.20	1.22 *	−0.01	0.81 **
Third quartile	1.93 ***	1.24 ***	−0.10	1.02	−0.36	0.84 **
Fourth quartile	3.34 ***	1.78 ***	−0.08	0.88	0.64	1.07 ***
Adjusted R^2	0.175	0.125	0.021	0.049	0.058	0.058

Females, on average, have significantly higher BMI than males in each of the six countries, though the differentials vary by country. For example, females, on average, have a BMI higher than that of males by 0.53 kg/m^2 in China, while females, on average, have a BMI higher than that of males by 3.86 kg/m^2 in South Africa. The sex differential is noticeably lower in China than that of the other countries. Age is significant and negative for all countries, except for South Africa and Russia, where the age variable is insignificant. That is, older ages are significantly associated with lower BMIs in four of the six SAGE countries. Those living in rural areas, on average, have significantly lower BMI than their counterparts living in urban areas in all SAGE countries but Russia. In Russia, the opposite is true – urban dwellers, on average, have significantly higher BMI than rural dwellers. This switch in coefficients from the other countries to Russia can also be seen in Table 2.1.

Educational attainment is not statistically significant in Ghana, South Africa, and Russia. In India, BMI for those who completed high school is significantly higher than that of those with less than a high school education, whereas in China, those who completed high school have significantly lower BMI. Similarly, the coefficient for completed college is significantly positive in India and negative in Mexico. In India, where both education categories are significant, the differential is greater between completed college and less than high school than between high school education and less than high school education, suggesting that more education is associated with higher BMI. It does seem counter-intuitive that in China, the coefficient for having completed college is not significant, while the coefficient for having completed high school is significantly negative, since having completed high school is academically between the other two categories of completed college and the reference group of less than a high school education.

The wealth quartile variables are all relative to the baseline category of the first quartile, or poorest quartile. In India and Russia, all the wealth quartile variables are significant with positive coefficients, with the coefficients increasing in magnitude as wealth increases. In Ghana, only the third and fourth quartiles are significant, and there is not a significant difference in BMI between the poorest quartile and the second poorest quartile. While both significant coefficients are positive, the coefficient for the fourth quarter is more so. South Africa presents a somewhat different situation. The second poorest quartile has a significant positive difference in BMI over the poorest quartile.

As before when studying BMI as a categorical variable, I consider interactions between log(GDPpC) and place of residence, educational attainment, and wealth. Table 2.4 shows these results.

Table 2.4: Coefficients of variables from multiple regression with BMI as a continuous dependent variable and log(GDPpC) as an additional independent variable

Intercept	−6.64 ***
Female	1.89 ***
Age	−0.03 ***
Rural	−11.14 ***
Completed high school Completed college	8.24 *** 12.76 ***
Second quartile Third quartile Fourth quartile	−0.86 6.15 *** 9.23 ***
log(GDPpC)	3.64 ***
Rural * log(GDPpC)	1.07 ***
Completed high school * log(GDPpC) Completed college * log(GDPpC)	−0.88 *** −1.36 ***
Second quartile * log(GDPpC) Third quartile * log(GDPpC) Fourth quartile * log(GDPpC)	0.11 −0.64 *** −0.94 ***
Adjusted R^2	0.173

Being female is associated with a higher BMI and being older is associated with a lower BMI. log(GDPpC) is positively associated with BMI, demonstrating that BMI is associated, not only with an individual's characteristics, but also with the level of economic development of the country where the individual is.

Now consider the development-related variables. Rural, completed high school, completed college, third quartile, and fourth quartile are all significant, as are their interactions. As evidenced by the negative coefficient of rural, rural dwellers, on average, have lower values of BMI than urban dwellers. The coefficient of the interaction between rural and log(GDPpC) is positive, so as GDPpC increases, the differential between urban and rural areas decreases. With a high enough level of GDPpC, the pattern switches such that rural dwellers, on average, have higher values of BMI than rural dwellers.

Completed high school and completed college have positive coefficients, relative to less than high school. That is, those who are more educated, on average, have higher BMI. The fact that the coefficient for completed college is more positive means that the BMI ordering is, in ascending order, less than high school, completed high school, and completed college. However, the negative coefficients of their interactions suggest that at a high enough level of GDPpC, less education is associated with higher BMI. Additionally, the coefficient for the interaction between completed college and log(GDPpC) is more negative than that of completed high school and log(GDPpC), so the differential of college education relative to less than high school decreases more quickly.

The third and fourth wealth quartiles, relative to the first quartile, can be interpreted similarly. Increasing wealth is associated with higher BMI at low GDPpC, and the differential decreases and may even change sign as GDPpC increases. For place of residence, educational attainment, and wealth quartiles, the patterns exhibited in Table 2.4 are similar to the ones in Table 2.2.

FROM BIRTH TO ADULTHOOD: ANTHROPOMETRIC TRAJECTORIES AND THEIR IMPLICATIONS FOR CHRONIC DISEASES

Introduction

Under-nutrition has long been a health problem in developing countries, but over-nutrition is rapidly growing in these countries as well (Shrimpton and Rokx 2012). Having both under- and over-nourished people within the same population is becoming increasingly common and is a manifestation of the so-called double burden of malnutrition, which refers to the co-existence of both under- and over-nutrition at relatively high levels. Besides being a population problem, the double burden can also manifest itself at the individual level. In other words, a person could be under- and over-nourished at different stages of his/her life.

To study changing nutritional statuses over the life course, I use a birth cohort study from Guatemala with several decades of data. Guatemala is an appropriate country for this investigation because of its high levels of childhood under-nutrition. The prevalence of stunting and underweight among Guatemalan children is among the highest in Latin America. Meanwhile, Guatemalan women also have among the highest prevalence of obesity in the region (Marini and Gragnolati 2003). With rich longitudinal data, I investigate whether the double burden over the life course is actually occurring in this sample of Guatemalans. In addition to the transitions between under-nutrition and over-nutrition over the life cycle, I analyze how childhood anthropometric measures and growth, as well as other demographic and socioeconomic characteristics, are associated with body mass index (BMI) as an adult.

Having high BMI as an adult, in and of itself, is not necessarily a health problem. But being overweight is a risk factor for many chronic conditions, including cardiovascular disease, stroke, and diabetes. With this Guatemalan birth cohort, I also investigate how childhood size and growth trajectories are related to various chronic disease indicators, which are used as proxies for chronic disease risk. This would allow me to examine whether childhood nutrition has longer-term implications.

Background

Child under-nutrition:

There are several measures of under-nutrition for children, including stunting (low height-for-age), underweight (low weight-for-age), and wasting (low weight-for-height). In developing countries, their levels of prevalence had generally been high, have been experiencing a decreasing trend, but are still worrisome. In 2011, at least 165 million children under the age of five were affected by stunting, 100 million by underweight, and 52 million by wasting. Almost all these children lived in low- and middle-income countries (Black et al. 2013).

Since children typically live with their parents at young ages, their nutritional status is largely a function of their parents' characteristics and decisions. Parental education (usually that of the mother in particular) is an important factor. Mothers with higher levels of education are more likely to invest in health, nutrition, and care for themselves during pregnancy and for their children once they are born. On the other hand, household poverty contributes to under-nutrition because it is associated with increased risk of food inaccessibility and insecurity (Vir 2011). There might also be macro-level factors at play, such as economic development, political stability, and food security, but the focus here is on measurable micro-level individual characteristics.

Under-nutrition is a major contributor to the global burden of disease, not only because of the sheer number of people who are under-nourished, but also because it is a significant risk factor for infectious diseases. Conditions associated with childhood under-nutrition include diarrhea, pneumonia, measles, malaria, and micronutrient deficiencies (Caulfield et al. 2004; Fishman et al. 2004). These have important implications for both mortality and morbidity.

Even if under-nourished individuals survive their childhood years, they might be at a disadvantage as adults. Those who received a nutritional supplement in their early years had substantial increases in wages (Hoddinott et al. 2008) and educational attainment (Maluccio et al. 2009). It has also been found that Guatemalan adults who were stunted as children had less schooling, a lower per capita expenditure, and (for women) a lower age at first birth, though there was little evidence of a relationship between stunting and many adult health measures (Hoddinott et al. 2013). However, there are studies showing that those who were under-nourished as children might indeed have higher risk of other diseases at older ages due to irreversible damages having been done to their body (Shrimpton and Rokx 2012). Small size at birth has been found to be associated with higher adult blood pressure, glucose level, and cholesterol level, all indicators of chronic diseases (Roseboom 2012). Low birth weight has been linked with an increased risk of coronary heart disease, stroke, hypertension, and type-two diabetes. These findings connecting under-nutrition in childhood and adult health outcomes have been replicated in several contexts, but with the exception of India, the contexts have been high-income countries (Barker 2004).

Adult over-nutrition:

Over-nutrition has been considered a public health problem in high-income countries for decades now, but low- and middle-income countries have recently had to deal with a rapid increase in overweight prevalence as well. In fact, overweight appears to be increasing at a faster rate than underweight is decreasing in developing countries (Shrimpton and Rokx 2012). This has led to high levels of both under- and over-nutrition simultaneously in these countries.

In developing countries, the prevalence of over-nutrition is much higher in urban than in rural areas. Over-nutrition has typically been thought of as a problem of the urban elite (Ramachandran 2011). High income and educational attainment have been found to be positively associated with obesity. But as a country develops, obesity prevalence shifts toward other segments of the population and it is no longer a problem reserved for people of high socioeconomic status (Monteiro et al. 2004). Sedentary life styles and tobacco use have also been found to be important risk factors (Chopra, Galbraith, and Darnton-Hill 2002).

According to the Global Burden of Disease Study, in 2010, an estimated 3.4 million deaths were attributable to overweight (Ng et al. 2014). "Excess body weight is an important risk factor for mortality and morbidity from cardiovascular diseases, diabetes, cancers, and musculoskeletal disorders" (Stevens et al. 2012). As mentioned before, under-nutrition at young ages is a risk factor for infectious diseases, but it could also lead to chronic diseases at older ages. I study whether the association between under-nutrition as a child and chronic diseases as an adult is mediated by over-nutrition as an adult, or whether over-nutrition in the middle of the pathway is a sufficient, but not necessary condition.

Linking under-nutrition with over-nutrition:

Human biology may explain why under-nutrition as a child could in fact place a person at higher risk of becoming obese as an adult. If a child lacks nutrients, either in utero through the mother's body or in early post-natal care, the child's natural biological reaction is to conserve energy. With this survival mechanism in place, any improvement in nutrition later in life could actually be detrimental in the long run, as it could result in excess accumulation of energy and body fat. This is known as the fetal origins hypothesis (Barker 2004; Caballero 2005). "Because intrauterine growth retardation and low birth weight are common in developing countries, this mechanism may result in the establishment of a population in which many adults are particularly susceptible to becoming obese" (Caballero 2005). While this refers specifically to fetal growth, the concept also extends to early life environments (Barker 2004).

Life course transitions cannot be analyzed properly without longitudinal data, preferably starting from birth (or even better, from conception) and continuing on through adult years. Most long-standing longitudinal studies were carried out in higher-income countries. Analyses using such data have found that childhood BMI is not necessarily a good predictor for adult BMI, as only a small proportion of those overweight/obese as adults were overweight/obese as children (Braddon et al. 1986; Power, Lake, and Cole 1997; Williams 2001). van Abeelen et al. study the women in the Prospect-European Prospective Investigation in Cancer and Nutrition (EPIC) cohort who were exposed to the Dutch Famine, an exogenous shock, in 1944 – 1945. They conclude "using individual famine exposure data that a relatively short period of moderate or severe under-nutrition during childhood is associated with an increase in BMI and waist circumference in adult life" (van Abeelen et al. 2012). While short-term famines may not be generalizable to other situations of chronic malnutrition, this is a prime example of the fetal origins hypothesis at play.

Of course, the context could be very different in lower-income than in higher-income countries, but there are not nearly as many analyses in the context of developing countries. The Young Lives cohort study finds that early-life stunting (or low height-for-age) of Peruvian children is not associated with increased BMI when they are older (Andersen et al. 2016). Yet, the children are only around 12 years of age at the end of this study. With aggregated data from the Consortium of Health-Orientated Research in Transitioning Societies (COHORTS), which consist of birth cohorts from five low- and middle-income countries, Victora et al. find that adult BMI appears to be strongly and positively associated with weight indices in childhood. The finding seems to contradict the fetal origins hypothesis. However, body mass consists of both lean and fat masses. Since lean and fat masses result from distinct biological processes, the implications of having high BMI might be different depending on the kind of body mass (Victora et al.

2008). These few available analyses in developing countries produce interesting conclusions worthy of further research.

This first prong of this study is to understand growth trajectories from childhood to adulthood in Guatemala, a country where under-nutrition in children is still prevalent. If the fetal origins hypothesis holds, moving upwards in nutritional status category should not be uncommon for those who are under-nourished as children, though this has not been found in the Peruvian or COHORTS study. Additionally, this study explores which characteristics might be associated with adulthood BMI.

Linking nutrition with chronic disease:

A natural extension of the analysis, the focus of this paper, is the path from nutritional status to chronic diseases. Eriksson et al. consider a sample of men born between 1934 and 1944 in the Helsinki University Hospital who attended childhood welfare clinics and were still in Finland by 1971. The authors use the data of those individuals who were admitted to a hospital or died between 1971 and 1997. They find that lower birth weight is associated with higher risk of coronary heart disease and that rapid weight gain during childhood could increase such risk for those who are thin (as measured by the ponderal index) at birth (Eriksson et al. 2001). In a study of five low- and middle-income countries, post-natal growth is associated with greater height and educational attainment, but there is no connection with higher blood pressure or blood glucose level (Stein et al. 2013). Rapid weight gain after infancy for under-nourished children is found to be linked with various chronic diseases, though the effects may vary depending on the age range in which that gain occurs, and the authors suggest that more evidence is still needed (Victora et al. 2008). These varying results show that more investigations are needed. Even if under-nutrition and later over-nutrition are not causally related, the combination of the two might be particularly detrimental.

Developing countries have been thought to be more affected by infectious than by chronic diseases, but chronic diseases are becoming increasingly common, giving rise to the term double burden of disease. It is important to learn more about chronic diseases in a context in which they have traditionally not been as common. The second prong of this study is to use childhood anthropometric measures and growth trajectories from childhood to adulthood to study chronic diseases in a developing country, using unusually rich longitudinal data from early childhood into adulthood in a population suffering high prevalence of early-life under-nutrition.

Data and Methods

COHORTS is a collaboration consisting of five birth cohort studies spanning a large geographical area (Brazil, Guatemala, India, the Philippines, and South Africa). For my purposes, I will be using the Institute of Nutrition of Central America and Panama (INCAP) Nutrition Trial Cohort Study data for Guatemala. It has one of the longest time spans among the five studies, an important consideration in a study of nutritional outcomes at birth and their association with chronic diseases at older ages. The cohort consists of children under seven years of age in 1969 and children born between then and 1977 in four Guatemalan villages. The original size of the birth cohort is 2392, though the sample size decreases in subsequent waves for reasons including death, migration, and inability to trace the respondents; in the 2002 – 2004 follow-up, 1570 individuals are available for data collection. Their characteristics can be found in the Stein et al. paper profiling these cohort members (Stein et al. 2008).

The INCAP dataset has an experimental aspect. A protein-enriched treatment drink (formulated as an *atole*) was given to children in two villages and a control drink (called *fresco*) was given to children in the other two. The objective of this experiment was to ascertain whether the nutritional supplement would accelerate growth and mental development in children, as protein intake had been found to have "an important and positive role in height and weight growth in the 6 – 24 month period" (Puentes et al. 2016). Now that data are available on these individuals in their adult years, studies have also been carried out to analyze the long-term effects of the nutritional supplement on human capital in adulthood (Hoddinott et al. 2008; Stein et al. 2008; Maluccio et al. 2009).

Length and weight were measured at several age points throughout childhood.[10] From these data, length-for-age, weight-for-age, and weight-for-length z-scores are calculated at these ages using software from the World Health Organization (WHO) (WHO 2011). (Results will be reported using length-for-age z-scores, unless otherwise stated, though these analyses have also been run using weight-for-age z-scores and weight-for-length z-scores.) However, there are often missing data and there is a lack of consistency as to which age points contain information. To take advantage as much as possible of the available information, I use a combination of z-score means over age

[10] In the INCAP study, recumbent length was measured up to age seven and standing height was measured thereafter. All childhood anthropometric measures in this paper are for children up to five years of age, and therefore length measurements are recumbent lengths.

intervals as a way to ascertain nutritional status, and slopes of the best fitting lines among the z-scores as a way to ascertain growth trajectory. For nutritional status at adulthood, I use BMI calculated from height and weight measurements in the year 2004.[11]

In the first year of a child's life, measurements were taken once a month. In the second and third years, measurements were taken once every three months. In the fourth and fifth years, measurements were taken once every six months. Between ages zero and five, I split the data into three segments according to the frequency of measurement – under age one, between ages one and under three, and between ages three and five. Doing so allows for investigating how various dependent variables are associated with nutritional status and growth at different ages.

The slopes, measured as the change in z-scores per month, are classified into downward, stagnant, and upward categories. In most cases, there are no significant differences between models with continuous slopes versus models with categorical slopes (as determined by Vuong's closeness test). When there is a significant difference, the model with categorical slopes performs better. From boxplots, it appears that the outliers are usually below 0.1 and above 0.1, regardless of which anthropometric measure is used. If those who have rapid growth are expected to face consequences (fetal origins hypothesis), it is important to distinguish such outliers. Therefore, decreases in slope of more than 0.1 and increases in slope of more than 0.1 are used as the downward and upward categories, respectively, though different thresholds are also tested. Between ages zero and five, 210 children had downward trajectories, 1303 stayed stagnant, and 19

[11] Height and weight from 1998 are also used for sensitivity checks.

had upward trajectories. Again, the following results will be reported for length-for-age slopes, unless otherwise stated.

I run ordinary least squares regressions with two sets of models. The general forms of these models are shown in (1) and (2) below. The first set looks at how these childhood anthropometrics and growth trajectories, as well as sex and adulthood characteristics, are associated with adult BMI.[12] The second set looks at how all of these same variables, along with adult BMI, are associated with various chronic disease indicators, such as blood pressure, cholesterol, and blood glucose. These indicators serve as proxies for the propensity of becoming afflicted by a range of chronic diseases. High levels of blood pressure and cholesterol (except high-density lipoprotein cholesterol) are usually considered to be associated with an increased risk of heart disease and stroke. High levels of blood glucose are linked with type two diabetes.

$$
\begin{aligned}
(1)\ & Adult\ BMI \\
& = \beta_0 + \beta_1 * sex + \beta_2 * mean\ 0\ to\ under\ 1 + \beta_3 * mean\ 1\ to\ under\ 3 \\
& + \beta_4 * mean\ 3\ to\ 5 + \beta_5 * slope\ 0\ to\ under\ 1 + \beta_6 * slope\ 1\ to\ under\ 3 \\
& + \beta_7 * slope\ 3\ to\ 5 + \beta_8 * educational\ attainment \\
& + \beta_9 * socioeconomic\ status + \beta_{10} * place\ of\ residence \\
& + \beta_{11} * ever\ smoked + error
\end{aligned}
$$

[12] Adult BMI is not measured for pregnant women or women under six months post-partum (Stein et al. 2008).

(2) $Chronic\ disease\ indicator$

$$= \gamma_0 + \gamma_1 * sex + \gamma_2 * mean\ 0\ to\ under\ 1 + \gamma_3 * mean\ 1\ to\ under\ 3$$

$$+ \gamma_4 * mean\ 3\ to\ 5 + \gamma_5 * slope\ 0\ to\ under\ 1 + \gamma_6 * slope\ 1\ to\ under\ 3$$

$$+ \gamma_7 * slope\ 3\ to\ 5 + \gamma_8 * educational\ attainment$$

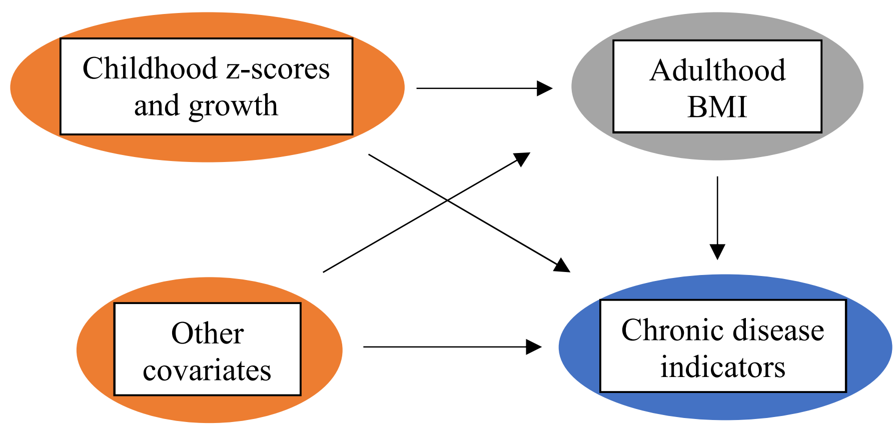
$$+\gamma_9 * socioeconomic\ status + \ \gamma_{10} * place\ of\ residence$$

$$+ \gamma_{11} * ever\ smoked + \ \gamma_{12} * adult\ BMI + error$$

In these regression models, the independent variables sex (reference group – male), slope (reference group – downward trajectory), place of residence (reference group – urban), and smoking status (reference group – never smoked) are categorical. All the other variables are continuous. Educational attainment is in grades completed, socioeconomic status is a combination of a wealth index and durable goods/household characteristics, blood pressure is in mmHg, and the other chronic disease indicators are in mg/dL.

The regressions above, while certainly useful, do not consider certain indirect effects on the chronic disease indicators. While sex, childhood anthropometrics, childhood growth, adulthood characteristics, and adult BMI are included as independent variables in (2), the first four are also embedded in adult BMI. As a result, if adult BMI is indeed significant for chronic disease indicators, part of the association is the direct effect of BMI, and part of it is the indirect effect of sex, childhood anthropometrics, childhood growth, and adulthood characteristics working through BMI. Figure 3.1 is a path diagram showing how these mechanisms potentially work. In my models, “Childhood z-scores and growth” and “Other covariates” in orange only act as independent variables, “Adulthood BMI” in gray acts as both dependent and independent variables, and “Chronic disease indicators” in blue only act as dependent variables.

Figure 3.1: Path diagram showing direct and indirect effects on chronic disease indicators



The above diagram shows the independent variables that have, according to the models under study, direct effects on chronic diseases and also indirect effects on chronic diseases through their effects on adult BMI. In Figure 3.1, “Childhood z-scores and growth” include z-score means and slopes, while “Other covariates” include sex, educational attainment, socioeconomic status, place of residence, and smoking status. Structural equation modeling (SEM) is used to parse out the direct and indirect effects of each variable. Specifically of interest here are the direct and indirect effects of the childhood z-scores and growth.

All analyses are run using the statistical software R (version 3.4.1) (R Core Team 2017). The R package lavaan is used for SEM (Rosseel 2012). When discussing the results, the term “significant” means significant at the level of five percent.

Results

Distribution of nutritional states and transitions:

First, it is important to characterize the distribution of nutritional states at childhood and adulthood, and the transitions that these individuals make. Table 3.1 displays the empirical conditional probabilities of nutritional transitions from childhood to adulthood for both the *atole* and *fresco* groups, among those who have information as both children and adults. The childhood categories are determined using mean childhood length-for-age z-score from ages zero to five, and the category cut-offs are the typical anthropometric thresholds, as established by the WHO.[13] The adulthood categories are determined using BMI in the year 2004, and the category cut-offs are the typical BMI thresholds, again, as established by the WHO.[14] By 2004, the study participants were between 25 and 42 years of age.

Table 3.1: Empirical conditional probabilities of nutritional status transitions from childhood to adulthood for the *atole* and *fresco* groups

<table>
<tr><td colspan="2" rowspan="2">Atole (N = 549)</td><td colspan="3">Adulthood nutritional status (BMI)</td></tr>
<tr><td>Under</td><td>Normal</td><td>Over</td></tr>
<tr><td rowspan="3">Childhood nutritional status (length-for-age z-scores)</td><td>Under</td><td>0.029</td><td>0.472</td><td>0.499</td></tr>
<tr><td>Normal</td><td>0.010</td><td>0.490</td><td>0.500</td></tr>
<tr><td>Over</td><td colspan="3">N/A</td></tr>
<tr><td colspan="2" rowspan="2">Fresco (N = 506)</td><td colspan="3">Adulthood nutritional status (BMI)</td></tr>
<tr><td>Under</td><td>Normal</td><td>Over</td></tr>
<tr><td rowspan="3">Childhood nutritional status (length-for-age z-scores)</td><td>Under</td><td>0.014</td><td>0.467</td><td>0.519</td></tr>
<tr><td>Normal</td><td>0.028</td><td>0.375</td><td>0.597</td></tr>
<tr><td>Over</td><td colspan="3">N/A</td></tr>
</table>

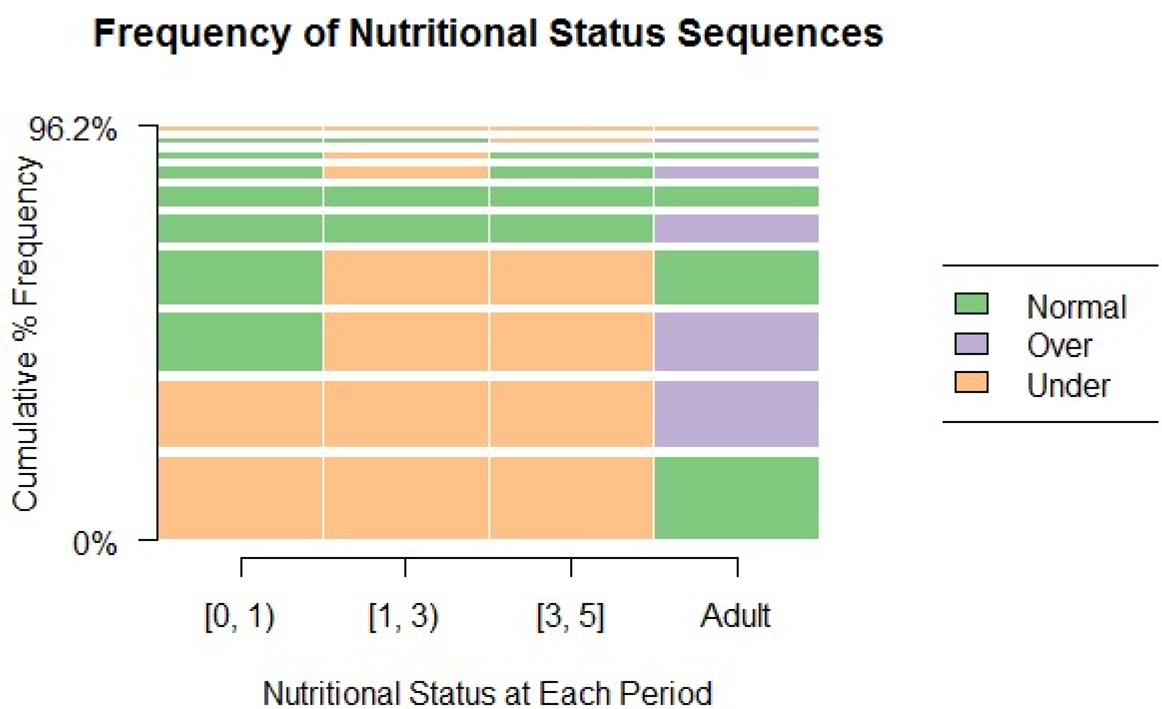
[13] Child under-nutrition is defined as having a length-for-age z-score under -2, over-nutrition is defined as having a z-score over 2, and the normal range falls in between (WHO 2016).
[14] Adult under-nutrition is defined as having a body mass index (BMI) under 18.5 kg/m^2, over-nutrition is defined as having a BMI of 25 kg/m^2 or above, and the normal range falls in between (WHO 2006).

Although the probabilities differ by nutritional supplement, the patterns are relatively similar; in fact, each pair of corresponding cells in the *atole* and *fresco* sections are not significantly different, except for the normal to normal transition. None of the study participants are considered over-nourished as children based on length-for-age z-scores. Of those who are under as children, only a few remain under as adults. Of those who transition upwards from under, about half of them go to the normal category and the other half to the over category. Conditional on being in the normal category as children, a little under half stay normal as adults, and most of the others transition to over. Even though upward trajectories are common, the probabilities in Table 3.1 do not suggest that being under-nourished as a child puts one at a higher risk of becoming over-nourished as an adult, for either the *atole* or *fresco* groups.

For the weight-for-age measure, again, there are no children in the over category. About half of the children in the under/normal categories transition to/stay in the normal category in adulthood, while another half move to the over category. Only a very few move to the under category as adults. For the weight-for-length measure, almost all of the children in the sample fall in the normal category. A little under half among them stay in the normal category and a little over half transition upwards to the over category. Only a few transition downwards from normal as children to under as adults.

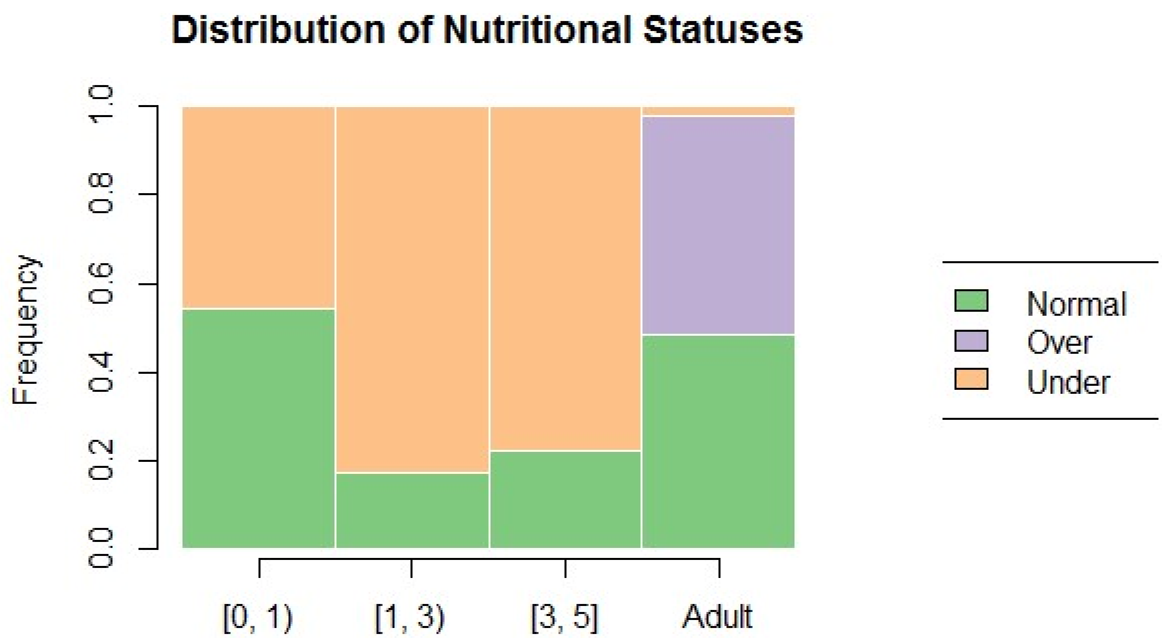
The above results describe the transitions in nutritional status from between ages zero and five, as measured by mean z-score during these ages, to adulthood, as measured by adult BMI. Figure 3.2 below depicts the most common transitions of study participants with data in the three childhood periods and adulthood. In any given period, someone could be under, normal, or over. The colors in each horizontal bar represent different sequences that a person can take from childhood to adulthood. The height of each horizontal bar is the relative frequency of children with such a sequence. For example, the lowest horizontal bar represents that almost 20% of children are under in the age interval [0, 1), under in the age interval [1, 3), under in the age interval [3, 5), and normal as adult. Note that the width of the rectangles does not represent a scale of duration.

Figure 3.2: Frequencies of nutritional status sequences from birth to adulthood



These ten sequences depict the pathways of 96.2% of study participants. In none of these sequences does over appear in any of the childhood age intervals. The most common sequence is being under throughout childhood and then transitioning to normal as adults, followed by being under throughout childhood and then transitioning to over. Transitioning upwards is not uncommon in this Guatemalan birth cohort. Figure 3.3 shows the distribution of nutritional statuses in each of these age groups for those with data in all four periods.

Figure 3.3: Distribution of nutritional statuses from birth to adulthood



Between ages zero and one, about half of those with complete data are under and half are normal. While there does appear to be a decrease in the number of people in normal and an increase in the number of people in under in the next two age groups, by the time these participants have become adults, almost none of them are under. Of the overwhelming majority who are not under, about half are normal and half are over. This suggests that there is still a lot of nutritional state transitioning after age five and before adulthood.

Adult BMI:

Table 3.2 shows which childhood means and slopes, and adulthood characteristics are significantly associated with adult BMI measured in the year 2004. The numbers in the table are coefficient estimates and the asterisks represent the level of significance.

Table 3.2: Multiple regression of adult BMI on sex, length-for-age childhood anthropometrics, growth trajectories, and adulthood characteristics

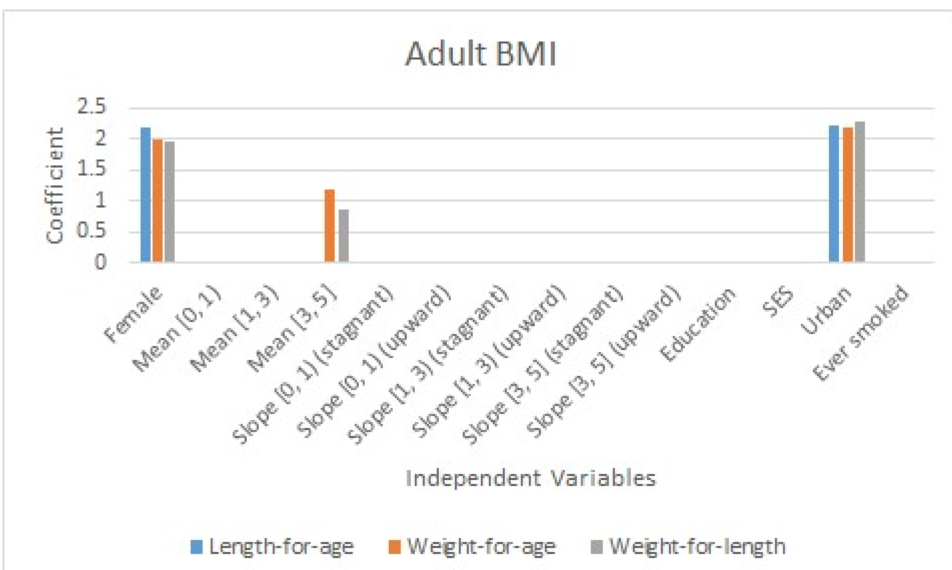
	Adult BMI
Intercept	27.67 ***
Female	2.19 ***
Mean [0, 1)	0.32
Mean [1, 3)	–0.15
Mean [3, 5]	0.39
Slope [0, 1) (stagnant)	–0.03
Slope [0, 1) (upward)	–0.60
Slope [1, 3) (stagnant)	–0.77
Slope [1, 3) (upward)	–1.14
Slope [3, 5] (stagnant)	–4.98
Slope [3, 5] (upward)	–4.24
Educational attainment	–0.11
Socioeconomic status	–0.48
Urban	2.22 ***
Ever smoked	–0.26
Adjusted R^2	0.119

In this table and all tables hereinafter, * denotes significance at the 0.05 level, ** at the 0.01 level, and *** at the 0.001 level.

In this regression, using length-for-age as the anthropometric measure, females and urban dwellers have a significantly higher average adult BMI than males and rural dwellers. Means and slopes do not appear to be significant; this suggests that childhood nutritional status and growth trajectory using length-for-age as the anthropometric measure are not very influential for adult BMI.

Figure 3.4 displays the significant variables in the same model, using length-for-age, weight-for-age, and weight-for-length measures. A caveat is in order. Although the vertical bars of the same independent variable give a visual representation of the magnitudes of the coefficients across the three measures, the vertical bars of different independent variables are not comparable. This is because different independent variables have different scales of measurement.

Figure 3.4: Significant variables for adult BMI by anthropometric measure



The significant variables have the same directions and similar coefficient magnitudes across measures. For weight-for-age and weight-for-length, z-score mean in [3, 5] is positively associated with adult BMI. That is, nutritional status at a young age (though not too young) is significant for nutritional status as an adult. This is not consistent with the finding that childhood status and adulthood status are uncorrelated (Power, Lake, and Cole 1997), as well as my results using length-for-age. However, Power et al. use childhood BMI, while I use length-for-age, weight-for-age, and weight-for-length measures to gauge childhood nutritional status. If I replace the three age-segment weight-for-age/weight-for-length z-score means with the overall weight-for-age/weight-for-length z-score mean, the z-score mean is significant, indicating that significance is driven by childhood anthropometrics between ages three and five. Slope is not at all significant, which suggests that there is no evidence pointing to an association of childhood growth trajectories with adult BMI.

In all of these models, sex and place of residence are consistently significant. However, adulthood characteristics such as educational attainment, socioeconomic status, and smoking statuses (having ever smoked, formerly smoking, currently smoking, and having never smoked) are not significant at the five-percent level. Neither their inclusion nor their exclusion from the models has much of an impact on the significance levels of the other variables or signs and magnitudes of their coefficients.

Chronic disease indicators:

Next, I am interested in how childhood anthropometrics, childhood growth trajectories, adulthood characteristics, and adulthood BMI are associated with chronic disease indicators. Table 3.3 shows these results. The continuous dependent variables of interest are systolic blood pressure, diastolic blood pressure, high-density lipoprotein (HDL) cholesterol, triglycerides, and fasting blood glucose. Regressions with LDL cholesterol, or “bad cholesterol,” do not inform much, as the models are extremely weak, so they are not displayed below.

Table 3.3: Multiple regressions of chronic disease indicators on sex, length-for-age childhood anthropometrics, growth trajectories, adulthood characteristics, and adulthood anthropometrics

	Systolic blood pressure	Diastolic blood pressure	HDL cholesterol	Triglycerides	Fasting blood glucose
Intercept	83.95 ***	43.94 ***	55.09 ***	80.44	88.19 ***
Female	–13.40 ***	–5.77 ***	8.50 ***	–35.35 *	–3.88
Mean [0, 1)	–0.02	1.22	–1.56	–21.72 *	–1.12
Mean [1, 3)	1.64	0.40	–0.13	5.38	1.48
Mean [3, 5]	0.00	–1.00	2.10	13.25	–1.69
Slope [0, 1) (stagnant)	–0.90	0.38	–3.61 *	–12.23	–3.19
Slope [0, 1) (upward)	–1.11	2.10	–5.94 *	–4.04	10.03 *
Slope [1, 3) (stagnant)	1.88	2.58	–1.49	–50.02	–0.98
Slope [1, 3) (upward)	–4.89	–2.67	–5.67	110.27	1.54
Slope [3, 5] (stagnant)[15]	17.27	10.14	ref level	ref level	ref level
Slope [3, 5] (upward)	13.31	4.39	–5.55	53.93	38.40 ***
Educational attainment	–0.26	–0.22	0.21	1.57	0.28
Socioeconomic status	–0.97	–0.66	0.58	1.89	–1.30
Urban	2.09	0.36	0.92	–20.60	–2.36
Ever smoked	–0.69	–0.42	2.23	–16.72	–1.55
Adult BMI	1.28 ***	0.89 ***	–0.99 ***	8.69 ***	0.17
Adjusted R^2	0.358	0.174	0.170	0.133	0.083

Sex and adult BMI are significant for systolic and diastolic blood pressure. Both kinds of blood pressure tend to be higher for males than for females, and adult BMI is positively associated with blood pressure. However, early anthropometrics and early growth do not seem to be associated with either blood pressure variable. The model for systolic blood pressure is noticeably stronger than the one for diastolic blood pressure.

[15] It should be noted that the baseline category for slope between ages three and five switches from downward to stagnant. There are no observations in the downward category for slope between ages three and five that also have information on HDL cholesterol, triglycerides, and fasting blood glucose, so the baseline category changes by default.

With HDL cholesterol, or "good cholesterol," as the dependent variable, adult BMI is a significantly negative variable. Females have a significantly higher HDL cholesterol level. With downward as the reference category, both stagnant and upward growth trajectories on [0, 1) are significant and negative. This result suggests that growth in the first year of life is associated with lower levels of good cholesterol as an adult. Furthermore, upward is more negative, signifying that more growth might have greater adverse consequences. Could this be evidence of the fetal origins hypothesis having significance in the post-natal period? However, it will later be shown in Figure 5 that the relationship between HDL cholesterol and this slope does not hold using weight-for-age and weight-for-length measures.

Females have a significantly lower triglycerides level. Nutritional status on [0, 1) is significantly negatively associated with triglycerides, i.e., having a higher mean z-score in the first year of life is associated with a lower level of triglycerides. And as with the other chronic disease indicators discussed up to now, adult BMI is significantly associated with triglycerides, the association being positive here.

Upward slopes on [0, 1) (relative to downward) as well as on [3, 5] (relative to stagnant) are significantly positively associated with fasting blood glucose, though it is more positive and more significant for slope between ages three and five. Having an upward slope between ages three and five increases the level of fasting blood glucose. Sex and adult BMI are not significant variables for fasting blood glucose, though they are for all the other models with chronic disease indicators as dependent variables.

Figure 3.5 shows the results by different anthropometric measures.

Figure 3.5: Significant variables for chronic disease indicators by anthropometric measure

Sex and BMI are consistently significant for all dependent variables (except fasting blood glucose) regardless of the anthropometric measure used. Nutritional status at [0, 1) registers as significant and negative on a couple occasions – diastolic blood pressure using weight-for-length and triglycerides using length-for-age and weight-for-age. However, using weight-for-length, nutritional status at [1, 3) registers as significant and positive for diastolic blood pressure. While the adjusted R^2 values for the fasting blood glucose models are not high, there is a clear pattern across measures. Upward slope at [3, 5] is significant using length-for-age and weight-for-age (marginally insignificant for weight-for-length) and the coefficient is always positive.

Interactions between childhood and adulthood nutritional statuses are not reported in the tables and figures above due to their insignificance. It has been hypothesized that people who are under-nourished as children and over-nourished as adults are at special risk of chronic diseases. Various specifications of interactions are tested between the three childhood means and adult BMI, both as continuous variables, one as a continuous variable and the other as a categorical variable, and both as categorical variables. However, none of these interactions ever registers as significant. This suggests that childhood z-scores and adulthood BMI make their impacts additively and do not interact. That is, the combination of being small in childhood and growth to a higher nutritional status in adulthood does not result in additional detriment for this birth cohort.

Structural equation modeling:

BMI is a significant variable for almost all chronic disease indicators. However, is adult BMI truly a significant variable, or is it just a mediating factor through which sex, adulthood characteristics, or childhood nutritional status and growth affect the development of chronic diseases? In the former case, policies with adult BMI as a goal could have a significant effect on chronic diseases. However, if adult BMI only acts as an intermediary between a component of sex, adulthood characteristics, or childhood nutrition and chronic diseases, then the focus should be on such a component. As a result, it is important to study both the direct effects of these variables with chronic disease indicators and the indirect effects of these variables with chronic disease that work through BMI. SEM can help evaluate the full role, which may be partially hidden in the regression models, that these variables play. Table 3.4 shows the coefficients of the direct effects and indirect effects (through adult BMI) of sex, adulthood characteristics, and childhood nutrition variables in the model. Length-for-age z-scores are used here for the mean and slope variables. Note that the coefficients for the direct effects are the same as those that have been reported in previous tables.

Table 3.4: Direct and indirect effects using SEM

	Systolic blood pressure		Diastolic blood pressure	
	Direct	Indirect	Direct	Indirect
Female	–13.40 ***	2.78 ***	–5.77 ***	1.93 ***
Mean [0, 1)	–0.02	0.51	1.22	0.36
Mean [1, 3)	1.64	–0.21	0.40	–0.14
Mean [3, 5]	0.00	0.44	–1.00	0.30
Slope [0, 1) (stagnant)	–0.90	0.06	0.38	0.04
Slope [0, 1) (upward)	–1.11	–0.69	2.10	–0.48
Slope [1, 3) (stagnant)	1.88	–1.08	2.58	–0.75
Slope [1, 3) (upward)	–4.89	–1.56	–2.67	–1.09
Slope [3, 5] (stagnant)	17.27	–6.25	10.14	–4.35
Slope [3, 5] (upward)	13.31	–5.31	4.39	–3.69
Educational attainment	–0.26	–0.14	–0.22	–0.10
Socioeconomic status	–0.97	–0.59	–0.66	–0.41
Urban	2.09	2.83 ***	0.36	1.97 ***
Ever smoked	–0.69	–0.44	–0.42	–0.31

	HDL cholesterol		Triglycerides		Fasting blood glucose	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
Female	8.50 ***	–2.22 **	–35.35 *	19.46 **	–3.88	0.38
Mean [0, 1)	–1.56	–0.21	–21.72 *	1.79	–1.12	0.04
Mean [1, 3)	–0.13	0.10	5.38	–0.85	1.48	–0.02
Mean [3, 5]	2.10	–0.34	13.25	2.94	–1.69	0.06
Slope [0, 1) (stagnant)	–3.61 *	–0.14	–12.23	1.20	–3.19	0.02
Slope [0, 1) (upward)	–5.94 *	0.68	–4.04	–5.99	10.03 *	–0.12
Slope [1, 3) (stagnant)	–1.49	0.81	–50.02	–7.14	–0.98	–0.14
Slope [1, 3) (upward)	–5.67	2.23	110.27	–19.54	1.54	–0.39
Slope [3, 5] (stagnant)	ref level	ref level	ref level	ref level	ref level	ref level
Slope [3, 5] (upward)	–5.55	–1.10	53.93	9.66	38.40 ***	0.19
Educational attainment	0.21	0.13	1.57	–1.16	0.28	–0.02
Socioeconomic status	0.58	0.34	1.89	–2.97	–1.30	–0.06
Urban	0.92	–2.38 ***	–20.60	20.84 ***	–2.36	0.41
Ever smoked	2.23	0.14	–16.72	–1.21	–1.55	–0.02

Being female is significantly negatively associated with both kinds of blood pressure and triglycerides directly, and significantly positively associated with them indirectly. The indirect associations are expected, as being female is associated with having a higher BMI, which is positively associated with blood pressure and triglycerides. This general pattern is reversed for HDL cholesterol. In addition, direct effects are generally stronger than indirect effects. Although place of residence usually does not have a direct association with chronic diseases, it has significant indirect association. Living in an urban area is indirectly positively associated with both kinds of blood pressure and triglycerides, and indirectly negatively associated with HDL cholesterol. Again, these might be due to the strong association of urban dwellers with having a higher BMI.

As with the regressions run previously using length-for-age as the anthropometric measure, childhood nutritional status and growth are not significant (directly or indirectly) for systolic blood pressure or diastolic blood pressure. For HDL cholesterol, triglycerides, and fasting blood glucose, there are some significant direct effects for the z-score means and slopes, but none of the indirect effects are significant. The z-score means and slopes that are significant work directly with the chronic disease indicators themselves, and do not manifest themselves through adult BMI. This is not too surprising, since these variables are almost always insignificant when used as independent variables for adult BMI.

Discussion

Transitioning out of under as a child to either normal or over as an adult is a common trajectory within this Guatemala sample, so a double burden over the life course seems to be a real phenomenon. However, it does not appear that under-nourished children are at significantly different risk of becoming overweight adults from those who begin in the normal category. What are associated with adult BMI? Being female, having a higher mean z-score between ages three and five (for weight-for-age and weight-for-length), and living in an urban area are associated with higher adult BMI.

While adult BMI is important in models for chronic disease indicators, childhood nutritional status and growth trajectories do not consistently register as significant across anthropometric measures. The only cases in which they do are for triglycerides and fasting blood glucose levels. Nutritional status in the first year is negatively associated with triglycerides using length-for-age and weight-for-age as anthropometric measures, and having an upward growth trajectory between the ages of three and five is positively associated with higher levels of fasting blood glucose using these same two measures. The first suggests that under-nutrition has consequences for adult health and the second suggests that growth has consequences for adult health, both of which corroborate the work that has been done on more developed countries. However, significant results have been found only for these two chronic disease indicators. Further research on biological processes linking childhood growth with various chronic diseases would be illuminating.

There are other potentially interesting results here as well, specifically for nutritional status between ages zero and under one, nutritional status between ages one and under three, and growth trajectory between ages zero and under one. However, the significance of these variables often differs depending on which anthropometric measure is used. It is not surprising that length-for-age, weight-for-age, and weight-for-length sometimes produce different results as these three measures are calculated using different components. While many of the substantive results are similar, these measures should not be used interchangeably, and researchers should understand the nuances of these anthropometric measures before choosing an appropriate one for analysis.

A notable insignificant result is that interactions between childhood and adulthood nutritional statuses are not significant. Nutritional status and growth trajectory between ages zero and five are sometimes individually significant for various chronic disease indicators. But from my analyses, childhood z-scores and adulthood BMI do not interact multiplicatively in their association with chronic disease indicators. Previous literature has found that those who are under-nourished and experience growth as children could be at a disadvantage later in life, in terms of both adulthood BMI and chronic disease outcomes. The lack of interactions for chronic disease indicators, in conjunction with the lack of material difference between transitioning from under to over and transitioning from normal to over in Table 3.1, seem to counter this.

This lack of interaction significance could be just a statistical artifact, due to the relatively small size of the sample. However, the explanation could also be potentially due to the context of the birth cohort. Many of the previous studies have relied on longitudinal data from higher-income countries. Perhaps such a hypothesis does not apply as well in settings that have not seen as much development or macro-level changes.

There may be some concern that the adjusted R^2 values for the models presented are not high. However, the objective of creating these models is not to get the highest R^2, but to ascertain which variables are associated with various outcomes. However, there are likely other variables that are also associated with our outcomes of interest but have not been taken into account. There is also concern about potential multicollinearity between the mean and slope variables, but variance inflation factors (VIFs) are calculated for each model, and these are never at worrisome levels.

Sensitivity checks are performed to test the robustness of the results. The way in which mean and slope variables are separated into various age segments does not make much of a difference. I use three segments since that makes the most sense given the frequency of measurements. I have also tried running two-segment models with ages zero to under one and one to five, as well as zero to under two and two to five. The results remain relatively consistent between models. Regressions using only the three means, but without the slopes, have also been run. The models with the additional slope variables are stronger, and they also reveal the significance of some of the slope variables. Other thresholds to classify slopes, such as 0.05, have also been used to test the sensitivity of the models to the data-driven choice of 0.1. Similar conclusions are obtained.

Additionally, the chronic disease indicators were taken in 2004. For my models, I use BMI measured in 2004. However, there could be some lag between nutritional status as measured by BMI and chronic disease incidence. To further validate the models, I also test these models using BMI measured in 1998 instead of in 2004. The conclusions are very similar, though the models using BMI in 2004 are stronger, perhaps due to larger sample sizes and typically higher correlations between BMI and chronic disease indicators in the same year.

Conclusion

These analyses on a Guatemalan birth cohort demonstrate the transitions that take place over the life course and provide insight as to how demographic characteristics and nutritional processes are associated with health outcomes. For the chronic disease indicators in this study, sex and adult BMI are consistently significant. In addition, nutritional processes at young ages could still have implications for later-in-life outcomes. This study shows a significant negative association between triglycerides level (associated with heart health) and nutritional status between ages zero and under one, and a significant positive association between fasting blood glucose level (associated with diabetes) and the growth trajectory between ages three and five, for multiple anthropometric measures.

Aid from higher-income countries and international organizations often goes to children who are under-nourished. While it is obviously not good to keep these children under-nourished, policy implementation might be precarious here. My analyses suggest that growth at young ages might be associated with at least some chronic disease indicators. More research is still needed to study the underlying biological processes and to determine how strong these associations are, with a view to optimally implement the timing and type of assistance to prevent exacerbating the harm to those who might already have been handed a disadvantage at birth.

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