Cultural and Economic Macro-Environmental Determinants of Obesity: An Analysis of 70 Countries.

A thesis submitted by

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To my parents, wife and daughters

For their unconditional love and support

This accomplishment belongs to you all as well

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Abstract

Background: Obesity is essentially caused by an energy imbalance whereby energy intake exceeds the amount of energy expenditure. Due to multifactorial nature of obesity, its determinants span from cell to society. Much of the research on obesity determinants has focused on individual level risk factors including genetic endowment, behavioural factors, socio-demographic and socio-economic status. Recent research has acknowledged the role of environmental factors that create obesity-promoting spaces for residents. The ANGELO (Analysis Grid for Environments Linked to Obesity) Framework is an appropriate tool for understanding the role of environment in obesity development. It divides environmental factors into multiple types (e.g., economic, physical, policy, socio and cultural) and scales (micro and macro) of environments. Among these, macro-level culture and economic environment are the most neglected factors in obesity research and most researches on culture and economics are focused on the micro-environment level. The aim of this study was to explore the effect of country level cultural and economic macro-environments on individual level BMI after controlling for individual and country level factors.

Methods: Seventy-two different datasets were used in this thesis including 70 datasets from World Health Survey (WHS) for 70 countries, World Bank Datasets and the Hofstede cultural dimensions dataset. The outcome variable (BMI) and all individual level explanatory variables (Age, gender, marital status, education level, household wealth, occupation, living in urban or rural area) were derived from the WHS datasets. Data on national income (GNI-PPP) and income inequality (Gini index) were collected from World Bank Datasets. Data on country level cultural dimensions, uncertainty avoidance, individualism power distance and masculinity were collected from Hofstede cultural dimensions data.

The design based descriptive analysis (analysis with sampling design features) was performed for BMI and all individual-level variables for 70 countries. Bivariate and multivariate associations were examined between the BMI and country level national income, income inequality and cultural dimensions after controlling for individual level variables. R-statistical software with survey and lme4 packages was used for analysis.

Results: A sample of 2,062,66 people from 70 countries was included. The weighted mean BMI(SE) in these 70 countries was 23.9(4.84). In high-income countries, male, married, had lower education level, lower household wealth, manual occupations and living in rural areas had higher BMI. In low-income countries female, married, had higher education level, higher household wealth, professional occupations and living in urban areas had higher BMI. Multilevel analysis shows that national income ($\beta=0.48, p<0.001$) was significantly associated with BMI after controlling for individual level factors.

To determine the association of country level cultural dimensions and BMI, a sample of 156,192 people from 53 countries was included. The weighted mean BMI(SE) in these 53 countries was 23.95(0.08). Uncertainty avoidance ($\beta=0.03, p<0.001$) and individualism ($\beta=0.03, p<0.001$) had a significant positive association with BMI. Income inequality ($\beta=0.06, p<0.05$) was significantly associated with BMI after controlling for cultural dimensions.

Conclusion: Higher uncertainty avoidance and individualism cultures of the countries were associated with a higher individual level BMI. However, power distance and masculinity cultures were not associated with individual level BMI. Countries higher national income and income inequality were associated higher BMI. These results indicate that culture should be a consideration in the development of public health policies to address obesity. For instance, a public health policy or programme in a country with higher uncertainty avoidance scores may focus on more familiar approaches, which may be more readily embraced. If new approaches are to be used then enough time needs to be allowed for people to develop an understanding of the initiative to help foster confidence in it. Involving the community in projects and project development may allow them a sense of understanding, and then decrease the element of the unknown.

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General Declaration

In accordance with Monash University Doctorate Regulation 17.2 Doctor of Philosophy and Research Master's regulations the following declarations are made:

I hereby declare that this thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

This thesis includes 1 original papers published in peer reviewed journals and 2 unpublished publications. The core theme of the thesis is Country level Determinants of Obesity. The ideas, development and writing up of all the papers in the thesis were the principal responsibility of myself, the candidate, working within the Department of Global Public Health under the supervision of Professor Daniel D Reidpath.

[redacted]

Signed: ………………………………………………………………………

Date: …4/5/2015……………………………

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Scientific Papers From This Thesis

1. Masood M., Reidpath D. Multi-country health surveys: are the analyses misleading? Current Medical Research and Opinion. 2014; 30:5; 857-863. (ISI Impact Factor 2.26) (Appendix E)
2. Masood M., Reidpath D. Comparison of model estimates from four analytic strategies for complex survey data: a case-study of World Health Survey data, Spain. (Under Review). (Appendix F)
3. Masood M., Reidpath D. Intraclass correlation and Design effect in BMI, physical activity and diet in 56 countries. (Under Review). (Appendix I)

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CHAPTER 1: Introduction

Obesity is a state of excess fat accumulation that accompanies a wide range of health problems. The World Health Organization (WHO) defines a body mass index (BMI) of ≥25 kg/m2 as overweight, and a BMI of ≥30 kg/m2 as obesity [WHO, 2013]. The prevalence of obesity and overweight has risen substantially in the past three decades in both developed and developing countries, with marked variations in the levels and trends in overweight and obesity across countries. The Global Burden of Disease Study estimated that the worldwide proportion of overweight or obese adults in 2013 was 36% in men and 37% in women [Ng et al., 2011]. Globally, the epidemic has affected both developed and developing countries, men and women, and adults and children. However, significant variations are observed in its prevalence and trends across countries. In developed countries, increases in obesity that began in the 1980s have attenuated in the past 8 years or so. Conversely, the Global burden of disease study suggested that there are likely to be continued increases in the developing world, where almost two in every three of the world's obese people live [Yatsuya et al., 2014].

This rising prevalence of overweight and obesity has a substantial economic and health burden globally. It is a major risk for many chronic diseases such as diabetes, hypertension, heart disease, osteoarthritis and certain types of cancer and they significantly reduce an individual's physical function, psychological well-being and overall quality of life [Crawford, 2010; Crawford and Ball, 2002; Nguyen and El-Serag, 2010; Swinburn et al., 2011; Wang et al., 2011]. In 2010, overweight and obesity were estimated to cause 3·4 million deaths, 4% of all years of life lost, and 4% of global disability-adjusted life-years (DALYs). Data from some studies has suggested that, unabated, the rise in obesity could lead to future falls in life expectancy [Ng et al., 2011].

Obesity is essentially caused by an energy imbalance whereby energy intake (caloric consumption) exceeds the amount of energy expenditure (physical activity) resulting in the storage of fat on the body. The relative contribution of changes in energy intake versus energy expenditure in obesity development has been vigorously debated [Ng et al., 2011]. Although this energy intake and expenditure equilibrium appears simplistic, the factors that contribute to imbalance in this equilibrium are undoubtedly complex. Due to the multifactorial nature of obesity, its determinants span from cell to society. To date, much of the research on obesity determinants has focused on individual risk factors. These include genetic endowment (i.e., the body's natural ability to burn fat) [Dyck et al., 2001; Heitmann et al., 1995], lifestyle or behavioural factors (i.e., eating habits, sedentary activity) [Dean, 2012; Jahns et al., 2001; Procter, 2007], socio-demographic and socio-economic status (i.e., gender, age, income) [Cairney and Wade, 1998; Lumeng et al., 2006; Willms et al., 2003].

While most of the existing research has been integral to a better understanding of how genes, behaviour, socio-demographics, and socio-economic status influence an individual's BMI, these factors alone do not provide a complete explanation of the etiology of obesity[1]. A more recent body of research has acknowledged the role of environmental factors that create obesity-promoting spaces for residents. Specifically, these 'obesogenic environments' are those places that promote an unhealthy lifestyle through inadequate food availability and increased sedentary activity [Davison and Birch, 2001; Egger and Swinburn, 1997; Swinburn et al., 1999a].

A useful tool for understanding the role of environment as a determinant of obesity is the analytical framework developed by Swinburn and colleagues (1999)[2] [Swinburn et al., 1999a]. The Analysis Grid for Environments Linked to Obesity Framework (ANGELO) involves multiple types (e.g., economic, physical, policy, socio and cultural) and scales (micro and macro) of environments. Micro-environments (settings) are those settings that individuals occupy in daily life (e.g., home, school, neighbourhood), and macro-environments (sectors) are those sectors that influence the micro settings (e.g. education system, health care system, food manufacturing/distribution sector). For example, a micro-environmental setting such as a supermarket will be influenced by a number of supporting macro-environmental sectors such as the food production, manufacturing, distribution, and marketing sectors. These sectors are common to the wider population and often operate at national, and international levels. Macro-environmental structures are largely beyond the influence of individuals and even governments often have difficulty in influencing these sectors because of their size, complexity, and other priorities [WHO, 2012].

The majority of existing research on environmental determinants of obesity have focused on the micro level of the physical (e.g., environmental quality, land use) [Booth et al., 2005; Graham, 2000; White, 2007], social (e.g., neighbourhood safety) [Lumeng et al., 2006; Stafford et al.,

[1] These determinants are guided by the Population Health Framework that acknowledges the importance of both individual and environmental factors in shaping the health of populations (Figure 1). These will be discussed in Chapter 2.

[2] The ANGELO (Analysis Grid for Environments Linked to Obesity) Framework (Figure 2) will be discussed in Chapter 2.

2007], economic (e.g. area deprivation) [Grundmann et al., 2014; Law et al., 2007] and cultural environments (e.g. ideal image) [Johnston, 2011; Johnston and Harkavy, 2009; Klaczynski et al., 2004]. However, the macro-environment is often neglected in obesity research. Thinking about countries or nations as an operational unit of the macro-environment, it becomes reasonable to study country as the largest unit of macro-environment (e.g. National income of the country influences the availability of food and working conditions in the country) that influences all the micro-environments within the country. There are only a few studies which have explored country level macro-environmental determinants of obesity, and even these studies have focused largely on the economic macro-environment of the country [Egger and Swinburn, 1997; Wilkinson and Pickett, 2007].

Thus, while individual's genes, biology, behaviour and micro-environment are important determinants of the body weight, so too are country level macro-environments in which these behaviours are expressed and micro-environments are operationalized [Canoy and Buchan, 2007; Chamieh, 2013]. There are many important reasons to study the country level[3] determinants of BMI. Firstly, some determinants of diseases genuinely operate at the country level, either directly causing a disease, but perhaps more commonly causing disease as effect modifiers or determinants of exposure to the individual level risk factors [Kunitz, 1994; Susser, 1994a]. For example, national income of a country might affect the BMI of the residents of that country. Being poor in a rich country may be worse than having the same income level in a poor country, because of the problems of social exclusion and lack of access to services and resources [Diez-Roux, 1998]. This may operate through relatively direct mechanisms, but may also involve aspects of individual lifestyle that are, in part, determined by the social context. Secondly, it is increasingly recognised that, even when studying individual level risk factors, the country level studies play an essential part in defining the most important public health problems to be tackled, and also their potential causes. Many important individual level risk factors for diseases simply do not vary enough within populations to enable their effects to be identified or studied [Susser, 1994a]. More specifically, Rose has noted that whole populations (a country) may be exposed to risk factors for a disease and the patterns may be apparent only when comparisons are made between, rather than within, populations (countries) [Rose, 1992]. For example, many of the recent discoveries on the causes of cancer (including dietary factors and

[3] These country level factors are distinct from the individual level factors because they characterize the country as a whole and are presumed to affect everyone in the country regardless of the individual characteristics.

colon cancer, hepatitis B and liver cancer, aflatoxins and liver cancer, human papilloma virus and cervical cancer) have their origins, directly or indirectly, in the systematic international comparisons of cancer incidence conducted in the 1950s and 1960s. More recently, standardised studies, which formed part of research studying the “known” causes of asthma in affluent countries (for example, air pollution, allergen exposure) are revealing major international differences in asthma prevalence that are not explained by these “established” risk factors such as air pollution, but are more consistent with recent theories on the protective role of some infant infections in the aetiology of asthma [Beasley, 1998]. These studies suggest investigation of the possible causes of the international patterns of BMI. Therefore, this study examines the effect of country level economic (national income and income inequality) and cultural (uncertainty avoidance, individualism, power distance and masculinity) macro-environmental determinants on the individual level BMI.

There are few studies that explored national income and national income inequality as the country level determinants. These studies suggested that national income may directly predispose individuals to obesity, but the supporting evidence is limited and inconsistent [Pickett et al., 2005]. Additionally, these country level studies are mostly from high-income countries due to poorer availability of the data from low and middle-income countries[4]. Due to a relative lack of studies from low- and middle-income countries, the findings from wealthier countries are often extrapolated to the other parts of the world. Such generalizations may be misleading, particularly if the determinants of obesity vary across different regions of the world [Wilkinson and Pickett, 2006]. In addition to national income, another economic factor whose contribution to health has attracted substantial attention over the past decade, and which has also been argued to exacerbate the prevalence of obesity is the income inequality (the distribution of incomes) [Kim et al., 2008]. Previous studies have documented an association between income inequality and population health [Beasley, 1998; Kaplan et al., 1996; Kawachi et al., 1997; Lynch et al., 2001; Subramanian and Kawachi, 2004; Wilkinson, 1992]. A majority of existing studies are wholly or partially supportive of the observation that, after adjusting for national income, health was worse in countries or regions where the income inequality was larger.

[4] For operational and analytical purposes, the World Bank‘s main criterion for classifying economies is gross national income (GNI) per capita, has been adopted in this thesis. Countries with GNI-PPP under US$ 3,035 are classified as low income group; GNI-PPP between US$ 3,036 to US$ 9385 as middle income group; and GNI-PPP US$ 9386 and above as high income group World Bank: World development indicators; in. Washington, DC, World Bank, 2005.. This grouping divided all the 70 countries into 30 high income, 19 middle income and 21 low-income countries. (http://data.worldbank.org/about/country-classification, accessed on Jan2015). In this thesis I have classified the countries according to this classification World Bank: World development indicators; in. Washington, DC, World Bank, 2005.

Culture at the macro-environment level is perhaps the most neglected factor in the obesity research and most researches on culture are focused on the micro-environment level. A classic definition of culture, defines culture as a “complex whole which includes knowledge, belief, art, morals, laws, custom, and any other capabilities and habits acquired by man as a member of the society” [Tylor, 1920]. The most important reason for this neglect is that it is difficult to conceptualize and quantify the culture. Consequently, this poses a challenge to the use of culture as a determinant of obesity. A number of approaches have been used to identify culture as an obesity determinant, allowing its inclusion in empirical research. Most researchers have followed through approaches based on beliefs/value systems to operationalize culture e.g. people belief about body image and body size [Johnston, 2011].

Several scholars discuss the choice of dimensions as the most appropriate one for conceptualizing and quantifying the culture [Clark, 1990; Connection, 1987; Hofstede, 2001b; Hofstede et al., 2010; Keillor and Hult, 1999; Schwartz and Bilsky, 1990; Smith et al., 1996; Steenkamp et al., 1999]. Hofstede’s framework is the most widely used national cultural framework in psychology, sociology and health related studies [Steenkamp, 2001]. In order to categorize the cultures of countries, Hofstede (1984, 1991, and 2001) defined four cultural dimensions. Hofstede’s model of cultural dimensions is one of the most popular approaches to analyse cultural differences between countries, with more than 9000 citations in peer-reviewed journals. Hofstede’s model defines culture as the collective programming of the mind that distinguishes the members of one group or category of people from another. Geert Hofstede has formulated a model showing that world cultures vary along consistent, fundamental dimensions, which can be grouped into specific constructs: uncertainty avoidance (UAI), individualism (IND), power distance (PDI) and masculinity (MAS) [Hofstede, 1984, 2001b; Hofstede et al., 2010].

It is important to look into the association of the culture of a country with BMI for various reasons. First, nations may differ substantially in culture, which determines the norms, values and behaviour related to food choices and physical activity in a country, and this seems to play an important role in obesity too. Secondly, the culture of a country as a probable determinant of high BMI through association with increases in the availability of opportunities to consume energy (food), decreases the availability of opportunities to expend energy (physical activity), or a combination of the two [Allender et al., 2012; Nishida et al., 2004]. More importantly, identification of these cultural determinants of obesity may help in modifying and adopting preventive policies and strategies specific to the culture of that country. Knowledge about these differences may contribute to the prevention of obesity and effective cooperation and integration of health care policies. Further studies will identify the country level factors that are most influential and which could be modified through external interventions.

Most of the research examining the effects of country-level and individual-level factors on health outcomes, adopted mainly three analytical methodologies [Dean, 2012]. More often than not, the research that has looked at the effect of country-level factors on health outcomes has used ecological analyses. An example of this would be the study by Olafsdottir et al. (2011) where the effect of national governance in 46 sub-Saharan African countries on the under-five mortality rate was examined [Olafsdottir et al., 2011]. Neither national governance nor the under-five mortality rate is measurable at the individual level, and the conclusions are necessarily about ecological relationships operating at a national level. This approach was quite rightly regarded as inadequate and unreliable because of the many additional forms of bias that can occur in such studies [Susser, 1994a, b]. Ecological analyses become flawed in exactly the same circumstances that individual level analyses do, i.e. in the presence of confounding. For example, almost any disease that is associated with affluence and westernisation has in the past been associated at the national level with sales of television sets, and nowadays is probably associated at the national level with the rates of Internet use [Pearce, 2000].

Another approach is to examine all the individual and group level factors at an individual level ignoring the country level effect. The failure to take into account the importance of ecological context (e.g. country level), as a determinant of individual level exposures is termed as "individualistic fallacy" [Diez-Roux, 1998]. Ignoring this context and attempting to study homogeneous populations can lead to the erroneous conclusion that individual characteristics are the main determinants of obesity and the most important ones for intervention, just as studying populations with homogeneous lifestyles can lead to the erroneous conclusion that other factors are the main determinants of obesity [Subramanian et al., 2009].

These considerations lead to an increasing interest in the statistical methods of multi-level analysis. Multi-level analysis has considerable merits as it permits the estimation of country level (ecological) effects while also including individual level effects, thus avoiding both the ecological fallacy and the individualistic fallacy [Pearce, 2000]. The advent of multilevel analysis allowed researchers to move beyond ecological relationships and examine individual level outcomes that are associated with higher-level factors, such as the national income. In the multilevel analysis, an individual health outcome can be predicted on the basis of an individual level factor, such as personal income, and a higher-level factor such as the national income [Elgar et al., 2005]. If national income is significant, its importance is above and beyond the importance of the individual wealth. It indicates that there is something operating at the country level, which that makes wealthier countries more or less likely to manifest a particular health outcome.

It is difficult, however, to look at multilevel effects with country as the top level, because there are only a few available data sets that are sampled at the individual and the country level. Some studies looked at the multilevel predictors at country level using Demographic and Health Surveys (DHS) data. This DHS data unfortunately includes only low and middle-income countries. Therefore, the results that use the DHS data exclude the high-income countries and do not show the global BMI pattern. One of the few data sets available to look at this kind of question is the World Health Survey (WHS). WHS collected the data from 70 low, middle and high-income (LMHI) countries using comparable data collection methodology. This thesis used WHS data from 70 countries to address the objectives of this study. Each of the surveys in WHS is itself based on a complex survey design which employs multistage sampling procedures with stratification, clustering and unequal probability of selection [Rabe-Hesketh and Skrondal, 2006]. Therefore I used the designed based analysis[5] methods for descriptive analysis.

A significant methodological challenge, however, arises about how these data sets from complex survey design with multilevel structures should be analysed for the investigation of country level effects. If one thinks about typical regression analysis, the unequal probability of selection and the multilevel nature of the data could lead to four possible approaches for the analysis of data collected using a complex survey design. The first approach is to analyse the data as if they were derived from a simple random sample of the population – a “model based analysis” (MBA) e.g., Harling et. al., [Harling et al., 2010]. In the analysis of predictors of a continuous outcome, this typically involves a straightforward application of ordinary least squares regression. The second approach is to take account of the unequal probability of selection, stratification and the clustering in the data, while still treating all predictors as if they were measured at the lowest level – a “design-based analysis” (DBA) e.g., Merikangas et.al., [Merikangas et al., 2011]. The design-based estimators using the weighted sample provide an unbiased estimate of the independent variables in the regression model [Diez-Roux, 2000;

[5] Design based analysis considers sampling design (stratification, clustering and unequal probability) in the analysis.

Ghosh and Pahwa, 2006; Reiter et al., 2005]. The third approach is an unweighted, multilevel analysis e.g., Subramanian et. al., [Subramanian et al., 2011]. In this approach, the unequal probability of selection is ignored, and the hierarchical nature of the data becomes an explicit focus of the analysis, allowing interpretations of individual and area level effects on individual outcomes. The purpose of the analysis is to explain variation in the dependent variable at one level as a function of variables defined at other levels, plus interactions within and between levels [Diez-Roux, 2000]. This type of analysis could be described as a “multilevel, model based analysis” (MMBA). Like its non-multilevel counterpart, the model-based analysis may lead to biased estimates when employed in samples that include unequal probability of selection [Carle, 2009]. Finally, the fourth approach is a weighted, multilevel analysis in which the unequal probability of selection is taken into account, and the hierarchical nature of the data becomes an explicit focus of the analysis – a “ multilevel, design-based analysis” (MDBA) e.g., Antai et. al., [Antai and Moradi, 2010] and Goldhaber-Fiebert et. al., [Goldhaber-Fiebert et al., 2011]. Although, theoretically MDBM is the best approach to address the research question of this thesis, till date it is not possible to integrate sampling design and multilevel analysis in a single model. Therefore for regression analysis, I have adopted MMBA in this thesis.

Using data from representative samples from 70 countries participating in the World Health Organization (WHO) World Health Surveys (WHS), I aimed to: (1) estimate variations in the prevalence of BMI across 70 countries, (2) examine the effect of the national income and income inequality on the individual level BMI (3) to measure the effect of national income on BMI in different household wealth categories, and (4) examine the effect of national culture (assessed by Hofstede cultural dimensions; uncertainty avoidance, individualism, power distance and masculinity) on the individual level BMI.

1.1 Organization of Dissertation

In Chapter 2, I first describe what is known about obesity, its global prevalence and its economic and health burden. This chapter also includes the discussion about the various determinants of obesity including individual level determinants (e.g., Age, gender, social factors) for BMI and obesity, based on a review of previous literature and relevant theoretical perspectives. I also address the relationship between some country level factors and obesity and review relevant research on this relationship, with a focus on national income, income inequality and cultural dimensions. Chapter 3 includes the aims and objectives of this thesis with a formal presentation of the hypotheses. The description of World Health Survey and variables is included in Chapter 4. This chapter also describes the sampling method and sample size in each country. I also discuss the measurement of the individual level and country level variables. This chapter also describes how I organized and merged the data from 70 countries into a workable single dataset. The procedure described in this chapter makes the results of this study reproducible. In Chapter 5, I describe the methods and the steps in the multi-level statistical procedures employed in the analyses in this thesis. I first describe the model building process using individual and country level variables. I also discuss the types of statistical packages and estimation methods used in this study. In this chapter, I also describe the methods used to calculate the coefficient of determination, model fit and model diagnostics. In Chapter 6, I first present weighted and unweighted descriptive results for the full sample. All the descriptive analysis for BMI by individual level variables for each country are presented in graphs. I divided this chapter into two subsections; the first section describes the results for the effect of national income and income inequality on BMI and the interaction effect of national income and household wealth. In next subsection, I examine the effects of the uncertainty avoidance, individualism, power distance and masculinity on BMI and present the findings related to the hypotheses that address these effects. Following this, I combine all these cultural dimensions in a model and observe the compare the relative strength of their effect on BMI. In Chapter 7, I summarize the findings of the overall model and discuss the theoretical, practical, and policy implications of the results. I start with the key finding and descriptive finding followed by the effect of the individual level factors on obesity. Further in this chapter I discussed the effect of national income and individual income on BMI, interaction effect of national income and individual income on BMI and country level cultural dimensions (Uncertainty avoidance, individualism, power distance and masculinity) on individual level BMI. I also describe the strengths and limitations of the study and the directions that this work suggests for future research to further our understanding of culture and obesity.

CHAPTER 2: Literature review

2.1 Obesity as a Global Problem

Obesity is a leading cause of morbidity, mortality and disability worldwide [Crawford, 2010; Swinburn et al., 2011]. Over 1.5 billion people, that represent about one third of all adults across the world, are obese or overweight (BMI, of 25 kg/m² or higher). Among them, approximately 500 million adults are obese (BMI, of 30 kg/m² or higher) which represents 10-14% of the global population [Finucane et al., 2011; HSPH, 2014; Kelly et al., 2008]. Over the last three decades, overweight and obesity have been transformed from relatively minor public health problems that primarily affect the most affluent societies to a major threat to global public health. Obesity is not only a problem of rich countries anymore; it has truly become a worldwide problem, affecting all low, middle and high-income countries. In the past 30 years, a large body of evidence has accumulated documenting the temporal increases in the prevalence of obesity across the globe. The rise of the obesity seemed to begin in most high-income countries about the same time in the 1970s and 1980s. Since then, most middle-income and many low-income countries have joined the global surge in obesity prevalence [Crawford, 2010; Swinburn et al., 2011]. While overall almost all countries have rising trends of obesity, some countries showed a falling trend in the prevalence of obesity in men (such as Denmark and Saudi Arabia), and some countries showed a falling trend in the prevalence of obesity in women (such as Ireland, Finland, and Spain) [Nguyen and El-Serag, 2010]. Despite these falling trends in some subgroups in some countries, the overall estimates of obesity prevalence in these countries remain high. The WHO projects that by 2020, approximately 2.3 billion adults will be overweight and at least 700 million will be obese. If nothing is done to reverse the epidemic, more than 1 billion adults are projected to be obese by 2030. Some researchers have postulated this as a potential threat to the continued increase in life expectancy achieved by medical and public health advances during the past century [Wang et al., 2011].

The number of people affected in the low and middle-income countries has more than tripled in the last three decades, from 250 million to 904 million. The highest rate of obesity has been reported in the Pacific Islands and the lowest rates have been seen in Asian countries such as Bangladesh, India and Vietnam. In the Middle East and China, obesity has increased at least threefold since 1980 [James, 2008]. The major problem in understanding the epidemiology of obesity in low and middle-income countries is the lack of high quality data from nationally representative samples. All the data from small non-representative surveys points towards the consistent rise in the prevalence of overweight and obesity over the past three decades in most of the low and middle income countries [HSPH, 2014; Popkin et al., 2012]. Additionally, in a number of low and middle-income countries, the prevalence of obesity has increased more rapidly than it has in high-income countries. Predictions indicate that over the next two decades, the greatest proportionate increase in the number of adults who are overweight or obese is expected to occur in low and middle income countries, where the rise in numbers is expected to be 62-205% for overweight and 71-263% for obesity [Malik et al., 2013]. In high-income countries the numbers are expected to increase by 1.7 times over the same period of time in future [Keats and Wiggins, 2014]. Many high-income countries especially the US, Canada, UK, Australia, and New Zealand have experienced dramatically escalating obesity rates during these three decades, rates that will continue to rise in the future [Nguyen and El-Serag, 2010]. The situation of the most affected populations from high-income countries such as the USA has been well publicized. However, less recognized have been the increases in population obesity elsewhere in the world but they are now increasingly being monitored in high-income countries. Most attention is devoted to the affluent countries with established market economies (e.g. North America, Europe, Australia, New Zealand, and Japan) because the data quality and time span covered by them are reasonably comparable. An important public health problem that arises from these trends is that the burden of obesity will continue to increase as a result of population growth even without an increase in prevalence [Malik et al., 2013].

The distribution of obesity in populations is strongly distributed with various socio-demographic factors such as gender, age, socioeconomic status etc. Clear gender differences are seen in most countries with more women than men being obese. In contrast, the proportion of men over women who are overweight tends to be greater. Since 1980, gender specific global obesity prevalence rose from 4.8% to 9.8% in men and from 7.9% to 13.8% in women [Malik et al., 2013]. Globally, the age-standardised mean BMI for men increased by 0.4 kg/m² per decade and female BMI increased by 0·5 kg/m² per decade between 1980 and 2008 [Finucane et al., 2011]. In the USA alone, in 2009-2010, 35.5% of men and 35.8% of women were obese. The sex-specific prevalence of obesity is highest in North America (US and Canada) (men: 29.2%) and in southern Africa (women: 36.5%) [Malik et al., 2013]. Patterns have also emerged across socio-economic groups. In developed countries, the levels of obesity are higher in the lower socio-economic groups, whereas, in developing countries, this relationship is reversed with higher obesity prevalence in higher socio-economic groups. However, the urban population in all the countries has a higher prevalence of overweight and obesity than the rural population [Crawford, 2010; Finucane et al., 2011].

2.2 Health Burden of Obesity

The effects of obesity on population health are significant; societies are burdened by premature mortality, morbidity associated with many chronic disorders, mental disorders and negative effects on health-related quality of life [Wang et al., 2011]. Obesity is an established risk factor for diseases such as type-2 diabetes, cardiovascular diseases, hypertension, stroke and many cancers [Swinburn et al., 2011]. Furthermore, obesity is linked to several digestive diseases, including gastroesophageal reflux disease and its complications (e.g. erosive esophagitis, Barrett's oesophagus and oesophageal adenocarcinoma), colorectal polyps and cancer, and liver disease (e.g. non-alcoholic fatty liver disease, cirrhosis and hepatocellular carcinoma) [Nguyen and El-Serag, 2010]. Excess bodyweight also contributes to non-fatal but costly or disabling disorders such as osteoarthritis. Evidence suggests that excess bodyweight is linked to many additional disorders, including benign prostate hypertrophy, infertility, asthma, and sleep apnoea. Maternal obesity has been linked to an increased risk of congenital anomalies [Wang et al., 2011]. In 2004, disabilities attributable to obesity and all the above mentioned consequences were at more than 36 million disability-adjusted life-years [Swinburn et al., 2011]. Obesity is now the dominant cause of preventable disease burden even in many LMICs, and it has overtaken tobacco as the largest preventable cause of disease burden in some regions [Swinburn et al., 2011].

All diseases affect quality of life; and obesity is no exception. Obesity has some major mental health consequences too, which stem from low self-esteem even in mildly overweight people. Most obese people complain of being 'depressed', the word 'depression' commonly reflects low self-esteem and stigmatization of obese people by others. It is a very common mental health symptom of obesity and it occurs in patients who attend health services for any of the health consequences of obesity. Obesity and its symptoms also commonly compound many psychiatric diseases through the obesogenic effects of antipsychotic and other drugs [Crawford, 2010; Leslie et al., 2007]. Some studies on obese participants reported that the mental wellbeing of obese people was worse than that of patients who were chronically ill, seriously injured, or had survived cancer [Crawford, 2010; Sullivan et al., 1993].

Obesity is also associated with an increased risk of death. Adams et al. estimated the mortality risk in a prospective cohort of more than 500,000 U.S. men and women with 10 years of follow-up, and reported that, among people who had never smoked, the risk of death increases by 20% to 40% in overweight patients and by 2- to 3-fold in obese compared to normal-weight patients [Adams et al., 2006; Nguyen and El-Serag, 2010].

2.3 Economic Burden of Obesity

The obesity epidemic places a large financial burden on the economy because of the increased risk of death and the increased risk of costly chronic diseases associated with it. Despite this large financial burden, in most countries there is very little provision for the clinical management of obesity, and often no designated budget for it. This is probably due to the high expenditure on secondary consequences of obesity not on obesity itself [Crawford, 2010; Malik et al., 2013].

The health economic analysis of obesity is complicated by the large number of health outcomes it affects, and the lack of mechanisms or databases to capture the costs of these health consequences [Crawford, 2010]. However, some evidences and projections are available to predict the direct and indirect cost of obesity. In a systematic review of the economic burden of obesity worldwide, Withrow and colleagues concluded that obesity accounts for 0·7–2·8% of a country's total health-care costs, and obese individuals have medical costs 30% higher than those with normal weight [Wang et al., 2011; Withrow and Alter, 2011].

The U.S. Department of Health and Human Services has estimated that the total economic cost of overweight and obesity in the United States was $117 billion in 2001 [Withrow and Alter, 2011]. In the early 1990s, obesity was estimated to account for 2% of health-care costs in France, 4% in the Netherlands, and 2% in Australia. European Union estimated for the combined direct and indirect costs of obesity in 2002 was approximately €33 billion a year. In 2007, a report developed by the UK's Office for Science Foresight Programme projected that the continuing rise in obesity will add £5·5 billion in medical costs to the National Health Service by 2050. Additionally, because the prevalence of overweight and obesity has increased consistently, the costs today are likely to be considerably higher than previous estimates [James, 2008]. In addition to the medical costs, society incurs substantial indirect costs from obesity as a result of the decreased years of disability-free life, increased mortality before retirement, early retirement, disability pensions, and work absenteeism or reduced productivity.

A number of studies suggest that the monetary value of the indirect cost is several times larger than the medical costs [Trogdon et al., 2008; Wang et al., 2011]. Low and middle-income countries currently carry the majority of the obesity and chronic disease burden, and are predicted to continue to do so in the future decades. The costs related to the treatment of obesity and its various comorbidities will be particularly detrimental to the public health and the economy of LMICs. Many of these countries have limited health care resources and their infrastructures are not sufficient to combat the escalating rates of these conditions alongside the coexisting burdens of under-nutrition and infectious diseases [Malik et al., 2013].

2.4 Global Differences in Obesity

The prevalence of obesity varies significantly across countries, even when estimated using comparable methods [Finucane et al., 2011]. The available data shows wide variations in obesity prevalence globally, ranging from India, where 1% or less of the population is obese, to the Pacific Islands, where the prevalence of obesity was up to 80% in some regions [Nguyen and El-Serag, 2010; Organization, 2014].

2.4.1 North America

Recent result shows that the prevalence of overweight or obesity in the United States adults are 69% with 34% respectively [Flegal et al., 2012]. Over the last 50 years, the proportion of the US population considered to be overweight and obese has steadily increased. In the 1960-1962 National Health Examination Survey, an estimated 31.6% of adults were overweight or obese, and 13.4% were obese [Flegal et al., 2012; Gaziano, 2010]. In 2011, the adult obesity prevalence ranged from 20.7% (Colorado) to 34.9% (Mississippi). In 2011, the prevalence of overweight or obesity in men was higher than in women, 72.3% compared with 64.1%. Among men, the obesity prevalence was 35.5% overall, and within race groups, prevalence ranged from 36.2% among non-Hispanic white men to 38.8% among non-Hispanic black men. For women, the prevalence was 35.8%, and the range was from 32.2% among non-Hispanic white women to 58.5% among non-Hispanic black women [Flegal et al., 2012]. There was no significant change in obesity prevalence in the U.S. among adults between 2003 and 2011. Although, the rates have remained steady since 2003 [Ogden et al., 2014] the prevalence is alarmingly high. These rates have continued climbing in some subgroups such as in men, Non-Hispanic Black women, and Mexican American women [Flegal et al., 2012; HSPH, 2014]. If same trends continued, it is predicted that roughly half of all men and women in the US will be obese by 2030 [Wang et al., 2011].

The prevalence of obesity in Canada is much lower than the neighbouring US. Canada has also experienced similar dramatic increase in the prevalence of overweight and obesity in the last three decades. Between 1985 and 2011, the prevalence of adults in the overweight category increased by 21% from 27.8% to 33.6%, and the prevalence of obesity increased by 200% from 6.1% to 18.3% [Twells et al., 2014]. The obesity prevalence in both men and women in Canada has increased over the past decade. In 2011, the prevalence of obesity was 24.3% in Canadian men and was 23.9% in Canadian women [Shields et al., 2011]. The prevalence of overweight and obesity was higher in the older age groups than that for the younger age group. Obesity is also more common among Canada's Aboriginal population than in the other groups. Surveys conducted in 2007-2008 found obesity rates of 25% among Aboriginal groups, compared with 17% in non-Aboriginal groups [Canada., 2011; HSPH, 2014].

2.4.2 Central and South America

Similar to other low and middle-income countries, there is a deficiency of comparable long-term reliable data on obesity rates in Central and South America. The available data shows that Central and South America have seen steady BMI increases over the past three decades. In 2008, more than 30% of women in Central and Southern Latin America were obese and about 25% of men in Southern Latin America and 20% of men in Central Latin America were obese. Overweight prevalence for both men and women was around 60% in Central and Southern Latin America. Between 1980 and 2008, a steep and consistent increase in the mean BMI by 1.4 units per decade in Central and Southern Latin America was observed. Men in these regions have seen similar increases in obesity, though not quite as steep as those in women [Finucane et al., 2011; HSPH, 2014].

In Mexico, a recent report, based on 2010 data, observed that roughly 30% of Mexican adults are obese and 70% are overweight or obese, projected to be 40% and 85% respectively in 2030. Obesity prevalence was higher in women (37%) than men (27%), but the reverse pattern was observed for overweight prevalence, 41% men and 37% women were overweight [Barquera et al., 2009; Rtveladze et al., 2014]. There are evidences that Mexico and other countries in Central and South America are already seeing the burden of obesity shift from the wealthy to the poor. In Mexico, for example, wealthier groups still have higher rates of obesity than lower socioeconomic groups, but the differences in average BMI between Mexico's more-developed regions in the north and less-developed areas in the south are small [HSPH, 2014].

The scenario has changed dramatically in Brazil, with strong reduction in the under-nutrition prevalence and constantly growing obesity prevalence from 5.7% in 1975 to 11.1% in 2003. Obesity prevalence reached 11.4% among men and 10.3% among women in 2006, rising to 13.5% in 2009 (13.9% among men and 13.2% among women). Women have been experiencing greater increase in the prevalence of obesity (28%) than men (22%) during this period. Obesity rates rose far more quickly among people with lower incomes than the wealthy ones, and the differences among women of different socioeconomic status has nearly disappeared [Moura and Claro, 2012; Silva et al., 2011].

2.4.3 Europe and Central Asia

The European obesity epidemic is far from uniform, perhaps, due to Europe's diverse economic and cultural landscape. Data is scarce for most of the European countries especially those of the former Soviet bloc. But it's clear from the existing data that obesity rates are rising across the continent, particularly in men, though not as rapidly as they are in the US. [Doak et al., 2012; HSPH, 2014]. Eastern Europe and the Mediterranean countries showed higher prevalence of obesity than countries in Western and Northern Europe [Berghofer et al., 2008; Branca et al., 2007].

The prevalence of obesity in European men ranges from 4.0% to 28.3% and in European women from 6.2% to 36.5% and the prevalence of overweight ranges from 31.9 to 79.3% in European men and 27.8–77.8% in European women [Berghofer et al., 2008; Branca et al., 2007]. The highest prevalence was found in Italy and Spain in both the genders, whereas in Portugal, Poland, the Czech Republic, Romania, and Albania the largest increment in numbers is expected to be in women. In 2008, men in Western and Central Europe had higher rates of obesity than men in Eastern Europe (20 to 25%, versus 15 to 20%). In women, obesity prevalence was higher in Eastern Europe (25 to 30%) than in Western Europe (15 to 20%) or Central Europe (20 to 25%). Over the past 30 years, average BMI in men has been rising more rapidly in Western and Central Europe than in Eastern Europe (0.6, 0.4, and 0.2 units per decade, respectively). The prevalence of obesity in men and women in European countries in the EU region is similar, with a female: male prevalence ratio of 1.07 (range 0.56 to 1.29). In the central and eastern European countries, the prevalence is generally much higher in women than in men (average female: male prevalence ratio 2.03; range: 1.27 to 2.87) [HSPH, 2014].

Within the Western Europe, there are marked differences in obesity rates from country to country [Finucane et al., 2011; HSPH, 2014]. The UK was amongst the countries with the highest rates in Western Europe. Data on overweight and obesity among adults is mainly from the Health Survey for England. Results for 2013 showed that around 62.1% of adults were overweight or obese (67.1% of men and 57.2% of women). The prevalence of obesity is similar among men and women, but men are more likely to be overweight than women (41.1% of men compared to 33.3% of women). The prevalence of obesity among adults rose from 14.9% to 24.9% between 1993 and 2013. The rise in the obesity prevalence rate in UK has slowed down since 2001, but is still moving upwards [England, 2014]. France and Switzerland had mean BMIs of 25.9 and 26.2 in men, and 24.8 and 24.1 in women, respectively. Self-reported data from Western Europe showed lower levels of overweight and obesity for men and women with the lowest prevalence in Switzerland for men (49.3% overweight and 8.6% obesity) and women (21.9% overweight and 5%obesity). Age-adjusted overweight and obesity prevalence based on measured height and weight was the highest in Bosnia-Herzegovina for men (63.2% for overweight and 15.9% for obesity). For women, the overweight prevalence was highest in Croatia (50.9%) and obesity prevalence was highest in Portugal (17%) [Doak et al., 2012].

Overall trends in Europe show a steady rise in the overweight and obesity prevalence. In Eastern Finland, there has been a steady high prevalence of obesity in women and a rapid increase in men. In Germany, data shows that there has been an increase in obesity, both in men and women. Studies show a high prevalence of obesity in the Baltic States and in some republics in Eastern Europe [Barquera et al., 2009]. In the Netherlands, the prevalence of obesity grew from 4% to 10% among men and 6% to 12% among women from 1981 to 2004 [Schokker et al., 2007]. In Portugal, the obesity levels rose from 10.3% among men and 11.4% among women to 16.0% and 16.9%, respectively [Moura and Claro, 2012]. Based on the self-reported data from the other European countries, annual increases in the obesity prevalence in Denmark was 1.2 and 0.9 percentage points in women and men respectively, from 1987 to 2001, in Ireland 1.1 percentage points for both sexes from 1998 to 2002, in France 0.8 percentage point among adults from 1997 to 2003, in Switzerland 0.8 and 0.6 percentage point in women and men respectively from 1992 to 2002 and in Hungary 0.6 percentage point for both sexes from 2000 to 2004. On the other hand, self-reported adult obesity rates have fallen in Estonia and Lithuania [Branca et al., 2007].

Another systematic examination of the prevalence of obesity across Europe comes from the European Prospective Investigation into Nutrition and Cancer (EPIC), which showed that the prevalence of obesity varied from 8% to 40% in men and 5% to 53% in women. The rates were highest in Albania (Tirana), Bosnia and Herzegovina and the United Kingdom, and lowest in Turkmenistan and Uzbekistan.

2.4.4 North Africa and the Middle East

Data is scarce for most of the North Africa and the Middle East, but even so, there's compelling evidence that obesity prevalence is high and the rates are on the rise since the discovery of oil reserves in the 1960s. Obesity rates in some of the Arab Gulf countries are very high: In Saudi Arabia, 28% of men and 44% of women are obese, 37% of men and 27 % of women are overweight and 66% of men and 71% of women are overweight or obese. In Kuwait, 36% of men and 48% of women are obese, 37% of men and 29% of women are overweight while 74% of men and 77% of women are overweight or obese. In UAE, 25% of men and 40% of women are obese. Though obesity rates are higher among the women in this region compared to men, they appear to be rising more quickly in men than in women. [HSPH, 2014; Ng et al., 2011]. Data collected in 2005 showed that the obesity prevalence in Iran and Morocco is relatively lower, 11% and 6% in men and 25% and 22% women respectively [Musaiger, 2011].

2.4.5 Sub-Saharan Africa

Sub-Saharan Africa is not immune to the obesity epidemic, despite the continued burden of under-nutrition in many Sub-Saharan Africa countries. As in the other developing regions, nationally representative studies on obesity in sub-Saharan Africa are scarce. The studies that are available, though, suggest that obesity rates vary widely from country to country but majority of countries have a low mean BMI. For example, in 2008, the average BMI in the Democratic Republic of the Congo was 19.9, the lowest in the world and 26.9 in South Africa, among highest in the world [Dalal et al., 2011; Ziraba et al., 2009]. Increase in the rates of overweight and obesity are also being observed in Sub-Saharan Africa, especially among women and people who are part of the in urban populations. The prevalence of obesity in urban West Africa has doubled from 1995 to 2005. Yet in South Africa, men have an average BMI of 26.9, on par with the average BMIs in Canada and the U.S. Fifty-six percent of South African women and 29% of men are overweight or obese according to a 2002 study. Some studies in urban settings have found that that obesity rates are rising more quickly in the poor than in the rich. More research is needed to give a full picture of obesity trends across the continent [Scott et al., 2013].

2.4.6 Asia

Though Asia is home to some of the leanest populations on the globe, there's no question that obesity has become a serious and growing problem across the region over the past two decades. Some countries in Asia have mean BMIs that are among the lowest in the world. In Bangladesh, for example, the estimated mean BMI in 2008 was less than 21, for both men (20.4) and women (20.5). Still for most of the Asian countries such as Bangladesh Cambodia, China, India, Nepal, and Vietnam under-nutrition remains a significant public health problem. At the same time, some of these countries are also facing an increasing prevalence of overweight and obesity in women and other subgroups such as the wealthy people [Popkin et al., 2012].

Mean male BMI in the world's two most populated countries was lower than the world average in 2008, by 0·9 kg/m^2 in China and 2·8 kg/m^2 in India. Mean female BMI was lower than the global average by 1·2 kg/m^2 in China and by 2·8 kg/m^2 in India; increase in female BMI was less than the global average in both the countries [Finucane et al., 2011; Xi et al., 2012]. In India, in 2005, nearly 14% of women were overweight or obese, with higher rates among urban women (25%) than rural women (8%). In recent years, mean male BMI in China has increased faster than the global mean, but in India the trend was estimated to be flat. In China, from 1993 to 2009, obesity increased from 3% to 11% in men and from 5% to 10% in women. The rates of overweight and obesity in women in India increased by 3.5% a year from 1998 to 2005. Despite the increases in BMI, both the countries were among the 30% of countries with the lowest male and female mean BMI in 2008. Although, obesity rates are fairly low, China and India are the most populous nations on the planet with more than 2.5 billion people. So even small percentage increases in obesity rates translate into millions more cases of chronic disease [Finucane et al., 2011; Xi et al., 2012]. In urban regions of China (excluding Beijing, Shanghai and Tianjin), the prevalence of overweight was observed in 12.3% of men and 14.4% of women (comparable figures for rural regions are 5.3% and 9.8%).The Republic of Korea's National Nutrition Survey of 1995, found that only 1.5% of the population was classified as obese, and 20.5% as overweight. In Thailand, 4% were obese and 16% overweight. In Malaysia, 4.7% of men and 7.7% of women were obese [Inoue and Zimmet, 2000].

2.4.7 Australia, New Zealand, Oceania, and Japan

Obesity rates in “Australasia” (Australia and New Zealand) are not far behind those in the U.S. and UK. The Australian data showed that the prevalence of obesity in 2000 was 19.3 per cent in men and 22.2 per cent in women. This prevalence was 2.5 times higher than the prevalence in 1980. The prevalence in young adult men was particularly high (17.4%) [Popkin et al., 2012]. In New Zealand, the obesity prevalence was 11 % in 1989 and in 1997, this had risen to17% (14.7 % in men and 19.3 % in women). Of the high-income countries, women in New Zealand, and Australia had one of the greatest gains in BMI after USA, with increases of 1· 2 kg/m^2 per decade [Health., 2004; Popkin et al., 2012].

In Oceania, the average BMI has climbed by 1.3 units per decade over the past three decades; 15 to 20% of men and 25 to 30% of women are obese in this region [Finucane et al., 2011]. There is data that indicates that some of the Pacific island populations have extremely high rates of obesity. The prevalence of obesity in Nauru in 1987, for example, was reported to be around 65% in men and 70% in women. Similar high rates have been observed in urban areas of Papua New Guinea (36% in men and 54% in women) whereas the prevalence in the highlands was not higher than about 5% in men and women. Urban Samoans, in 1991, had an obesity prevalence of 58% in men and 77% in women. In rural areas, the obesity prevalence was high as well (42% in men and 59% in women) [Walls et al., 2012].

Japan had one of the lowest mean BMIs for men in high-income countries, less than 24· 0 kg/m^2. However, the prevalence of obesity over the past 20 years has increased in Japanese men from 0.8 per cent in 1980 to 2.0 per cent in 1995. Women in Japan, with mean BMI of 21· 9 kg/m^2, were more similar to women in low-income countries than to those in most high-income countries and there has been no change in mean BMI over the period in Japanese women [Moreno Aznar et al., 2011].

2.5 Determinants of Obesity

To study the global variation in the obesity prevalence, it is important to understand the various determinants of overweight and obesity. Determinants of a disease are the range of personal, social, economic, and environmental factors that influence the health status of the people and population [Wilkinson and Marmot, 2003]. This section of determinants of BMI is guided by "the multi-casual ecological model for understanding Obesity" given by Powell and colleagues in 2005 [Powell et al., 2005]. It is an ecological model relating the ecological determinants to food consumption (energy intake), physical activity (energy expenditure), and BMI. This model acknowledges the importance of both individual and environmental factors in determining the obesity of individuals and populations (Figure 2.1). It proposes two main types of factors influencing the equilibrium levels of body weight; individual level factors and environmental level factors. The individual level factors include biological, behavioural, and social factors. The environmental level factors include various types of environments such as built and economic environment. This model is particularly useful as it provides a lens through which the multifactorial and complex nature of obesity development can be understood. However, its definition of environment is limited, and thus the framework falls short in its capacity to comprehensively conceptualize the multiple factors within the environment that potentially influence the body weight. Therefore, I will introduce a model (ANGELO) for environmental determinants of obesity in the later subsections of this chapter [Swinburn et al., 1999a].

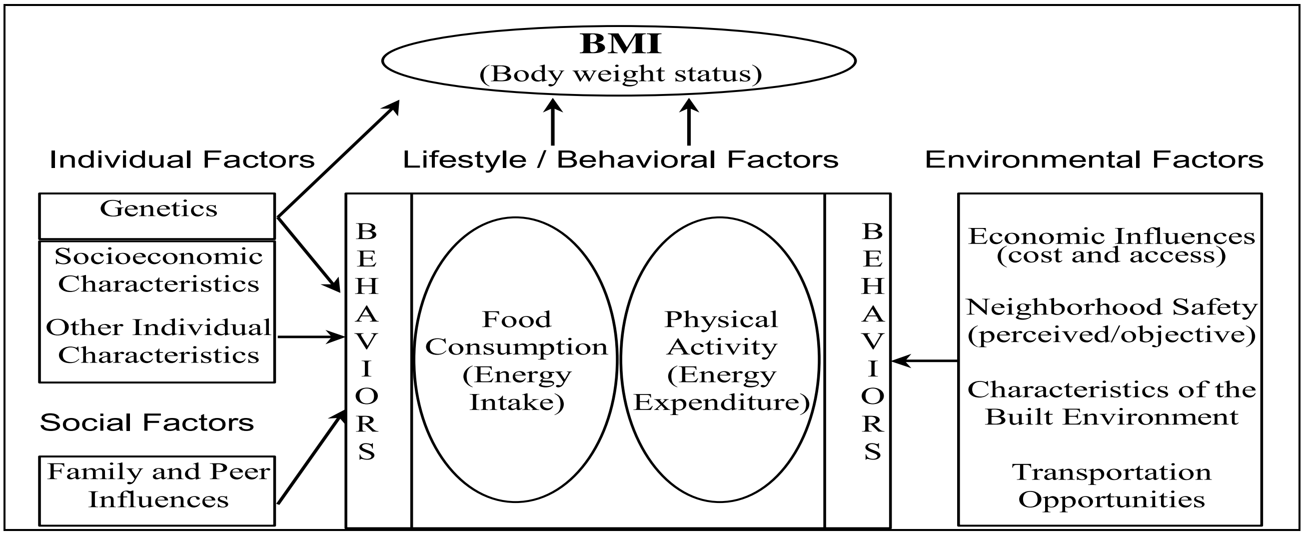

Figure 2.1 An ecological model relating the environment to physical activity, diet and body weight. Reprinted from: Powell, L., S. Slater, F. Chaloupka. 2005. A Multi-Causal Model of Eating, Physical Activity and Obesity. www.impacteen.org/. [Powell and Chaloupka, 2009]

2.5.1 Energy Intake and Energy Expenditure Equilibrium

According to the obesity ecological model, to understand the determinants of obesity, it is critical to understand the factors contributing to the energy intake and energy expenditure equilibrium [Egger and Swinburn, 1997]. At the central core, obesity lies on a fundamental principle of nutrition and metabolism: bodyweight change is associated with an imbalance between the energy content of food eaten and energy expended by the body to maintain life and perform physical work [Hall et al., 2011a]. Consequently, the most direct cause of the obesity is the imbalance in the equilibrium of energy intake and energy expenditure. Hill and colleagues suggest that a slight but consistent positive energy balance has led to gradual yearly weight gain in the U.S. population and the subsequent obesity epidemic that has ensued [Crawford, 2010; Hall et al., 2011a]. In particular, their studies showed that weight gain in 90% of the adult population is attributable to a positive energy balance of merely 100 kcal per day or less [Hill et al., 2003]. The average adult in the US has gained approximately 0.5–1 kg per year for the past two to three decades. Moreover, if the energy intake exceeds energy expenditure by 5% each day, this results in a 5-kg weight gain over a year, and, over several years, can lead to severe obesity [Selassie and Sinha, 2011].

Physiological adjustment refers to the metabolic changes that follow the disequilibrium in energy balance and which minimise large fluctuations in the body weight. However, there is considerable debate as to whether the body possesses physiological mechanisms to maintain the energy balance. It is clear that the changes on one side of the energy balance equation with respect to the energy intake or expenditure lead to changes on the other side of the equation that tends to maintain homeostasis [Blundell et al., 2003]. However, it is also clear that the homeostatic mechanisms can be overcome with large perturbations in the energy balance equation [Selassie and Sinha, 2011]. Physiological adjustment may be more vigorous in some people, as a result of biological factors such as sex, age, or genetic makeup.

At first glance, this energy intake and expenditure equation seems simple. But it hides the complexities inherent in how we acquire and use energy [Vandenbroeck et al., 2007]. In fact, the determinants of obesity are a complex and multifaceted interaction between biological, behavioural, and environmental factors. The complex interaction between these factors controls the energy intake and expenditure, and consequently obesity [Vandenbroeck et al., 2007].

2.5.2 Biological Determinants

Biological factors known to influence body weight levels include age, sex, hormonal factors, and genetic predisposition.

2.5.2.1 Genetic Predisposition

Several studies have shown that biological and genetic factors influence an individual's susceptibility to obesity [Selassie and Sinha, 2011]. Some studies explored the hereditary association of family members and obesity. For example, adoption studies suggest that an adopted child's BMI is more strongly correlated with her biological parents' BMI than the BMI of her adoptive parents. Twin studies show heritability estimates ranging from 50% to 90%, with the highest concordance rates among monozygotic twins, whether they were reared together or apart [Bouchard and Perusse, 1993; Stunkard et al., 1990]. These associations suggest that there is a significant genetic role in obesity in addition to other factors (such as social and environmental factors) [Selassie and Sinha, 2011].

Additionally, genes play a crucial role in how the body obtains, stores and expends energy, which has direct implications for overweight and obesity [Caballero, 2005; Scott et al., 2013]. Genes have been identified that influence the urge to eat; an inclination to physical inactivity; an increased capacity to store fat; and a minimal ability to expend dietary fat [Scott et al., 2013]. Most of the identified genetic causes for obesity are monogenic (single gene), such as the melanocortin-4 receptor gene present in 4% of obese individuals that acts to suppress food intake, with its subsequent deficiency leading to severe obesity [Farooqi et al., 2000]. The leptin gene responsible for the regulation of body weight and adipose stores has also been implicated in obesity. The deficiency of this gene leads to severe obesity in children, while treatment of leptin deficiency causes weight loss [Clement et al., 1998]. Other genes associated with obesity are PPAR, the peroxisome proliferator activator receptor gene, and PC-1, prohormone convertase-1 gene [Comuzzie and Allison, 1998; Selassie and Sinha, 2011]. However, the majority of obesity present in a population is likely to br due to polygenic influences as opposed to a single metabolic defect. Over 250 genes and chromosomal regions are associated with obesity and likely code for proteins that influence energy intake or energy expenditure. Multiple genes that increase one's susceptibility to obesity most likely interact with environmental factors to produce the current pandemic of obesity [Nguyen and El-Serag, 2010].

The importance of genetic or biological factors as determinants of obesity cannot be ignored but from a public health perspective, their role is relatively insignificant compared to other determinants since purely hereditary diseases are very rare and account for a small proportion of the overall disease count [Yang et al., 2007]. Additionally, the effect size of the individual genetic variants on a polygenic disorder such as obesity is typically moderate to small; particularly when adjusting for other confounders or when examining gene-gene or gene-environment interactions [Caballero, 2005]. Genetic research may lead to some important discoveries to explain individual susceptibility, but may explain rather little about the population differences in incidence. Consequently the research will likely benefit a few high risk individuals rather than the population as a whole [Pearce, 2011]. Although genetic explanations reveal an important dimension of obesity, the increasing prevalence of obesity cannot be explained exclusively by changes in the gene pool [Zhang, 2012]. Genes do not function in isolation. They are impacted by behavioural and environmental factors, and this gene environment interaction can create an additional risk of overweight and obesity [Idemyor, 2010].

2.5.2.2 Age

People usually gain weight throughout the life. However, several cross-sectional and longitudinal community studies have shown that the most substantial weight gain occurs during the middle age [Hu, 2008; Thorpe and Ferraro, 2004]. Waist circumference consistently increases with age throughout the life; even older adults after age 65 continue to have progressive increases in waist circumference [Chamieh, 2013]. The mechanism suggested for this weight gain during aging process is mainly biological (some authors consider it as physiological change): as people age, the metabolism of energy input and output changes so that people gain weight more easily. Moreover, fat-free body mass progressively decreases after reaching its maximum level at the age 20, and fat mass increases reaching its maximum level at the age of 60-70 years [Zamboni et al., 2005]. Thus, the age related decline of energy requirements at rest, or in other words the decline in basal metabolic rate, is mainly attributed to the reduction in fat-free mass quantity (Lazzer et al., 2010); Though much emphasis has been given to the biological changes, one should not ignore the various behavioural changes that occur to individuals over the life course [Nooyens et al., 2009]. E.g. leisure physical activities decrease with age due to more involvement in work and family matters [Chamieh, 2013].

2.5.3 Behavioural Determinants

The imbalance in energy intake and energy expenditure is largely a result of factors relating to certain eating and physical inactivity behaviours [Crawford and Ball, 2002]. Therefore, high-energy intake and low physical activity are the identified important risk behaviours for overweight and obesity.

It is likely that a multitude of behavioural factors contribute to this energy imbalance through increasing the overall energy intake and promoting low levels of energy expenditure [Crawford, 2010]. Recent reviews have suggested a number of dietary behavioural risk factors, such as high intake of energy-dense micronutrient poor foods; high consumption of sugar-sweetened beverages; large portion sizes, eating outside [Rennie et al., 2005] and behaviours that may contribute to a lower risk for weight gain such as physical activity and high fibre intake [Zhang, 2012].

However, studies and reviews have also reported inconsistent results on the role of specific dietary and physical activity behaviours [Rennie et al., 2005; van der Horst et al., 2008]. With respect to food intake, convincing evidence for an association with overweight and obesity exists for sugar-sweetened beverage consumption and fiber intake. The evidence for associations with overweight and obesity are less clear for other behaviours such as breakfast consumption, portion sizes and consumption of dairy products and fast food or snack consumption. Snacking, fast food intake and large portion sizes have been found to be associated with energy and fat intake in some studies, but none of these factors have been found to be consistently related to obesity [Moreno and Rodriguez, 2007]. Limited evidence implicates skipping breakfast, low intake of fruit and vegetables and meat eating as risk factors for the development of obesity [Crawford, 2010; van der Horst et al., 2008]. The increase in obesity and overweight strongly parallels increased consumption of sugar-sweetened beverages. Most, but not all, of the studies, have shown a strong positive association between sugar-sweetened beverages drinking behaviour and obesity. In addition to sugar-sweetened beverages, high-fructose corn syrup consumption has also increased steadily since the 1970s, closely paralleling the rise of the obesity epidemic in the U.S. Conversely, sucrose consumption has decreased from nearly 80% in 1970 to 40% in 1997 because it is now being replaced by high-fructose corn syrup [Moreno and Rodriguez, 2007].

Extensive epidemiological research has revealed the role of physical activity in obesity in the past few decades. High levels of sedentary behaviour and low levels of physical activity were found to be the key risk factors for obesity [Crawford, 2010; Zhang, 2012]. This was reported by many studies, which focused on patterns and trends of physical activity in weight control. The designs of these studies varied from ecological, cross-sectional to prospective cohort studies [Trost et al., 2001]. A decrease in physical activity behaviour, directly related to caloric imbalance and weight gain, has been observed globally. WHO reported in 2010 that 60% of the world's population does not obtain the level of physical activity recommended for health benefits [Scott et al., 2013]. Physical inactivity rates have been found to vary greatly from 17 to 91% in different countries [Oldridge, 2008]. Despite all these evidences, the relative importance of different aspects of physical activity is poorly understood. It is unclear whether obesity is similarly related to a reduction in physical activity behaviours and/or an increase in sedentary behaviours [Rennie et al., 2005; Van Der Horst et al., 2007b]. A small but significant association has been found between television viewing and body fatness among children and adolescents, while evidence for specific physical activity such as active transport and leisure time sports, such as walking and bicycling is lacking [van der Horst et al., 2008].

Despite the efforts to identify behavioural factors leading to obesity in health literature, the limitations of this approach are apparent. As Hu et al. (2008) suggested, although diet is generally believed to be important in weight control, there is no "magic bullet" diet for preventing obesity, and the effects of physical activity are generally modest. Additionally, these behavioural determinants of obesity are conditioned by other factors (social, cultural or environmental) [Hu, 2013]. Individuals interact with people in their social environment such as parents and peers and the individual behaviour takes place in cultural environmental settings such as the family norms. Behavioural factors are believed to be important factors in obesity, and are taken as the pathway of social, cultural and environmental determinants in affecting the obesity outcome. Therefore, these factors are also important for examining determinants of obesity related behaviours [van der Horst et al., 2008].

2.5.4 Social Determinants

In addition to the individual level biological and behavioural factors discussed earlier in this chapter, it is important to discuss the social determinants of obesity. Obesity prevalence varies considerably by social characteristics. Gender, ethnicity, socio-economic status and social relations (especially marital status) are the most frequently studied social factors influencing overweight and obesity prevalence [Gallagher et al., 1996; Ogden et al., 2006]. These social determinants provide important insight in the distribution of obesity in various countries [Chamieh, 2013; Sobal et al., 2009; Tzotzas et al., 2010]. This Section discusses these social determinants for obesity.

2.5.4.1 Gender

The effect of being male or female on obesity is both biological and social. According to WHO, sex "refers to the biological and physiological characteristics that define men and women," whereas gender "refers to the socially constructed roles, behaviours, activities, and attributes that a given society considers appropriate for men and women" [WHO, 2014]. The causes of obesity are both biological and social and may vary considerably by sex or gender [Kanter and Caballero, 2012]. Sex differences are mostly related to the difference in fat storage, for example the difference in carbohydrate metabolism between sexes that causes a greater increase in triglyceride levels in women [Kanter and Caballero, 2012]. The differences between the sexes that are apparent early in life become greatest with the onset of menses, and then tend to decrease with the changes in hormone status in postmenopausal women [Power and Schulkin, 2008; Swinburn et al., 2011]. Despite these biological differences related to the sex-specific differences in excess weight gain, gender disparities and related socio-cultural factors are important too. In the context of this thesis, it is more relevant to discuss gender as a social determinant rather sex as a biological determinant of obesity.

Previous studies show that gender deference in obesity is present in all low, middle and high-income countries. Higher prevalence of overweight or obesity in men than women was found in majority of the high-income countries. For example, in Netherlands, men were heavier than women [van Lenthe et al., 2000], in the U.S., NHANES data from 1999-2008 showed that the obesity prevalence in women was 3% lower than that in men [Flegal et al., 2012; Flegal et al., 2010]. In contrast, a higher prevalence of overweight or obesity in women than men was found in a majority of the low and middle-income countries. For example, in Saudi Arabia, 66% of men and 77% of women were overweight or obese.

Researchers suggested that such gender effects were usually explained by cultural belief, psychological mechanism and weight perception on body weight status [Trost et al., 2002; Zhang, 2012]. There are observed differences in social and cultural risk patterns to obesity development according to the economic development of the country. Women in a low, middle-income country have different attitudes toward body weight status and body mage than the women in high-income countries. These attitudes determine the value of practicing healthy food choices and exercise to control the body weight [Wardle et al., 2002; Yoon et al., 2006]. Women in general may face greater social pressures to conform to the ideals of body image than men [Sanchez-Vaznaugh et al., 2009], and those in high income countries may be more prone to media messages of pervasive pictures of the perfect model figure, or are better able to pursue methods of achieving ideal body weight [Sanchez-Vaznaugh et al., 2009]. However, in low and middle income countries, obesity is more culturally acceptable among women because excess weight gain is associated with maternity and nurturing[Kanter and Caballero, 2012].

Additionally, difference in the occupational pattern for male and female in all low middle and high income countries aggravates other socioeconomic and daily life factors that are positively associated with obesity [Meshkani et al., 2006]. In many developing countries, occupation remains a significant source of physical activity. In a number of low and middle-income countries, men perform a much higher daily amount of physical activity than women. More research is required to address the potential sociocultural causes of gender disparities in obesity to better assess gender-specific characteristics [Kanter and Caballero, 2012].

2.5.4.2 Marital Status

Much of the research on social roles/relationship in relation to obesity has focused on marital status. Research findings for this relationship are inconsistent, particularly in cross-sectional studies. Some suggest that married and previously married men and women have more body weight than never married individuals [Sobal et al., 1992]; others suggest that associations of marital status with body weight are gender and ethnicity specific after controlling for age [Crawford, 2010; French et al., 1994].

Many cross-sectional studies have observed a higher prevalence of overweight and obesity among married people than those living alone [Sobal et al., 2009]. In a cross sectional study based on data drawn from the National Health and Nutrition Examination Survey (NHANES) US, white divorced men were less likely to be overweight than white married men, whereas among women, body weight status did not differ with marital status implying a consistency of weight norms among white women. On the other hand, black women who were separated/widowed had higher body weight than those who were married, a phenomenon that might be related to cultural expectations [Sobal et al., 2009; Tzotzas et al., 2010]. Results from longitudinal studies are more consistent, suggesting that marriage predicts weight gain in both men and women, whereas marital termination (through divorce or widowhood) predicts weight loss in both men and women [Crawford, 2010; Janghorbani et al., 2008].

A marital causation model could be a potential mechanism that suggests people in the marital role are more likely to be obese [Lipowicz et al., 2002]. This model explores the positive relationship between the marital status and body weight through social obligations leading to increased food consumption and decreased time for physical activity, and less focus on body image related to the lack of concerns to attract a potential marital partner [Janghorbani et al., 2008; Tzotzas et al., 2010]. Being single was also found to increase the participation in structured physical activity or exercise, thus contributing to a better weight status. This was also attributed to the fact that single adults have more leisure time and less life stressors than the married ones. However, marital status effect could differ in different populations. For example in America, the marital role appeared to influence obesity among men, but not women [Sobal et al., 1992], and in low and middle income countries such as India, marital role appeared to influence obesity among both men and women [Subramanian et al., 2007].

2.5.4.3 Socio-economic Status

Socioeconomic status is commonly conceptualized as the social and economic standing or position of an individual in relation to others in the society. It is often measured as a combination of education, income wealth and occupation. In previous researches, SES is mostly assessed using one or more of the following indicators including income or wealth, education, and occupation [Canoy and Buchan, 2007; Chamieh, 2013; Wardle et al., 2002]. Socioeconomic status (SES) comprises a number of characteristics that influence energy balance equation and obesity. According to Social Cognitive Theory, SES could be working at each level and influencing both energy intake and energy expenditure, that is, income education and occupation could determine one's ability to participate in physical activity and choice of healthy food [Crawford, 2010; Giskes et al., 2008].

In 1989, a review on SES and obesity was published by Sobal and Stunkard [Sobal and Stunkard, 1989]. On the basis of a search of literature from 1960s through the mid-1980s, these authors found 144 published studies on the SES obesity in low middle and high-income countries [Sobal and Stunkard, 1989]. That review concluded that, in high-income countries, SES was inversely associated with obesity among women, but the relationship was inconsistent among men [Crawford, 2010; McLaren, 2007]. Numerous studies have been published after Sobal and Stunkard's review to support the inverse relationship between SES and obesity in high-income countries such as the USA, Australia, France, Great Britain and Spain [Brodersen et al., 2007; Lioret et al., 2007; Proper et al., 2007]. However, literature to study the relationship between SES and obesity is still lacking for low and middle income countries [Chamieh, 2013].

In relation to the low and middle income countries, Sobal and Stunkard's review showed that SES was directly associated with obesity for both men and women. However, most studies included in that review were cross-sectional and therefore could not provide insight into the long-term relationships between SES and obesity risk [Albright et al., 2005; Crawford, 2010; Sobal and Stunkard, 1989]. According to a review published by Macleren in 2007 (including a total of 333 studies published between 1988-2004, representing 1,914 primarily cross-sectional studies from the low and middle income countries), a strong direct relationship of obesity and SES was observed in both men and women [McLaren, 2007].

A recent systematic review by Densa et. al. in 2012, included 42 studies from 36 low and middle income countries [Dinsa et al., 2012]. This review concluded a positive association between SES and obesity for both men and women in low-income countries. The review indicated that more affluent and/or those with higher educational attainment are more likely to be obese. However, in middle-income countries, the association was largely mixed for men and mainly negative for women.

In general, obesity has been associated with high socioeconomic status in middle and low-income countries and with low socioeconomic status in the high-income countries [Neuman et al., 2011]. This pattern suggests a social effect. However these findings vary by the SES indicator used in the study; for example, negative associations for women in highly developed countries were most common with education and occupation, while positive associations for women in medium- and low-development countries were most common with income and material possessions [McLaren, 2007]. Moreover, different SES indicators were related to obesity in different directions. In high-income countries, education and occupation were found to be most common indicators contributing to the inverse SES-obesity association. In low and middle income countries, income and material possessions were most common indicators in the positive SES-obesity association [Zhang, 2012]. Previous researches identified that occupation was most consistently related to obesity, education somewhat less consistently related, and income relatively inconsistently related [Crawford, 2010]. A review on different SES measures and obesity included a total of 135 distinct tests of the hypotheses. Of these, 73 (33 men, 35 women, 5 not stratified) involved tests of education and weight change; 39 (17 men, 18 women, 4 not stratified) tested occupation and weight change; and 23 (9 men, 12 women, 2 not stratified) investigated income and weight change [Ball and Crawford, 2005]. Therefore, it might be reasonable to disaggregate the SES into these three components (education, occupation and income or wealth) in order to find out which component is mainly responsible for this association of obesity and SES. In the following section, education, income or wealth and occupation are discussed separately.

2.5.4.3.1 Education

For a number of reasons, education is one of the most commonly used indicators of SES. Unlike occupation or income, determination of education is relatively easy for all individuals. More importantly, education gives an objective and easy measure for SES [Doblhammer et al., 2009].

Education is chronologically and causally prior to occupation and income. Therefore, the attained educational level anticipates future occupational and potential earnings, and thus access to material resources. The level of education also influences health behaviour, providing better knowledge, access to information and attitude that enables people to integrate healthy behaviours into their lifestyle [Hoffmann, 2008; Monteiro et al., 2004]. The associations between an individual‘s education and healthy food habits and health life style are well documented in high-income countries. Many studies found that education is coupled with increased awareness of healthy dietary intake [Grabauskas et al., 2004; Groth et al., 2001], and to some extent with added resistance to obesogenic environments through higher income [Chamieh, 2013]. However, an important point to note is that many studies, not specifically for obesity, demonstrated that the effect of education is largely reduced when controlled for income [Doblhammer et al., 2009; Hoffmann, 2008].

It is generally agreed that in high-income countries people with lower levels of education tend to have higher probability of being overweight, than people with higher educational levels [Freedman and Martin, 1999; Minicuci and Noale, 2005]. Data from the Health Survey for England, carried out between 2004 and 2008, indicated that people who left school at an early age were more likely to be overweight or obese than those with more education. Likewise, studies from United States, Sweden, Canada and Finland showed similar relations between education and obesity [McLaren, 2007; Moura and Claro, 2012; Wardle et al., 2002].

Data from low and middle-income countries is relatively ambiguous. Dinsa et. al. in a systematic review in 2012 reviewed association of obesity and education in low and middle-income countries[Dinsa et al., 2012]. Education was used as an SES indicator by 17 studies on men, out of which seven studies reported men with more education were more likely to be obese compared with men with no education, while another seven studies reported that men with a lower level of education were more likely to be obese. The remaining three studies found no association between the level of education and obesity. Among women, out of the 26 studies that employed education as an SES indicator, 13 studies found a positive association and 13 studies found a negative association [Dinsa et al., 2012]. A few more cross sectional studies in low and middle income countries have reported that the level of education was found to be inversely associated with obesity in both sexes in Iran [Hajian-Tilaki and Heidari, 2010] and in females only in Turkey [Tanyolac et al., 2008] and Greece [Tzotzas et al., 2010].

2.5.4.3.2 Income/Wealth

As mentioned earlier, among the SES indicators the income/wealth is the least popular indicator. In high-income countries, including America and Europe, the inverse income-obesity relationship has been established; obesity rates are higher among low income/wealth and other disadvantaged groups [Chang and Lauderdale, 2005; Robert and Reither, 2004; van Lenthe and Mackenbach, 2002]. For example, the Health Survey for England 2004-2008, showed that obesity prevalence rises steadily with a falling household income predominantly in women, whereas in men, the variation in obesity prevalence between the highest and lowest income/wealth is small [Observatory, 2010]. In high-income countries, a higher consumption of less expensive and more energy-dense foods is expected from individuals with lower income/wealth accompanied by an inclination towards less leisure-time and fewer chances for recreational exercise [Drewnowski, 2004; Sobal and Stunkard, 1989]. A study carried out in Australia reported that food purchasing behaviours among the socio-economically disadvantaged were least in agreement with the national dietary recommendations [Turrell et al., 2010]. Similarly, in France, energy-dense diets high in fat and sugar continue to be a much cheaper choice than the more nutrient-dense foods [Andrieu et al., 2006; Drewnowski, 2004].

A systemic review done on low and middle income countries by Dinsa et al. concluded, for men, 16 studies used income or wealth as an SES indicator, out of which 11 reported a positive association, one reported a negative and three reported no association between income or wealth and obesity. For women, out of the 23 studies that employed income or wealth as SES indicator, 16 reported positive, four reported negative and three reported no association between income or wealth and obesity. Hence, for both men and women, the majority of the studies, which used income or wealth as an SES indicator, showed that the rich were more likely to be obese in low and middle income countries [Dinsa et al., 2012]. Some reasons for the positive association of obesity and income in low and middle-income countries are food insecurity in poor people [Adams et al., 2003; Martin and Ferris, 2007]. Food insecurity is defined as not having access at all times to sufficient food for an active healthy lifestyle, because nutritious food products are either not consistently available or households are not consistently able to afford such food products [Martin and Ferris, 2007]. Therefore, low-income people in low and middle-income countries suffer more from malnutrition rather obesity.

2.5.4.3.3 Occupation

Occupation is the most consistently associated measure of SES with obesity. The impact of occupation may be seen more in males than females. Given that male adults spend much of each day working, the impact of occupational related total daily energy expenditure can be significant for men [Allman-Farinelli et al., 2010; Scott et al., 2013].

In high-income countries, the overall obesity prevalence in unskilled or lower-status occupations is higher than in professional occupations [Wardle et al., 2002]. There are several possible pathways linking occupation to energy intake and expenditure in high-income countries. Unskilled or low-status occupations are associated with less physical activity at work due to availability of machines and less free leisure time, which makes it more difficult for one to incorporate recreational physical activity into a day to day routine [Estabrooks et al., 2003; Masood et al., 2015a; Misra and Khurana, 2008; Scott et al., 2013]. For example, in Australian workers, a strong association was found between 'occupational sitting time' and obesity. Additionally, people with low status jobs are more likely to buy quick, cheap energy dense food [Mummery et al., 2005]. On the other hand, professionals or people with higher status job although having more sedentary working hours, are reported to have more frequent and vigorous leisure physical activities and more preventive dietary practices [Wardle and Griffith, 2001]. Even with leisure-time activity, sufficient energy expenditure may not be attained to offset the effects of sedentary occupations in relation to overweight and obesity [Allman-Farinelli et al., 2010].

This relationship in low and middle-income countries is reverse where unskilled or lower status occupations are less obese then professional workers. In a study carried out in Cameroon, obesity in men increased as jobs became more professional, with physically demanding jobs appearing to protect people from overweight and obesity [Fezeu et al., 2006]. A study in Ghana found that people engaged in farm or garden work were significantly less likely to be overweight compared with those who were not employed [Chamieh, 2013]. The reason for this is that people in unskilled jobs in low and middle-income countries have more occupational related physical activity and less affordability of enough food quantity. Additionally, occupational status is also indicative of social status in low and middle-income countries and may be a marker of shared beliefs regarding the acceptability of obesity [Wardle and Griffith, 2001]. For men in a higher ranking occupation, particularly those involving management or supervisory responsibilities, a larger body size could be valued as a symbol of authority [Ball and Crawford, 2005].

2.5.5 Environmental Determinants

In addition to the factors discussed so far, researchers are beginning to pinpoint environmental features that are integral to influencing energy consumption and reducing energy expenditure, and consequently obesity. Central to understanding the impact of environment on obesity is the concept of “obesogenicity” of an environment. 'Obesogenic' and 'leptogenic' are the environments that raise or lower the risk of overweight and obesity in populations. 'Obesogenicity' refers to 'the sum of influences of the surroundings, opportunities, or conditions of life that promote an unhealthy lifestyle through inadequate food availability and increased sedentary activity [Swinburn et al., 1999a]. By contrast, the term 'leptogenic' environment corresponds to environments which maintain and promote healthy weights, such as through the encouragement of healthy food choices and engagement in physical activity [Swinburn et al., 1999b]. Obesogenic factors may be viewed as the barriers and leptogenic factors the enabling and reinforcing factors for maintaining a healthy weight [Pearce and Witten, 2010; Swinburn et al., 1999b].

There are a wide variety of ways available in the literature to classify environments [Handy et al., 2002; McLeroy et al., 1988; Winett et al., 1989]. These classifications contained important categories related to obesity. The selection of the model for this thesis will depend on its ability to extend our understanding of the environments related to obesity and to identify opportunities for intervention for obesity control [Giskes et al., 2011; Holman, 1997; van der Horst et al., 2007a]. Previously described classification models of environments contain important categories related to obesity but in the context of obesity, we have adopted the ANGELO (Analysis Grid for Environments Linked to Obesity) framework [Swinburn et al., 1999a]. This model is an appropriate framework to describe the effect of environment on obesity because it was specifically developed to conceptualize obesogenic environments.

Figure 2.2 shows the ANGELO framework. It is a grid which comprises two sizes of environment on one axis and four types of environment on the other (Figure 2.2) [Swinburn et al., 1999a]. The environment can exert a putative influence on obesity at different sizes ranging from micro-environment or settings (e.g. schools or neighbourhood). These micro-environments, in turn, are influenced by the broader macro-environments or sectors, (e.g. global or national), which are less amenable to the control of individuals. Macro-environmental structures are largely beyond the influence of individuals and even governments often have difficulty in influencing these structures because of their size, complexity, and other priorities. Considering countries or nations as an operational unit for macro-environment, it is reasonable to study countries as the largest unit of macro-environment that influences all the micro-environments within the country (e.g. National income of the country influences the availability of food and working conditions in the country). Both these micro and macro-environments have combinations of four types of environments; physical, economic, policy, or sociocultural. Put in simple terms, these environments are related to what is accessible, what is affordable, what are the rules, and what are the attitudes and beliefs. The following section discusses these types and sizes of environments with some related factors that potentially shape individual level food consumption (energy in), physical activity (energy out) and consequently obesity.

ANGELO Framework		
Size / Type	Micro-environment (Setting)	Macro-environment (Sector)
Physical		
Policy		
Economic		
Sociocultural/cultural		

Figure 2.2 Analysis Grid for Environments Linked to Obesity (ANGELO) framework. [Egger and Swinburn, 1997]

2.5.5.1 Physical Environment

The physical environment includes the natural and built environments with physical access to opportunities for physical activity and healthy food. In relation to food, the physical environment refers to what is available in a variety of food outlets including restaurants, supermarkets, vending machines, schools, worksites, and community areas. For physical activity, the physical environment includes the opportunities for participation in leisure, occupational, or incidental physical activities. Factors that influence participation in active leisure activities include the availability of quality recreation spaces, parks, sports grounds, and community clubs. Following sections will discuss the micro and macro food and physical activity environments. Recreational environmental factors are those, which influence the use of active transport (walking, cycling) over motorized transport (cars, lifts, escalators) including the availability of cycle paths, footpaths, street lighting, public transport, and accessible stairs in buildings.

Food consumption can be influenced by macro-environment through factors such as global food production or international trade agreements. These factors can alter the availability and cost of different types of foods of different nutritional value [Pearce and Witten, 2010]. At the country-level, factors such as the national income, national income inequality, the regulations or codes of conduct for advertising food vary between countries and determine obesogenicity of the environment. At the micro-environment level, factors such as the availability and affordability of the type of food in a neighbourhood supermarket and restaurants influence the purchasing decisions, and ultimately the nutritional intake of its customers [Pearce and Witten, 2010].

The relationship between one's access to food and obesity has been a major research field in the studies on the environment and obesity. In various scenarios, the local availability of fast food and supermarket is used as a proxy of fast food intake or food intake leading to obesity. In many countries, fast food restaurants have been identified as an environmental risk factor for obesity [Jeffery and French, 1998]. A study in United States demonstrated that the presence of supermarkets was associated with a lower prevalence of obese and overweight in the residents, while the presence of convenience stores was associated with a higher prevalence [Morland et al., 2006]. Fast food outlets tend to be disproportionately placed. In developed countries, fast food outlets are present more in poorer neighbourhoods whereas in developing countries more outlets are present in affluent areas [Reidpath et al., 2002]. Stafford et al. (2010) discussed how some studies have found that there are more fast-food outlets per capita and fewer healthful food stores per capita in deprived neighbourhoods [Stafford et al., 2010]. Li et al. examined the density of neighbourhood fast food outlets among 1,221 older residents from 120 neighbourhoods. They found that the increased density of neighbourhood fast food outlets was associated with unhealthy lifestyles, poorer psychosocial profiles, and increased risk of obesity [Li et al., 2009]. Cummins and MacIntyre (2006) and Moore et al. (2008) both found that the positioning of supermarkets, convenience stores and grocery stores in a neighbourhood have an effect on obesity [Cummins and Macintyre, 2006; Moore et al., 2008]. Moore et al. (2008) found that participants with no supermarkets near their homes were 25-46% less likely to have a healthy diet [Moore et al., 2008]. Poorer communities have deprivation amplified when it comes to the food environment.

Morland et al. (2002) compared the food retail environment between deprived and wealthy neighbourhoods. They found that a limited access to supermarkets in the poor neighbourhoods hindered the healthy food choices compared with the wealthy neighbourhoods [Morland et al., 2002]. Other than the availability of food, emphasis is given on convenience in food availability. Convenience in food availability includes not only the proximity of food outlets but also how much time is required to purchase and prepare food for consumption. People have dramatically increased the proportion of their food money spent away from home; and the majority is spent at 'fast food' restaurant outlets with limited menus, quick service, and the option to take food out to be eaten elsewhere [Crawford, 2010]. This trend is reflected not only in developed countries but, with globalization, it appears in developing countries such as India and China as well where these fast food outlets are opening quickly. Additionally, the amount and variety of the food distributed through automated vending machines has also increased [Crawford, 2010]. Foods available in traditional food stores are also increasingly processed to facilitate ease of preparation.

It is not only the availability of food but also portion size which is important. It is also one of the most ignored aspect in the food environment research. This portion size problem has worsened due to the promotion practices over the last two decades to promote larger portion sizes for small increase in price. Products ranging from soft drinks to burgers are now available in much larger sizes than in previous decades [Young and Nestle, 1995]. When products are available in multiple sizes, the unit price for larger servings is usually less [French et al., 2001]. People often prefer quantity over quality especially people from low socioeconomic status. Food manufacturers and restaurants provide larger food portions as a sign of a good deal for consumers. The Food and Drug Administration (FDA) as well as the United States Department of Agriculture (USDA) developed standard serving size determinations for different food items. However, most marketplace portion sizes range from two to eight times of the standard serving sizes recommended by the USDA and FDA [Diliberti et al., 2004]. Keeping all the other factors equal, merely increasing food intake leads to increased daily calorie consumption and subsequent weight gain [Nielsen and Popkin, 2003; Selassie and Sinha, 2011]. One major change over time is the increase in perceived standard portion size. Some portion sizes that were at one time considered standard (e.g. 177- and 237-ml bottles of Coca Cola) are no longer sold at all; and are replaced by now considered standard size (e.g. 592-ml bottles of soft drink). It has been shown experimentally that portion size has a significant impact on food consumption in single-meal settings and that the effects of larger portion sizes on chronic food intake persist for at least a month without compensatory reductions in consumption of other foods [Crawford, 2010].

Regarding the energy expenditure, the levels of physical activity are influenced by the macro-environment factors such as patterns of trade associated with globalization, which in turn shape the types of employment opportunities available in different places. In many countries, these structural adjustments have been associated with a shift from physically active manual occupations to more sedentary employment opportunities. The urban design strategies of central and local governments also influence the physical activity facilities in the areas. For instance, mixed land use and the variety of community resources accessible locally, such as places of work, parks, etc. increase the opportunities for local residents to walk or cycle around their neighbourhood, which in turn is likely to increase physical activity of the population.

At a micro-environmental level, similar to food access, the access to the facilities promoting the physical activity also affect the obesity status of the people that area [Ferreira et al., 2007; Wendel-Vos et al., 2007; Zhang, 2012]. But the data on population exposures to physical activity is in shorter supply than those on the trends in food supply, thereby making an appraisal of activity factors in the obesity epidemic difficult [Crawford, 2010]. Environmental factors related to physical activity range from recreation facilities, energy saving equipment, transportation facilities to sedentary entertainment devices.

Availability of gyms, parks, and other sports facilities are part of the environment that offers structured settings for physical exercise. Individuals with greater access to recreation facilities are more likely to engage in physical activity, hence are at a lower risk of obesity [Crawford, 2010; Zhang, 2012]. Many studies have demonstrated that the presence or proximity of recreational spaces and facilities in local communities could significantly influence physical activity levels and health outcomes of the members of the community [Jeffery and French, 1998]. Researchers have specifically examined the association between parks and physical activity [Bedimo-Rung et al., 2005]. Many studies have shown that those with more access to parks engaged in more physical activity than those with fewer parks [Cohen et al., 2006]. Both cross-sectional and longitudinal studies in the U.S. have shown that the access to the facilities such as walking trails, swimming pools and gyms were positively correlated to physical activity in the American adults and reduced the risk of obesity [Brownson et al., 2001]. Similar evidence is found in the inverse associations between playground accessibility and obesity [Scott et al., 2007].

Increased availability of labour saving devices at domestic and occupational level in the last three decades has resulted in a shift from traditional active lifestyles to a sedentary lifestyle [Lanningham-Foster et al., 2003]. Example of some commonly used labour saving devices are power lawn mowers, automatic garage doors, television remote controls, keyless entry devices, automatic garden sprinklers, electric pencil sharpeners, and microwave ovens [Crawford, 2010]. Lanningham – Foster et al. (2003) completed a study that compared traditional labour methods with current labour saving methods. Their results concluded that participants used greater energy expenditure while performing the domestic tasks by hand compared with using the machine and that current methods of living are most likely contributing to increased weight issues [Lanningham-Foster et al., 2003]. Nevertheless, it is certainly plausible that the cumulative effects of labour saving devices can contribute, in part, to the steadily declining number of hours that US adults spend on energy expending housework (a reduction of 20% since 1965) [Suzanne M. Bianchi, 2000].

More people are using cars to commute to and from work. Research findings also illustrate how the reliance on the motorcar also interconnects to the environment. Urban expansion and the changed built environment have caused individuals to rely on the motorcar to get from place A to place B rather than relying on traditional methods of walking and cycling. The increased demand for motorcars has caused many cities to be designed around the car, altering the built environment and disregarding the beneficial health and environmental effects that individuals can receive from alternative transport modes. Because of the decreased street connectivity, less social cohesion, increased traffic volume and less cycle lanes, there is an increasing numbers of safety conscious parents and caregivers who do not allow their child to walk or cycle to school [Wolch et al., 2011].

Increase in time spent in front of a television screen and computers play a large role in increasing obesity. One study suggests that time spent watching TV was more closely correlated to BMI than the amount of time spent doing vigorous activity. Aside from the fact that people are quite sedentary when watching TV and spend very few calories, some studies suggested that the targeted advertising in television commercials may encourage excessive calorie intake by continuous snacking [Selassie and Sinha, 2011]. However, the most explosive growth of these technologies has been in the developing world; where the number of television sets and computers has increased dramatically. In the developed world, multiple electronic entertainment devices are already normative. In the USA, for example, the proportion of households with multiple television sets increased from 35% in 1970 to 75% in 2000. During the same time period, the percentage of households with cable television access increased from 7% to 76% [Crawford, 2010].

2.5.5.2 Policy Environment

The policy environment refers to the rules related to food and physical activity and includes laws, regulations, policies (formal or informal), and institutional rules such as school and household rules. When considering food, for example, at the micro-environmental level of the household, the policy environment includes the household nutrition policy and household rules related to food. At the macro- environment level, the policy environment refers to government food and nutrition policies, regulations and laws, and food industry policies and standards [Swinburn et al., 1999a]. When considering physical activity at the micro-environmental level, the policy environment influencing physical activity in the home could be family rules on the amount of involvement in active games.

Policy micro-environment has been investigated in various setting such as households, school and workplaces. Schools are the most commonly investigated setting for policies. For example, at the school setting, the policy micro-environment includes the school nutrition policy and school rules related to food [Booth and Samdal, 1997]. The evidence evaluating the association between school obesity prevention policies and student weight is mixed. The lack of consistent findings may result, in part, from limited evaluation approaches [Nanney et al., 2014]. In the workplace setting, various studies investigated the ways to prevent obesity among workers through micro-environment interventions using incentive strategies, including price discounts for low-fat snacks and sugar-free beverages at workplace cafeterias or vending machines, and the provision of a free salad bar in cafeterias [Sutton, 1974]. Measuring policy influences may be quite difficult at the micro level as rules in these environments are often not formalized or overt.

At a macro level, the regulations, laws, and town planning policies which give priority to active transport (cycling or walking) or public transport use over car use will increase the physical activity levels [King et al., 1995]. For example, some studies have concluded that promoting bicycling resulting in having fewer overweight/obese residents, partially because the policies are related to supportive bicycling infrastructures that promote bicycling to work or school [Suminski et al., 2014]. Local government policies have a profound effect on recreational activity through provision of parks, community recreation centers, and sporting facilities. Building codes and regulations can be used to promote “physical-activity-friendly” buildings with attractive, safe, and readily accessible stairs [King et al., 1995]. The evidence related to recreational facilities and physical activity has been discussed in detail in the physical environment section of this thesis. Related to food pricing policies at the micro-environment level, limited existing evidence suggests that small taxes or subsidies are not likely to produce significant changes in BMI or obesity prevalence [Powell and Chaloupka, 2009]. The focus of this study was to examine the effect of economic and cultural environment on obesity. Therefore, this policy environment has not been discussed in detail in this thesis.

2.5.5.3 Economic Environment

The economic environment refers to the costs related to food and physical activity and people's ability to pay for these items. In relation to food, the major economic influences are the costs of food production, manufacturing, distribution, and retailing. These costs are determined largely by market forces, but some opportunities exist for public health interventions. The relative cost of healthy choices can be reduced by reducing the actual costs (e.g. by subsidising vegetables) or by increasing the ability to pay (e.g. by reducing income tax for low-income earners). As mentioned earlier, the economic environment is an important factor, not only in terms of costs but also in terms of income. Factors that affect income (national and personal) are important determinants of body weight, through food choices and physical activity. Some personal (household wealth, education level and occupation) and national (national income, national income inequality) factors have been included in this thesis as micro and macro-environment factors respectively.

Some studies have reported that socioeconomic status, both at the individual and environmental levels, is linked with unequal exposure to healthy or unhealthy food and exposure to physical activity. Individuals with lower socioeconomic status or living in lower socioeconomic status neighbourhood or country are more vulnerable in their exposure to unhealthy food. Studies have also reported that lower socioeconomic status subgroups are more vulnerable in their exposure to unhealthy local physical activity settings. In a study of physical activity settings and SES in U.S. communities, it was found that the availability of pro-physical activity environmental factors (such as sports areas, parks and green spaces, public pools and beaches, and the presence of bike paths/lanes) were significantly and positively associated with socioeconomic status factors [Scott et al., 2007]. People household wealth, educational level and occupation are important factors that affect obesity through energy intake and energy expenditure behaviour. These individual level socioeconomic factors and their relationship with obesity have been discussed in detail in the social determinants section of this thesis.

There are a range of economic macro-environment factors, such as food production and distribution, affordable physical activity environment, economic development and income inequality of the country, that can affect obesity. National income and income inequality have been the most frequently used country level economic macro-environment factors in relation to health and obesity. In this thesis, I have used these two country level factors as economic macro-environment factors. Therefore these two factors are discussed here.

Recent studies have concluded that national income, as measured with the Gross Domestic Product (GDP) per capita or Gross National Income Purchasing Power Party (GNI-PPP), is associated with many health outcomes such as cardiovascular disease, depression, BMI and obesity. However, there are a few health outcomes (e.g. high blood pressure) that were not associated with the national income [Su et al., 2012]. There are some studies especially from high-income countries, which observed no association between national income and obesity [Su et al., 2012]. The lack of this association of national income in explaining obesity prevalence tends to suggest that absolute national income is no longer a powerful predictor of obesity prevalence across high-income countries. Presumably, national income should be more relevant in predicting obesity prevalence in less developed countries where starvation, malnutrition or high level of manual labour occurs. In low and middle-income countries, national income should be more strongly correlated with net calorie intake than in high-income countries. In a cross-national analysis of 85 low, middle and high-income countries, Ezzati, Vander Hoorn, et al. (2005) observed an association between national income and mean BMI [Ezzati et al., 2005]. These results suggested that after national income increases to a certain level, whereby most people in the population have enough to eat, its importance in explaining differences in obesity prevalence across countries gradually dwindles. A similar lack of explanatory power of national income has also been observed when it comes to disparities in life expectancy [Marmot and Wilkinson, 2001].

Clearly, economic growth is currently a primary means by which low-income countries can lift themselves out of poverty. It has also undoubtedly been one of the single biggest influences on health improvements throughout human history [Riley, 2001]. However, by the law of diminishing returns, beyond a certain point, the benefits from continued economic growth start diminishing and ‘costs’ start rising [Egger, 2009]. Egger and Swinburn (2010) thus postulated that there may be a theoretical national income which is high enough to produce good health, sufficient prosperity and happiness, but not so high that it produces the overconsumption and problems of obesity [Egger and Swinburn, 2010; Egger et al., 2012]. A reason for these mixed results of national income and obesity relationship may be the lack of inclusion of low, middle and high-income countries together in a single study. It is also important to observe that the nature of the relationship of the determinants of obesity with obesity varies with national income. As discussed in previous sections, women have a higher BMI than men in low and middle-income countries whereas men have a higher BMI than women in high-income countries. In high-income countries, people with lower education, low income and manual jobs are heavier than the people with higher education, high income and professional jobs. In contrast, in low and middle-income countries people with higher education, high income and professional jobs are heavier than people from lower education, low income and manual jobs.

In addition to national income, another economic factor whose contribution to general health and mortality has attracted substantial attention over the past decade, and which has also been argued to exacerbate the prevalence of obesity is the inequality in the distribution of incomes in the population ("income inequality") [Kim et al., 2008; Masood et al., 2012; Pickett et al., 2005; Wilkinson and Pickett, 2009]. Previous studies have documented an association between income inequality and population health including obesity [Kahn et al., 2000; Kaplan and Nunes, 2003; Kawachi et al., 1997; Montefiori et al., 1992; Wilkinson, 1992]. A majority of existing studies are wholly or partially supportive of the observation that, after adjusting for national income, health was worse in countries or regions where income inequality was greater. Most of these studies used mortality (e.g. life expectancy, infant mortality or adult mortality) as an indicator of population health, relatively little is known about the relation between income inequality and the prevalence of specific health conditions such as obesity [Su et al., 2012]. Using aggregate information Pickett et al. (2005) and Wilkinson and Pickett (2009) find strong support for an association between income inequality and obesity across 21 high-income countries and 50 U.S. states. Similar results have been reported by Diez-Roux et al. (2000) using individual data from the 1990 BRFSS, and by Subramanian et al. (2007) for a sample of Indian women. However, Chang and Christakis (2005) using data from the 1996-98 BRFSS find no effects of inequality measured at the level of Metropolitan Statistical Areas [Chang and Lauderdale, 2005; Diez-Roux et al., 2000; Pickett et al., 2005; Subramanian et al., 2007; Volland, 2012; Wilkinson and Pickett, 2009]. Similar to national income, there is no multicountry study available that observed the relationship of obesity and income inequality across low, middle and high-income countries together in a study.

A review of the literature on income inequality and health suggests three pathways by which income inequality and obesity may be associated [Subramanian and Kawachi, 2004]. Each of these three pathways can shed light on the nature of the association between income inequality and obesity prevalence, as discussed below [Su et al., 2012; Subramanian and Kawachi, 2004].

One of the most fundamental pathways concerns the so-called ‘concavity-induced income inequality effect’ [Subramanian and Kawachi, 2004]. Societies or regions with a higher-level income inequality are usually associated with under-investment in human resources such as education and medical care [Kaplan et al., 1996; Lynch and Kaplan, 1997]. This leads to a ‘structural pathway’ which points to a causal effect of income inequality on residential segregation and spatial concentrations of poverty in economically disadvantaged communities. Residents from these deprived communities face elevated risks of obesity due to various factors such as inadequate supply of affordable nutritional food, poor street or pavement conditions that discourage walking, higher crime rates that deter outdoor activities and lack of adequate facilities to exercise [Lopez, 2007; Su et al., 2012].

The second pathway is what Subramanian and Kawachi termed as ‘social cohesion’ or ‘social capital’. This pathway has been based on the observations that higher level of income inequality is associated with disinvestment in social capital, which in turn can contribute to a series of negative health outcomes [Kawachi et al., 1997]. The ‘social capital’ pathway has rich implications for the association between income inequality and obesity. According to this pathway, when societies become more unequal and polarized, mistrust and lack of reciprocity becomes more commonplace. This, in turn, creates more psychological stress at the individual level, which can contribute to an increase in behaviours that are detrimental to health such as smoking, alcohol abuse and the use of illicit drugs. In this sense, the ‘social capital’ pathway can be viewed as a component of the psychosocial pathway that has been documented in the literature [Lynch and Kaplan, 1997; Wilkinson and Pickett, 2006]. Presumably, an individual who has experienced emotional or psychological stress will become less attentive to issues related to diet, exercise and weight gain. Several psychological and neurobiological mechanisms have been suggested as an explanation to stress-induced overindulgence in food, usually emphasizing the stimulating effect of food consumption on the reward systems in the brain stem [Dallman, 2010]. Animal studies also suggest that stress hormones directly influence the incentive salience of food cues, and thus contribute to compulsive intake [Pecina et al., 2006]. Indeed, there is overwhelming evidence for a strong association between abdominal obesity and (chronic) stress measured in various ways among human individuals [Kyrou et al., 2006]. For instance, high levels of stress in a baseline year significantly increase the odds of a more than 10kg weight gain over the following 6 years [Korkeila et al., 1998]. Therefore, rising levels of psychological ill-being have been suggested as a cause of the on-going rise in obesity prevalence within wealthy societies [Dallman, 2010; Volland, 2012].

The third pathway mentioned by Subramanian and Kawachi is the ‘policy pathway’, whereby the adverse influence of income inequality on obesity may operate through the formulation and implementation of general social policies as well as through health related policies. Usually, the more polarized a society is, the more difficult it will be to implement policy initiatives that can effectively address health or health care challenges faced by both the low income and the high income segments of the population [Kawachi et al., 1997; Su et al., 2012].

However, in some studies, the role of income inequality as one of the major determinants of population health has been questioned. Lynch and colleagues have suggested that the relation between income inequality and life expectancy may have resulted only from the analysis from a small number of countries; this relationship weakens to a large extent when new studies with better data from different countries was available [Lynch et al., 2001]. Various studies from Canada, Denmark, Japan, and New Zealand did not show any association of health with income inequality [De Vogli et al., 2005; Fiscella and Franks, 1997; Muller, 2002; Ross et al., 2000; Shibuya et al., 2002]. A recent study from Canada did not find any significant association between income inequality and health outcomes concluding that the relation between income inequality and health is not universal, but instead dependent on social, cultural and policy characteristics of the specific country [Ross et al., 2000]. As results on the relation between income distribution and health outcomes have been inconsistent, previous evidence has been dismissed as spurious. At least, two major factors have been proposed to explain away the effect of income inequality on health: per capita income and educational attainment. Others still maintain that population health does not depend on how income is distributed, but is dependent more on individual level income [Muller, 2002]. These findings have been subsequently augmented with data from Brazil, which showed that the introduction of illiteracy into the analysis explained away the association between life expectancy and income inequality. A majority of empirical studies relating individual health to the distribution of income yielded mixed or unsupportive results, notably when controlling for diminishing returns to absolute income [De

Vogli et al., 2005; Lorgelly and Lindley, 2008; Zheng, 2012]. Nonetheless, national income and income inequality regularly remain as viable economic measures at the country level.

In summary, many questions remain unanswered about whether and why there is an association between income inequality and BMI, which require further evidence from a variety of social, economic, and cultural contexts including low, middle and high income countries. If the relation between income inequality and BMI varies according to the characteristics specific to a country, it is Income inequality and culture of the country that is of great interest to investigate such association in different nations. To date, we are not aware of studies that have undertaken this research on low, middle and high-income countries.

2.5.5.4 Cultural Environment

The obesity related cultural environment refers principally to the norms, attitudes, beliefs, and values related to food and physical activity of a community or a society. It also includes the attitudes, beliefs, and values towards the body size and ideal body image. Similar to the other three types of environments (physical, policy and economic), the cultural environment also operates at both micro and macro-environment level. Culture however remains one of the least explored determinants of obesity, especially at the macro-environment level. The most likely reason for this lack of exploration is the difficulty in conceptualizing and quantifying the culture. On the other hand, at micro-environment level most researchers have followed a beliefs/value systems approach to operationalize culture e.g. beliefs of people about the impact of body image and body size [Johnston, 2011].

Surely the “Cultural Environment” relates to more than just food, physical activity and attitudes about body size/image. The influence that culture (through norms, attitudes and beliefs) has on changes in a population's weight is not simply through relationships to the obvious direct influences.

Looking at the relationship between culture and health is not new [Allotey and Reidpath, 2001; Bhui, 2009; Dillip et al., 2012; Trostle, 2005]. In general, the interest has been on (a) the relationship between local beliefs and practices (the culture) and the understanding that research scientists have of disease categories, aetiology and prevention [Allotey and Reidpath, 2001] [Allotey and Reidpath, 2001; Dillip et al., 2012] and (b) the effect that cultural beliefs and practices have on disease incidence in specific communities [Sutan and Berkat, 2014]. The application of “mixed methods” to provide a deeper understanding of the meaning underlying relationships revealed in quantitative analyses of the data [Allotey and Reidpath, 2007; Allotey et al., 2003].

In line with the anthropological locus of the research the data on cultural beliefs and practices has tended to rely on more qualitative data and ethnographic methods that can provide a detailed understanding of specific groups and specific communities [Kiawi et al., 2006; Kumar, 2001; Mays and Pope, 1995]. Many of the studies on the relationship between food and culture take this kind of “thick”, data rich, often heavily qualitative approach [Cappellini and Yen, 2013; Orji and Mandryk, 2014; Tannahill, 2002].

In this section, I first try to define the culture and then summarise the available literature on cultural micro-environmental and obesity. Later, I discuss the difficulties and rationales considering cultural macro-environment (country level) as an obesity determinant. This section also discusses the methods of quantification of culture at macro-environment (country level) with particular reference to Hofstede cultural dimensions [Hofstede, 2011; Hofstede et al., 2010; Meeuwesen et al., 2009b; Minkov and Hofstede, 2012].

2.5.5.4.1 Definition of Culture

There are many challenges in studying culture as a determinant of health. The first and perhaps the most important challenge is arriving at an appropriate definition. “Culture” has myriad definition which are hotly contested within anthropology, and between anthropology and other disciplines [Baldwin, 2006; Barnard and Spencer, 2010; Trostle, 2005]. As you will see, however, while subtleties may be contested, there appears to be workable agreement around the broad-brush strokes of the concept.

The English anthropologist Edward Tylor (1832–1917), proposed a now classic definition of culture, as a “complex whole which includes knowledge, belief, art, morals, laws, custom, and any other capabilities and habits acquired by man as a member of society” [Tylor, 1920]. The American anthropologist Clifford Geertz, suggested that culture was “a system of inherited conceptions expressed in symbolic forms by means of which people communicate, perpetuate, and develop their knowledge about and attitudes toward life” [Geertz, 1973]. Hall defined culture in terms of the visible dimension of behaviour and the invisible dimension comprising values, assumptions, and beliefs [Hall, 1976]. More recently, Triandis (1995) suggested that culture was an individual's characteristic way of perceiving the man-made section of his or her environment [Triandis, 1995]. It involved the perception of values, norms, rules, and roles which is influenced by gender, race, language, religion, place of residence, and occupation. Drawing together the commonalities of earlier definitions. Doherty and Groeschl (2000, p.14) acknowledged the difficulty in defining culture, but concluded that most often it was defined in terms of norms, values, behaviour and basic assumptions [Groeschl and Doherty, 2000].

Bates and Plog (1990) provide a widely adopted definition of culture as shared beliefs, norms and values transmitted across generations [Bates and Plog, 1990]. In *Social Causes of Health and Disease*, William Cockerham defined culture thus:

> [W]ays of living that have been passed on from one generation to the next in the form of abstract ideas, norms, habits, customs, and in the creation of material objects such as food, dress, housing, …. Culture thus refers to a body of common understandings that represent what groups of people and societies think, feel, and act upon. The knowledge, beliefs, values, customs, and behaviours shared by people in a particular society reflect the culture of that society [Cockerham, 2013].

Geert Hofstede in his studies of national cultures draws on these ideas of shared values, norms, and beliefs when he writes of culture in terms of "software of the mind" [Hofstede et al., 2010]. Hofstede (2001) defines culture as "the collective programming of the mind which distinguishes the members of one group or society from another". Hofstede's definition of culture clearly draws on other existing definitions. It is however most relevant definition for my thesis because in its empirical application it was used explicitly to describe and quantify differences in the national culture of countries. The Hofstede's definition and dimensions of national culture have been extensively validated and widely cited in research and is one of the few definitions that has been readily quantifiable [Hofstede, 2001b].

2.5.5.4.2 Cultural Micro-Environment and Obesity

The majority of research on culture and obesity has been done at the individual and the micro-environment level to study views and attitudes of body image, and explain variation in levels and types of food consumption and physical activities [Brewis et al., 1998; Levy-Navarro, 2008; Rush et al., 2004; Swinburn et al., 1999b; van Lenthe et al., 2014; Wardle et al., 2006].

In the developed nations, especially western societies, cultural motivators for a healthy weight include the social value of attractiveness, the strong correlation between attractiveness and perceived fitness, the interrelation among attractiveness, a good body image, and feelings of self-esteem, and the relation among pressures to succeed in the appearance- and work-related domains [Rodin, 1993]. Studies have shown that weight-based stigmatization is common among the obese people in America and obese individuals are stereotyped as being ugly, stupid, mean, sloppy, lazy, dishonest, worried, sad, self-indulgent, unlikable, and emotionally impaired [Friedman et al., 2005; Latner and Stunkard, 2003; Zhang, 2012].

There is a widespread culturally related tolerance to fatness in many low and middle-income countries including Arab, African, Asian, Indian countries [al-Isa, 1999; Musaiger, 2011; Musaiger et al., 2004]. In many low and middle income countries, overweight and obesity have been historically associated with wealth, health and happiness. This was the case in the high income countries at the turn of the twentieth century, where, to quote Grivetti, 'fat cheeks and ample stomachs were visual cues that individuals were healthy, not infected with the dreaded slim tuberculosis' [Grivetti, 2001]. These same issues are at play today in low income countries, where HIV, tuberculosis and other diseases associated with wasting are highly prevalent, along with under-nutrition, chronic poverty, war and natural disasters [Renzaho, 2004]. In this context, it makes sense that ample weight marks privilege and power. Women who would be considered overweight in a Western context are referred to as 'nzele ya vundese' in central Africa (a lady with a good bottom) or 'hilib fiican' in Somalia (a lady with good flesh) [Renzaho, 2004]. Across African, Gulf countries and Indian subcontinents, there is a universal preference for a curvy body shape among women [Scott et al., 2007]. Once married, extra weight is seen as an indicator that her husband is caring for her well; in turn, a chubby husband is being well-fed by his wife and is seen as a symbol of social status [Brown, 1991; Puoane et al., 2005]. A study in Cameroon found that heavy men were perceived as imposing and authoritative; thinness was antithetical to power [Kiawi et al., 2006]. Previous studies on obesity in China suggested that there was a belief in China that excess body fat represented health and prosperity, and that traditional Chinese culture even conceived greater body weight as associated with a higher social status [Chen and Meltzer, 2008; Wu, 2006]. These beliefs and values about body weight and size are prevalent in most of the low and middle income countries such as African, Gulf and Asian regions. These cultural norms may serve to catalyze increases in overweight and obesity and act as a significant barrier to success of any intervention program [Kumanyika, 1993].

Apart from body weight, beliefs and perceptions about food varies in different cultures and determine the BMI of people. The 'luxurious' food includes meat, fizzy drinks, fried foods, butter and margarine, sugar, packaged foods, and other foods associated with the West, which have traditionally been very expensive. Vegetables, legumes, and fruits are seen as foods for survival, or poor people's food [Scott et al., 2013]. As 'food of white people' becomes more broadly available, this system of symbolism could accelerate the nutrition transition and the prevalence of obesity across low-income countries. As such, it is pivotal that anthropological research helps set the stage for interventions in any context, to identify and seek to address local meanings surrounding obesogenic foods. Some research has looked into the impact of culture on food intake. Food intake behaviour plays a major part in the construction of the individual, social and cultural identity [Chamieh, 2013]. Culture of a country or people also have influence on the type, choice and portion size of food. For example the traditional diet in Mediterranean countries includes olive oil, plant foods, fresh fruits, minimally consumed red meats, and moderately consumed red wine [Nasreddine et al., 2006].

Leisure or structured physical activity of a person is also influenced by the culture of the society that he/she is part of. Therefore, it is important to discuss different cultures. For example, in some countries such as the Middle East, North Africa and Asian countries, many sociocultural barriers generally challenge women more than men for engaging in physical activity. In conservative societies, women are often overprotected and due to cultural or religious barriers, cannot publicly participate in physical activity [Kanter and Caballero, 2012]. In general, men have more freedom, sports facilities and other recreational activities. In an exploratory study on sports and culture carried out in Iran, women perceived that culture-based constraints and traditions delimited their freedom, including participating in sports activities [Arab-Moghaddam et al., 2007]. Women reported that they were to get permission from family members to participate in leisure activities, and were not allowed to engage in gender-integrated activities [Wilhelm Stanis et al., 2010]. Furthermore, sports was purely perceived as leisure for men, and only reading, watching TV and family gatherings were perceived as types of leisure for women [Arab-Moghaddam et al., 2007]. Turkish women reported being confronted most of the time with negative attitudes by family and relatives towards their practicing exercise [Musaiger, 2011; Wilhelm Stanis et al., 2010]. It has been generally observed that ethics of care and family responsibilities were the most reported constraints to physical activity, followed by economics which was more evident for people from the lower class [Chamieh, 2013; Koca et al., 2009].

Cultural differences regarding the role of women in society is another important explanation of cultural variations in obesity among women. It is likely that the accepted role of women in traditional Muslim societies may make them less likely to be physically active and thus more susceptible to obesity than men, whereas women's roles in Asian countries may make them less so. On the other hand, the high value placed on education and academic pursuits in some Asian cultures (e.g. Singapore) may mean that many of these children spend a large amount of their free time being tutored, leaving little free time for sport or active play, and this may have contributed to the recent rise in childhood obesity observed in some Asian cultures [Caprio et al., 2008]. Religious beliefs and ceremonies (e.g. feasting and fasting), and attitudes and beliefs relating to the role of food in social settings, the role of physical activity, and the importance of appearance may also be significant in translating cultural values into weight-related behaviours [Caprio et al., 2008].

2.5.5.4.3 Cultural Macro-Environment and Obesity

No attempt appears to have been made by obesity researchers to relate the macro-environmental culture to the occurrence of obesity. As I mentioned earlier, the most important operationalized unit for macro-environment is a country. Therefore, it is important to measure culture at the country level to determine its effect on people's BMI. There are several other important reasons to explore the culture of countries as a determinant of variation in obesity among countries. According to Tayeb (1994), these reasons are related to (1) the fact that, if not in absolute terms, cultural values and attitudes are different in degree at least in some cases from one country to another, (2) the fact that under similar circumstances different cultural groups behave differently because of the differences in their underlying attitudes and values, and (3) the important role that culture plays in shaping social norms and behaviour [Tayeb, 1994]. If we accept that at least some of the variations in obesity are attributable to cultural variations, we might then question why obesity or overweight are culturally patterned. Despite a large body of literature on the influences on eating and physical activity generally, there has been much less research that directly investigates the extent to which the determinants of eating and physical activity vary by cultural factors and, if so, whether cultural differentials in these determinants contribute to explaining cultural variations in diet and physical activity, or in obesity risk [Crawford, 2010].

A key question that has arisen in studies that rely on the measurement of country level cultural macro-environment is the extent to which one can actually write of such a thing [Groeschl and

Doherty, 2000]. Does “country level culture” make sense? Countries are often agglomerations of diverse ethnic groups, each of which, one might imagine, have different shared norms and values [Tung, 2008]. The intra-national variation in values and beliefs may, therefore, be quite substantial. In a series of recent studies based on World Values Survey data, Minkov and Hofstede considered just this question [Minkov and Hofstede, 2012; Minkov and Hofstede, 2014]. They conducted a series of cluster analyses allowing for agglomeration of values within random geographies versus real, national geographies. If “country level culture” had no explanatory power, one would not expect the cluster analyses of national geographies to outperform the cluster analyses of random geographies, but they do. Minkov and Hofstede found clear evidence for country level cultures; although there were exceptions [Minkov and Hofstede, 2012; Minkov and Hofstede, 2014]. This is not to say that there was no diversity of values within countries, but that there are some broad “averagely” shared national values.

> This [variation] is true even of countries like Malaysia and Indonesia, or Mexico and Guatemala, despite their shared official languages, religions, ethnic groups, historical experiences, and various traditions. Even the regions of neighbouring African nations, such as Ghana, Burkina Faso, and Mali, do not intermix much when they are clustered on the basis of cultural values [Minkov and Hofstede, 2012]

We would suggest that eating is culturally patterned[6], and by extension secular changes in population obesity will be influenced *inter alia* by the shared national culture of a population. Our relationship to food is deeply embedded in our cultures [Tannahill, 2002].

> “Eating is … a cultural act that reaffirms one's identity and worldview each time one sits down to a plate of home-cooked beans” [Salmo\n, 2012]

Culture affects the circumstances in which we eat it, the types of food we eat, with whom we eat it, the times of day we eat it, and the quantities we eat. To borrow from E. N Anderson's paraphrasing of Marx, humans make food, but they do not make it just as they please

[6] Current evidence appears to favour excess energy intake rather than a deficiency in energy expenditure as the greater influence on increases in population obesity (Malhotra, Noakes, & Phinney, 2015; Luke & Cooper, 2013; Swinburn, 2013). Therefore, most of the literature and discussion on cultural determinants is presented around excess energy intake rather low energy expenditure.

[Anderson, 2005]. Our dietary choices are patterned by biology, psychology, and economics. These choices reflect our cultures and our cultural identities [Beagan and Chapman, 2012; Salmo\n, 2012; Weller and Turkon, 2015], Sociological and marketing studies underline how food represents an everyday materialization of ethnic identity and the fact that food choices are resistant to change [Cappellini and Yen, 2013].

While these ideas about our cultural relationship to food may have intuitive appeal, it is difficult to sit within a culture and point to this norm or that social value and say “Aha! There is evidence of culture affecting food consumption”. Migration, however, does provide a natural experiment in which we can observe shifts in food preferences as migrants acculturate, or resist acculturation. If eating patterns shift towards the eating patterns of the background population, there is evidence of a national, cultural influence, even if one cannot point exactly to what norms or social values have effected the change. In one study of young Hmong in America, for example, it was found that those Hmong who were more acculturated also had greater obesity [Franzen and Smith, 2009]. Forty percent (40%) of the more acculturated Hmong in the study were obese compared to zero (0%) of the less acculturated Hmong. The precise mechanism of “acculturation” however remains elusive, though it appears in some fashion to be expressed through food preferences and dietary choices.

2.5.5.4.4 Measurement of Country Level Cultural Macro-Environment

Despite evidence of cultural variations in diet, physical activity and obesity, it is noteworthy that no studies to our knowledge have attempted to measure the effect of country level cultural macro-environment on obesity. One challenge in attempting to explore culturally bound influences and their effect on obesity risk is the complexity inherent in measuring factors such as cultural values and beliefs. Approaches to deal with the effect of country level cultural macro-environment on obesity should begin with understanding how obesity is culturally internalized by individuals and countries [Ulijaszek and Lofink, 2006]. For this reason it is required to have a quantifiable matrices for the culture that can provide comparable values for different cultures or societies or countries. One of the distinct advantages of the notion of culture as a set of shared norms, values, and beliefs is that it is amenable to measurement. By asking groups of people to respond to a set of questions about their values and beliefs, it becomes possible to aggregate those responses to see which of those responses are shared at a group level; and how one group's culture differs from another group's culture. The obvious caveat to this approach is to be cautious about the levels of measurement and not fall into the trap of the ecological fallacy [Smith, 2004].

Edward T. Hall (1976), Parsons and Edward Shils (1951), Fred Strodtbeck (1961), Kluckhohn and Strodtbeck's (1961), Mary Douglas (1973) are some authors who have provided quantifiable matrices for the culture of the societies [Douglas, 1970; Hall, 1976; Kluckhohn et al., 1961; Parsons et al., 1962]. These one- or more-dimensional classifications represent subjective attempts to order a complex reality. Each of them is strongly coloured by the subjective choices of its author(s). They show some overlap, but their lack of clarity about and mixing of levels of analysis (individual-group) are severe methodological weaknesses. There have been two relatively well known attempts to measure national culture globally. The World Values Survey is an on-going survey conducted in six waves starting in 1981 with the last wave finishing in 2014 [Assocaition, 2014]. The other well known attempt was by Hofstede, who surveyed IBM employees, from all strata of work, around the world, and later supplemented the data with national data [Hofstede, 2011; Hofstede and McCrae, 2004; Hofstede, 2001b; Hofstede et al., 2010]. Hofstede national cultural data has been used in a wide range of studies [Bergmuller, 2013; Cheng et al., 2013; Havold, 2007; Helmreich and Merritt, 2001; Jensen and Rakovan, 1997; Pack et al., 2009], including health studies [Matsumoto and Fletcher, 1996]; however they have never been used in a study of obesity. Hofstede empirically developed four dimensions for countries' culture. Validations show no loss of validity, indicating that the differences between countries these dimensions describe are, indeed, basic and enduring [Hofstede, 2011; Hofstede, 2001b]. Several scholars have suggested the use of Hofstede dimensions as the most appropriate dimensions for conceptualizing and operationalizing culture at the country level [Clark, 1990; Connection, 1987; Hofstede, 2001b; Hofstede et al., 2010; Keillor and Hult, 1999; Schwartz and Bilsky, 1990; Smith et al., 1996; Steenkamp et al., 1999].

Hofstede's framework is the most widely used national cultural framework in psychology, sociology and health related studies [Steenkamp, 2001]. Hofstede used 117,000 questionnaires from over 60,000 respondents in 71 countries in his development of the dimensions [Hofstede, 2001b; Hofstede et al., 2010]. The survey had the advantage of all the respondents working for the same company – IBM – thereby reducing one possible source of variation in their responses not directly related to culture. Hofstede statistically analysed the data to try identifying any underlying themes, or patterns, present for the whole sample. He identified four dimensions and subsequently appreciated the presence of a fifth dimension. Survey studies of large samples of similar respondents in different countries enabled Hofstede and others to attach indices (on a continuum between 100 and 0) to countries on these five dimensions. The four dimensions so identified were: uncertainty avoidance (UAI), individualism (IDV), power distance (PDI) and masculinity (MAS)[7]. These indices describe societies and should not be applied to individuals. These dimensions are extensively validated against other aspects of national societies and for their cross-time stability [Meeuwesen et al., 2009b]. Hofstede linked the dimensions with demographic, geographic, economic, and policy aspects of a society [Hofstede, 2011; Hofstede and McCrae, 2004; Hofstede, 2001a; Hofstede et al., 2010], a feature unmatched by other frameworks. It is the most comprehensive and robust framework in terms of the number of national cultures samples [Smith, 2004; Smith et al., 1996]. Moreover, the framework is useful in formulating hypotheses for comparative cross-cultural studies. Consequently, Hofstede's operationalization of cultures (1984) is the norm used in research studies [Dawar et al., 1996; Samiee and Jeong, 1994; Samli, 1995; Sivakumar and Nakata, 2001].

Although the Hofstede dimensions arose in the domain of industrial psychology, they deal with issues that seem equally relevant to health and diseases. For example, power distance as a cultural artefact could be used to explore hierarchical versus equalitarian relations in doctor–patient communication, degree of conformism, information exchange, and shared decision-making [Meeuwesen et al., 2009b]. For uncertainty avoidance, these could be patient's emotionality or anxiety and stress, doctor's task-orientation, preference for technological solutions, belief in specialists, doctor's uncertainty avoidance, degree of medicalization [Hofstede, 1984, 2001b; Kuntsche et al., 2006; Märcker, 2001]. For individualism they could be patient autonomy, possibility of choice, flexibility of social roles, less conformity, and psychosocial information exchange [Hofstede, 1984, 2001b; Kuntsche et al., 2006; Märcker, 2001]. And for masculinity there could be an association with instrumental (or curing) behaviour, disease centred communication, biomedical talk, and doctor's gender [Hofstede, 1984, 2001b; Kuntsche et al., 2006; Märcker, 2001]. In the following section, these four cultural dimensions i.e. uncertainty avoidance, individualism, power distance and masculinity are described in turn.

[7] Minkov et. al. (2010) generated two additional dimensions for 93 countries using World Values Survey data from representative samples of national populations. These dimensions were termed Long Term Orientation versus Short Term Orientation (LTO) and Indulgence versus Restraint (IND). Data on LTO and IND was not available for all the 53 WHS countries for which UAI, IDV, PDI and MAS data was available. Hofstede describes that the values that distinguished country cultures from each other could be statistically categorised by these four (UAI, IDV, PDI and MAS) Hofstede dimensions of national culture. Therefore, these four original Hofstede dimensions were used in this study.

Uncertainty Avoidance

Uncertainty avoidance is defined as 'the extent to which people feel threatened by uncertainty and ambiguity and try to avoid these situations'. It indicates the extent to which a culture programs its members to feel either uncomfortable or comfortable in unstructured situations. Unstructured situations are the situations that are novel, unknown, surprising, and different from usual [Flynn and Saladin, 2006; Lu et al., 2012]. Uncertainty Avoidance is not the same as risk avoidance; it is the degree to which the members of a society feel uncomfortable with uncertainty and ambiguity, which leads them to support beliefs promising certainty and to maintain institutional norms for protecting conformity.

People from countries with high uncertainty-avoiding culture try to minimize the possibility of uncertainties by strict rules, regulations and formality to structure life, by safety and security measures, and, on the philosophical and religious level, by a belief in the absolute truth. This translates into a search for truth and a belief in experts. Shackleton and Ali (1990) find that people from the uncertainty avoidance culture are strongly and positively associated with formalization and motivation to acquire information such that the uncertainty in future can be reduced [Shackleton and Ali, 1990]. In the social context, people in the countries characterized by high uncertainty avoidance tend to avoid ambiguous situations by strict behavioural codes, laws and rules, and a disapproval of deviant opinions. They prefer clearly designated lines of authority and appear to be more emotional, active, fidgety, and aggressive. People from high uncertainty avoidance cultures are less open to change and innovation than people of low uncertainty avoidance cultures. This explains differences in the adoption of innovations [Donthu and Sayrac, 2000].

The opposite type, i.e. uncertainty accepting cultures, are more tolerant of opinions which are different from what they are used to; they try to have fewer rules, and on the philosophical and religious level they are empiricist, relativist and allow different currents to flow side by side [Hofstede and McCrae, 2004]. People within these cultures are more phlegmatic and contemplative, and not expected by their environment to express emotions. In this culture, people tend to explore ambiguous situations, where they are more open to change and rely on their own views to determine what they should do.

In Hofstede et al. (2010) Uncertainty Avoidance Index scores are listed for 76 countries; they tend to be higher in East and Central European countries, in Latin countries, in Japan and in

German speaking countries, lower in English speaking, Nordic and Chinese culture countries [Hofstede et al., 2010].

The effect of uncertainty avoidance has been investigated by researchers in several non-health related areas, for example: utilization of e-government services [Carter and Bélanger, 2005], management innovation and cultural adaptability [Singer et al., 2008], cultural influence on global corporate [Robbins and Stylianou, 2003], Cross-cultural dimensions of Internet Portals [Zahir et al., 2002], trust beliefs [Gefen, 2000] and optimism Chang (1996) [[Chang, 1996].

However, limited amount of research has been devoted to study the uncertainty avoidance as a cultural dimension in the context of health related outcomes. A study on uncertainty avoidance and medical communication showed that different levels of uncertainty avoidance resulted in different patterns of medical communication. Studies also found that physicians in high uncertainty avoidance countries are less satisfied with their job [Meeuwesen et al., 2009b]. Some studies using data from European countries identified uncertainty avoidance as the strongest cultural dimension positively related to the prevalence of MRSA and use of antibiotics use [Antoci et al., 2013]. Hofstede and Hofstede present some research on uncertainty avoidance and health. Hofstede explored the association of anxiety/depression with uncertainty avoidance [Hofstede et al., 2010]. They refer to the 1990 World Values Survey data and argue that the uncertainty avoidance is negatively correlated with 'happiness', and that people from high uncertainty avoidance countries worried more about money and about their health. People in low uncertainty avoidance countries reported feeling better about their health than people in high uncertainty avoidance countries, even though the medical data did not show any evidence of differences in levels of health. In low uncertainty avoidance countries such as UK and USA, low blood pressure is perceived as a positive thing. However, in high uncertainty avoidance countries such as Germany, it is treated as an illness. Hofstede observed that high uncertainty avoidance countries tend to have more specialists and fewer generalists in most fields–including medicine [Hofstede, 2011].

Individualism

Individualism versus its opposite, Collectivism, is the degree to which people in a society are integrated into social groups. In individualism culture 'people look after themselves and their immediate family only whereas, in collectivism culture people belong to in-groups that look after them in exchange for loyalty'.

In individualistic cultures, one's identity is in the person. People are 'I'-conscious and self-actualisation is important. Hofstede (1984) finds that societies with a high degree of individualism have loose ties among social members, everyone looks after their own interests and those of their immediate family. Individuals from individualistic countries determine personal standards on their own [Hofstede, 1984].

In collectivist cultures, people are 'we'-conscious. Their identity is based on the social system to which they belong [de Mooij and Hofstede, 2010]. In collectivism cultures, people from birth onwards are integrated into strong, cohesive in-groups, often extended families (uncles, aunts and grandparents). These groups or families continue protecting them in exchange for unquestioning loyalty. In nations with a collectivist national culture, societies are viewed like a family. People in collective societies achieve satisfaction in well recognized jobs, striving to preserve face and avoid shame, so as not to bring disrespect to their peer group [Flynn and Saladin, 2006]. Individuals from collectivist cultures are more likely to define their personal standards with reference to the group norm. A collectivist culture includes a prominent emphasis on hierarchy, harmony, and saving face [Triandis et al., 1990].

Hofstede et al. (2010) listed individualism scores for 76 countries; Individualism tends to prevail in developed and Western countries, while collectivism prevails in less developed and Eastern countries. Japan takes a middle position on this dimension. Typical individualistic countries are Canada, the UK, and the US, whereas societies experiencing less individualism include Iran, India, China and Taiwan, where people hold group values and beliefs and pursue collective interests [Hofstede, 2011]. Individualism scores for each country are given the table 3.3.

In the field of empirical cultural research, Hofstede's individualism and collectivism cultural dimension is one of the most commonly explored dimensions. Research has shown that among all cultural dimensions, the individualism and collectivism dimensions account for most of the variation in global differences in many health and non-health related outcomes [Deschepper et al., 2008; Hofstede, 1998; Hofstede and McCrae, 2004]. Effect of individualism and collectivism cultures has been explored in various non-health related outcomes such as advertising, aggression in school children, and optimism behaviour [Bergmuller, 2013; Cheng et al., 2013; Pack et al., 2009]. Studies found association between individualism, collectivism and self-medication, frequency of prescribing antibiotics by doctors [Deschepper et al., 2008], ability to cope with health problems, the self-care abilities, spending on healthcare, and dealing with disability [Bailey and Kind, 2010; Hofstede et al., 2010].

It is widely established that social relationships can have powerful impacts on health, both physical and mental [Berkman et al., 2000]. Collectivism is a culture where social relationships are bounded more tightly and closer relationships can be seen between family members. Benefits of the social relationships can be emotional (intimacy, sense of belonging, comfort), instrumental (guidance, advice, physical assistance) and material (money, goods, other resources) [Berkman et al., 2000]. This social integration in collectivist societies (more social integration are seen in more collectivism society) can reduce mortality and disability risks [Kana'laupuni et al., 2005; Seeman, 1996], improve disease recovery rates [Kana'laupuni et al., 2005] and protect against mental illness [Harpham, 1994; Seeman, 1996]. In the realm of obesity, studies have shown social support to be important in maintaining healthy diet and exercise behaviours [Sallis et al., 1987] and to be a potential predictor of healthy weight [Gerald et al., 1994]. Studies have found that lower level of social support is associated with a greater caloric intake and weight [Hall et al., 2011b; Ziraba et al., 2009]. Eating as a comfort mechanism, in the absence of other emotional support, has been found to have physiological roots [Kruger et al., 2005]. In a 2007 study, social network analysis suggested that obesity may spread through social ties, perhaps as a result of peer normalization [Christakis and Fowler, 2007]. There is also a growing body of research exploring links between chronic stress related to poverty and discrimination and increased obesity risk, through metabolic changes related to the stress response [Bose et al., 2009]. Social support may serve as a buffer against the physiological effects of stress and as such, may moderate stress-related obesity risk [Scott et al., 2013]. Therefore, I hypothesise a positive relationship for higher individualism and higher BMI.

Power Distance

Power Distance describes the inequalities in the society. It has been defined as the extent to which the less powerful members of a society (or a family) accept and expect that power is distributed unequally. This represents inequality (more versus less), but defined from below (less powerful members of the society), not from above (more powerful members of the society). It suggests that a society's level of inequality is endorsed by the followers as much as by the leaders. Power and inequality, of course, are fundamental facts of any society. All societies are unequal, but some are more unequal than others. Hofstede suggested that people in high power distance countries tend to prefer, or at least are more willing to accept, greater centralization of decision making authority and less participation of less powerful members of the country in the decision-making processes [Merchant et al., 1995]. On the other hand, subordinates possessing low power distance consider themselves to have the same rights as their superiors, and they expect to be consulted and to participate in making decisions that affect them [Chow et al., 1999; Hofstede, 1983]. In Hofstede et al. (2010), Power Distance Index scores are listed for 76 countries; they tend to be higher for East European, Latin, Asian and African countries and lower for Germanic and English-speaking Western countries [Hofstede et al., 2010].

A majority of the research on power distance was done in the field of business, management and industrial organizations. There are very few health related studies that explored the effect of power distance on health related outcomes. Lower power distance has been identified as a protective factor against nonfatal MI in women [Conduit, 2001]. In an ecological study, power distance showed a positive association with the rates of cerebrovascular diseases, infections and parasitic diseases and a negative association with malignant neoplasms, circulatory system diseases and heart diseases [Matsumoto and Fletcher, 1996]. The findings of one study also suggested a positive correlation for antibiotic use with Power distance [Deschepper et al., 2008]. Helmreich and Merritt (1998), Jensen and Rakovan (1997) and Håvold (2007) found a positive association between power distance and work safety [Havold, 2007; Helmreich and Merritt, 2001; Jensen and Rakovan, 1997]. A Substantial amount of work on power distance culture has been done for the psychological outcomes. For example, lower power distance was associated with higher optimism levels and higher sense of inadequacy and failure for not meeting conventional standards of success [Draguns and Tanaka-Matsumi, 2003]. There are a few studies that looked at the power distance association with medical communication. In high power distance countries like Romania, Poland, Belgium and Spain doctor patient consultations are shorter than in low power distance countries such as UK and Switzerland [Meeuwesen et al., 2009b].

I hypothesise a positive relationship of higher power distance with a higher BMI. In large power distance cultures, everyone has his or her rightful place in a social hierarchy. The rightful place concept is important for understanding the obesity or health related outcomes in different power distance societies or countries. Less powerful people in a high power distance country do not feel themselves responsible for health related outcomes and for decision making in controlling that health problem. Therefore, they might feel that powerful people of the society (or a family) are responsible for high prevalence of overweight or obesity in the society. It is also important for public health programmes where people empowerment is important. All the groups of the societies with low power distance feel empowered and take part in health related decision-making. However, societies with high power distance feel dependent on the higher authority or leaders of the society and do not show much community participation [Lu et al., 2012].

Masculinity

Masculinity dimension is defined as “the degree to which a society is characterized by assertiveness (masculinity) versus nurturance (femininity)”. The dominant values in a masculine society are achievement and success; the dominant values in a feminine society are caring for others and quality of life [Hofstede et al., 2010; Nakata and Sivakumar, 1996].

Masculinity refers to a preference for achievement, heroism, assertiveness, and material success, whereas femininity stands for a preference for relationships, modesty, caring for the weak groups, and quality of life. In masculine societies, performance and achievement are important; and achievement must be demonstrated. Therefore, status brands or products such as jewellery are important to show one’s success [de Mooij and Hofstede, 2010]. An important aspect of this dimension is role differentiation. In masculine cultures, household work is less shared between husband and wife than in feminine cultures. Men also do more household shopping in the feminine cultures [de Mooij and Hofstede, 2010]. High masculine societies place a low value on caring for others, inclusion, cooperation, and solidarity. Cooperation is considered a sign of weakness. Career advancement, material success, and competition are paramount. Ringov and Zollo (2007) suggest that people from more masculine countries have a lower appreciation of cooperative strategies [Ringov and Zollo, 2007].

Masculinity versus its opposite, Femininity, should be interpreted as a societal, not as an individual characteristic. It refers to the distribution of values between the genders which is another fundamental issue for any society, to which a range of solutions can be found. The assertive pole has been called 'masculine' and the modest, caring pole 'feminine'. The women in feminine countries have the same modest, caring values as the men; whereas in the masculine countries they are somewhat assertive and competitive, but not as much as the men, so that these countries show a gap between men's values and women's values [Hofstede et al., 2010].

In Hofstede et al. (2010), Masculinity versus Femininity Index scores are presented for 76 countries; Masculinity is high in Japan, in German speaking countries, and in some Latin countries like Italy and Mexico; it is moderately high in English speaking Western countries; it is low in Nordic countries and in the Netherlands and moderately low in some Latin and Asian countries like France, Spain, Portugal, Chile, Korea and Thailand [Hofstede et al., 2010].

I hypothesize that the people living in countries with higher masculinity culture should have higher BMI. I have certain reasons to support this hypothesis. As mentioned above in the characteristics of masculine cultures, high masculine societies have a preference for achievement, heroism, assertiveness, and material success that leads to stressful long working hours. Working hours are often compounded by long commutes to and from work. Long hours mean that parents may not be home to eat with their families, and that there is less time for food preparation. This work patterns mean that families are much more likely to eat snacks and convenience foods containing increased levels of fat, salt and sugar and have risk of higher BMI [Hofstede, 2011]. United Kingdom is an example of a country hat has more than world's average working hours per week and a high mean BMI. The significance of long working hours for obesity has been recognised in the House of Commons Select Committee Report on Health [Martin, 2008].

I also hypothesize that male and females have different relationships for masculinity and BMI. The reason for this hypothesis is that the masculine societies are more heterogeneous in terms of gender role and values. In masculine societies, men are expected to be tough and strong. For example, men should suppress their needs and refuse to admit or acknowledge their pain [Brod and Kaufman, 1994]. Additional health-related beliefs and behaviours that can be used in the demonstration of masculinity include the denial of weakness or vulnerability, emotional and physical control, the appearance of being strong and robust, dismissal of any need for help, the display of aggressive behaviour and physical dominance. That asking for help and caring for one's health are feminine; and that the most powerful men among men are those for whom health and safety are irrelevant are some more beliefs. Therefore, unhealthy eating behaviour is irrelevant for them and not a challenge or threat for their manhood. It has been demonstrated that the resources available in the United States for constructing masculinities are largely unhealthy [Courtenay, 2000].

2.6 The Levels of Analysis

The above-mentioned determinants operate at various levels, for example age, gender, and behavioural factors operate at individual level and national income, while national income inequality and national culture operate at the country level. These country level factors are distinct from the individual level factors because they characterize the country as a whole and are presumed to affect everyone in the country regardless of the individual characteristics. While analyzing data from various levels, there are a few important issues need to be considered. These issues have been described in the following section.

2.6.1 Choice of Multilevel Analysis

Previous research addressing such a research question to examine the independent and interacting effects of group-level and individual-level factors on health outcomes adopted various methodologies. The groups or contexts investigated using these methods have included countries, states, regions, neighborhoods or communities, schools, families, workplaces, and health care providers.

The first approach involves examining all the individual and group level factors at the individual level, ignoring the group-level effect. Ignoring the role of group-level variables leads to an incomplete understanding of the determinants of an outcome (eg a disease) being studied in the individuals. The failure to take account of the importance of the population context, as an effect modifier and determinant of individual level exposures is termed as the “individualistic fallacy” in which the major population determinants of health are ignored and undue attention is focused on individual characteristics [Diez-Roux, 1998]. Ignoring this context and attempting to study homogeneous populations can lead to the erroneous conclusion that individual characteristics are the main determinants of a disease and most important for intervention, just as studying populations with homogeneous lifestyles can lead to the erroneous conclusion that other factors are the main determinants of the disease [Pearce, 2000].

Another type of that approach researchers have adopted in the past to address these type of questions is the ecological design. However, these ecological studies are prone to the ecological fallacy. For example, national dietary and cancer incidence data can be used and a strong correlation between the fat intake and breast cancer can be seen internationally. This approach was quite rightly regarded as inadequate and unreliable because of many additional forms of bias that can occur in such studies compared with the studies of individuals within a population. Ecological analyses become flawed in exactly the same circumstances that individual level analyses do, i.e. in the presence of confounding. However, the consequences of confounding bias in ecological analysis are more severe. In particular, the "ecological fallacy" can occur in that factors that are associated with national disease rates may not be associated with diseases in individuals. For example, almost any disease that is associated with affluence and Westernisation has in the past been associated at the national level with the sales of television sets, and nowadays is probably associated at the national level with the rates of internet use [Susser, 1994b, a].

These considerations have led to an increasing interest in statistical methods of multi-level analysis. These have considerable merits as they permit the estimation of population level (ecological) effects while also including individual level effects, thus avoiding both the ecological fallacy and the individualistic fallacy [Pearce, 2000].

2.6.2 Multilevel Analysis

The statistical models referred here as multilevel models have appeared in different literature under a variety of names including hierarchical linear models, random-effects or random-coefficient models, and covariance components models [Diez-Roux, 2000; Diggle, 2002; Raudenbush and Bryk, 2002]. Multilevel analysis was first developed for educational research [Goldstein, 1987; Twisk, 2006]. Since then it has been used in various other fields of education, demography, sociology and public health [Costner, 1974; Diez-Roux, 2000; Raudenbush and Bryk, 2002].

Populations or the data from the population are usually hierarchical in structure. The hierarchies represent different levels at which the units of an individual are grouped [Goldstein, 2011]. For example, a two-level hierarchical structure is illustrated in Figure 2.3. For the sake of simplicity, I have illustrated only two levels here. However, the real data can be more complex with several levels.

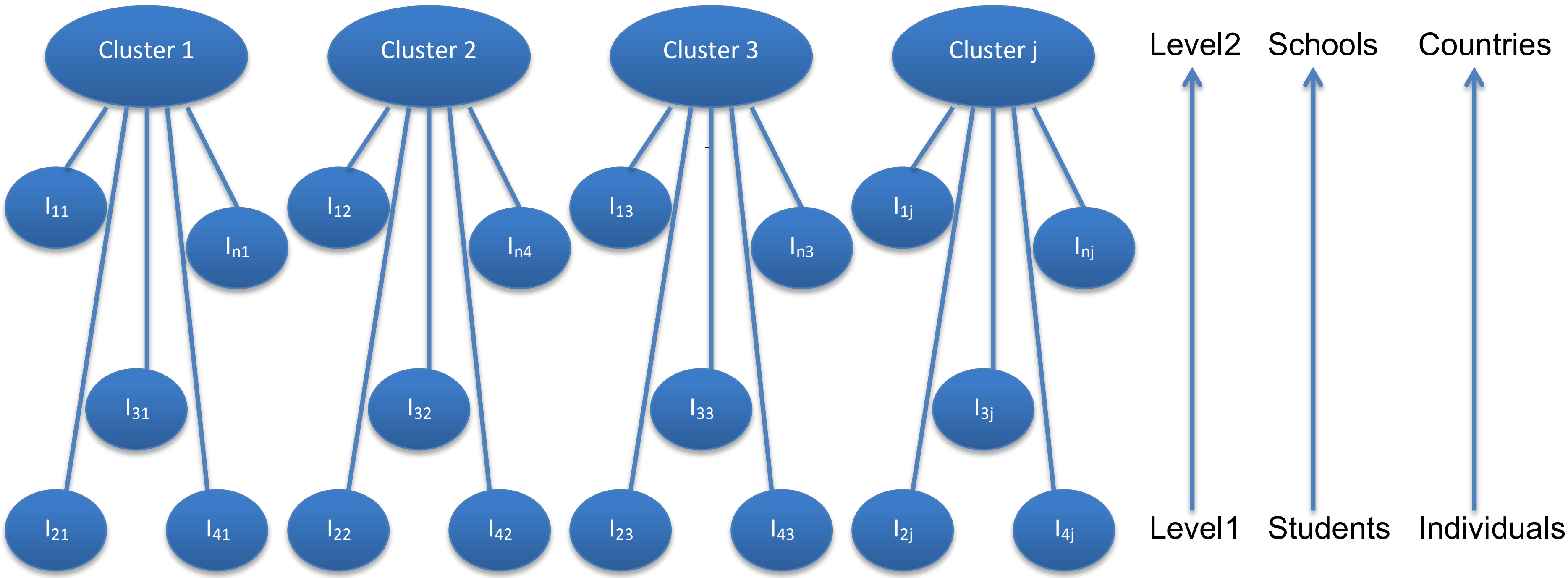

Figure 2.3 A two-level hierarchical structure where Level 1 items (I_{nj}) are clustered in level 2 clusters (J). Examples of level 1 items can be students, individuals, patients, teeth and corresponding level 2 clusters can be Schools, Countries, Doctors, Individuals.

An example of the multilevel approach in educational research is a study where the researcher analyses the performance of students in different schools. The students in the schools can be described as hierarchy; students are clustered within schools. This situation is known as a two-level data structure, the first level being the students and the second level being the schools [Twisk, 2006]. Thus, in educational research, the population consists of schools and students within these schools, and the sampling procedure often proceeds in two stages: First, we take a sample of schools, and next we take a sample of students within each school. In this example, students are nested within schools [Hox, 2010].

Similarly, social research also regularly involves problems that investigate the relationship between individuals and the society. The general concept is that individuals interact with the social contexts to which they belong, and that individual persons are influenced by the social groups or contexts to which they belong [Burton et al., 1998; Hox, 2010]. The individuals and social groups are conceptualized as a hierarchical system of individuals nested within groups, with individuals and groups defined at separate levels of this hierarchical system. Naturally, such systems can be observed at different hierarchical levels, and variables may be defined at each level. This leads to research into the relationships between variables characterizing individuals and variables characterizing groups [Diez-Roux, 2000].

Multilevel analysis is not restricted to educational or social science research. As we see more and more multilevel analysis in different scenarios, it becomes evident that once we have discovered ways to deal with hierarchical data structures, we see them everywhere. The notion of individuals, or any other type of objects, that are naturally nested in groups, with membership in the same group leading to a possible correlation between the individuals, turned out to be very compelling in many disciplines [Goldstein, 2011]. A recent paper discussed the clustering effects of surfaces within the tooth and teeth within individuals [Masood et al., 2015b]. Organizational research with individuals nested within departments within organizations, family research with family members within families, and methodological research into interviewer effects with respondents nested within interviewers. Less obvious applications of multilevel models are longitudinal research and growth curve research, where a series of several distinct observations are viewed as nested within individuals, and meta-analysis where the subjects are nested within different studies. For simplicity, this thesis describes the multilevel models mostly in terms of individuals nested within groups, but note that the models apply to a much larger class of analytic problems [Hox, 2010].

Over the past few years, interest in the use of multilevel analysis to investigate public health problems has grown [Diez-Roux, 1998, 2000; Duncan et al., 1998; Von Korff et al., 1992]. Recently, the interest in multicountry research has increased in cross-national studies where the individuals are nested within their national units or countries. The general idea of multilevel analysis is that the hierarchy of the data is taken into account in the analysis, or in other words, it takes into account the dependency of observations. With the hierarchical structure, we often assume that there should be some correlation between the lower level units (i.e. subjects), which are within an upper level unit, (group in the above example). Multilevel models can help to account for this correlation. Additionally, it allows the simultaneous examination of the effects of group-level and individual-level variables on individual-level outcomes [Ka-yan, 2011]. This growth has been stimulated in part by a resurgence of interest in the potential group-level determinants of health and the notion that variables referring to groups or to how individuals are related to each other within groups may be relevant to understanding the distribution of health outcomes [Diez Roux, 2002a; Diez-Roux, 1998; Duncan et al., 1996; Thomas et al., 1994].

After considering the disadvantages of ecological and individualistic fallacies, multilevel analysis is the most appropriate approach while analyzing contextual data. Following section will describe the concept and mathematics of multilevel modeling [Diez Roux, 2002a].

2.6.3 Multilevel Statistical Models

This section will describe multilevel models that allow the simultaneous examination of the effects of group-level and individual-level variables on individual-level outcomes. I have discussed the multilevel model using an example involving two levels only. However, the model can be extended to more levels. To keep the illustration simple, I focused on the case of only one explanatory variable at the individual and one explanatory variable at the group level (although models can be extended to include as many independent variables as needed) [Diez-Roux et al., 2000; Peugh, 2010]. This model can be conceptualized as a two-stage system of equations in which the individual variation within each group is explained by an individual-level equation, and the variation across groups in the group-specific regression coefficients is explained by a group-level equation [Diez Roux, 2002b; Hofelmann et al., 2013]. To make mathematical explanation and equations more understandable, an example of body mass index (BMI) is used in this illustration. We used a simple two-level data, with one continuous explanatory variable BMI at the individual level (gender) and one explanatory variable at the group level (national income). Assume that we have a data from *J* groups, with a different number of respondents *nj* in each group. On the respondent level, we have the outcome of respondent *i* in group *j*, variable *Yij* (BMI). We have one explanatory variable *Xij* (gender) on the respondent level, and one group-level explanatory variable *Zj* (national income) (This terminology will be used in the equations of the following sections).

2.6.3.1 Null Model

To begin the description of multilevel analysis, we start with the simplest model. Variance components models or intercept only models or null models are the simplest multilevel models. The primary objective of the null model is to investigate the extent of the heterogeneity between the clusters, thereby establishing the rationale for analyzing multilevel modeling [Glaser and Hastings, 2011]. These models are built without including any explanatory variable from level 1 and level 2. A regression without explanatory variables generates an equation with no slope. It generates an intercept that is equal to the mean of the outcome variable [Leyland and Goldstein, 2001].

As an illustration, a 2-level null model with BMI example can be written as by [Goldstein, 1995].

$$Y_{ij} = \beta_{0j} + e_{ij} \qquad (2.1)$$

$$\beta_{0j} = \beta_{00} + u_{0j} \qquad (2.2)$$

Combined models $$Y_{ij} = \underbrace{\beta_{00}}_{\text{Fixed part}} + \underbrace{u_{0j} + e_{ij}}_{\text{Random part}} \qquad (2.3)$$

$$e_{ij} \sim N(0, \sigma_e^2)\ ;\ u_{0j} \sim N(0, \sigma_{u0}^2); \qquad (2.4)$$

where $i = 1, 2, \ldots\ldots, N_j\,;\ j = 1, 2, \ldots., J$

Here, Y_{ij} denotes the response of the *i*-th subject in the *j*-th group and is assumed to follow a normal distribution; β_{0j} denotes the mean response of the individuals in the *j*-th group, which consists of a fixed part β_{00}, denoting the overall mean of the response of all the *j* groups, and a random part u_{0j}as shown in equation. The group mean β_{0j} can be interpreted as sharing some common features among all the groups, represented by the overall mean β_{00} and having some variations between different groups which can be characterized by the random term u_{0j}. u_{0j} and e_{ij} together denote the random part of the model corresponding to level 2 and level 1, respectively [Leyland and Goldstein, 2001]. The fixed part of the model is not allowed to change across groups, while the random part is allowed to change between different groups [Diez Roux, 2008]. u_{0j} and e_{ij} are assumed to follow normal distributions with mean zero and constant variance σ_{u0}^2 and σ_e^2, respectively. They are also assumed to be independent of each other.

The null model averages the outcome variable for the level 1 across the level 2 and partitions the variance between level 1 and level 2. The level 1 variances or within cluster variance (σ_e^2) represent the heterogeneity within the cluster, whereas, the level 2 or between-cluster variance (σ_{u0}^2) then represents the heterogeneity between the clusters [Glaser and Hastings, 2011]. The variation in BMI at level-1 (σ_e^2) is the average variance of individuals' BMI within schools. The variation in BMI at level-2 (σ_{u0}^2) quantifies the variation in BMI across schools.

The purpose of building null model is to investigate the variances of the response variable at different levels, which in turn helps to determine whether the levels should be taken into account when identifying the data structure. If it is tested that one of the levels is not significant, one can eliminate that variance component from the working model. The procedures are then repeated until all the variance components are significant [Ka-yan, 2011].

2.6.3.2 Intra-cluster Correlation Coefficient (ICC)

What makes the intercept only model particularly useful is the computation of the intra-cluster or intra-class correlation coefficient (ICC). ICC gives a measure of how homogeneous the data is within a group or a cluster, i.e., how well the data sets within a group or a cluster correlate with each other, compared with datasets between groups or clusters.

In the above intercept only model, σ_{u0}^2 represents the between-group variance and (σ_e^2) the within group variance, and their summation comes up with the total variance of the model. With these variances, ICC can be estimated, which measures the proportion of the total variance accounted for by the between groups variations [Gelman and Hill, 2007; Twisk, 2006].

$$ICC = \frac{\sigma_b^2}{\sigma_x^2}\ , \qquad (2.5)$$

where σ_b^2 is the between-cluster variance of outcome variable *x*, and (for continuous variable outcomes) $\sigma_x^2 = \sigma_b^2 + \sigma_w^2$, where σ_w^2 is the within-cluster variance. That is, ICC is the ratio of the between cluster-variance to the total variance.

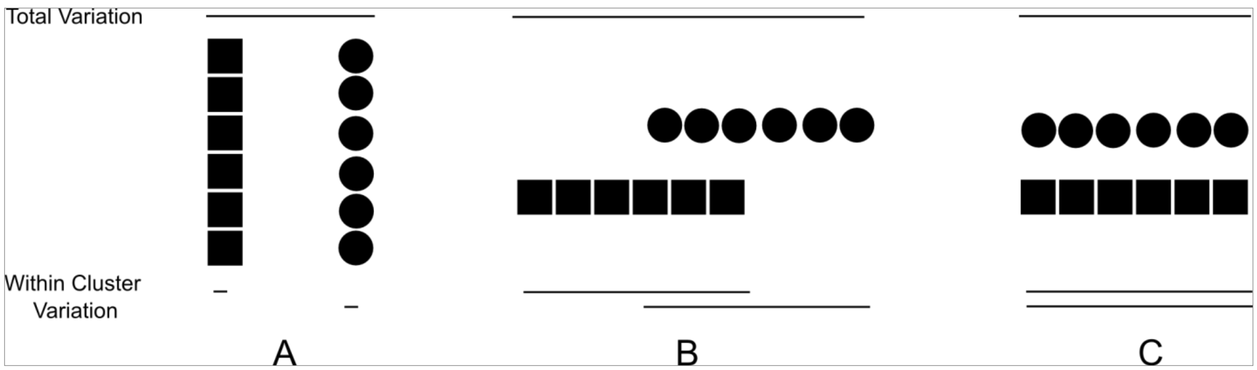

Figure 2.4 Graphic representation of Intraclass correlation coefficient.

An intuitive feel for the ICC can be made by considering Figure 2.4. The figure shows three distinct situations (A, B, and C), in which data is sampled from within two clusters (■ and ●). Within each situation, the horizontal displacement is indicative of the variation in the outcome measure. The horizontal lines at the top of the figure indicate the total variation in the data. The horizontal lines at the bottom of the figure indicate the within cluster variation in the data. In situation A, the variation within each cluster is small, but the total variation between the clusters is much more substantial. This would have a high ICC because knowing from which cluster a measurement was drawn tells you everything you need to know about the value of the measurement. In situation B, the variation within each cluster is much larger, and there is also an overlap in the measures between the clusters. This would result in a moderate ICC. Finally in situation C, there is no variation between the clusters, which is distinct from the variation within the clusters, resulting in a low ICC.

It means that the larger the within group variance, the smaller the intra-cluster correlation coefficient [Twisk, 2006]. Similar to other correlation coefficients, the value of ICC varies from 0 to 1. These are two extreme cases for the value of ICC, namely ICC = 0 and ICC = 1. For the first case where ICC = 0, this means that the variations within the group are the same for all groups, which implies that the group level analysis is not necessary. Specifically, an ICC value of zero indicates: (a) no mean BMI variation across groups (i.e., level-2), (b) all BMI variation occurs across individuals within a group (i.e., level-1), and (c) traditional analysis techniques such as regression can be used to analyze the data. However, as the ICC value increases, the proportion of BMI variation that occurs across groups increases, resulting in violations of the independence assumption. At the other end of the spectrum with ICC = 1, the interpretation is that all the individuals within the same group are identical, so considering only one individual from each group would be adequate, and no individual level analysis is needed. In the above two cases, single level model is sufficient for the analysis. Otherwise, multilevel model is more appropriate for the hierarchical structured data [Ka-yan, 2011].

Large ICCs indicate that the cluster membership is accounting for a large proportion of variance, but it is not clear how small an ICC must be before the nested structure can be ignored [Vijver et al., 2008]. Various authors have suggested that if the level of variance accounted for at the group level is not large, it does not necessarily mean that we should ignore the nested design. Gulliford, Ukomunne, and Chin (1999) used a large health survey to describe ICCs found at various levels of nesting ranging from household to postal code, and found that ICCs varied inversely with the cluster size [Gulliford et al., 1999]. Gulliford and colleagues (1999) went on to state that even when the ICCs are low, the design effects $(1 + (n - 1)P)$ or the impact of the nested design, where n is the cluster size and P is the ICC, could still be large when the cluster size is large [Gulliford et al., 1999; Vijver et al., 2008]. As further evidence that even small ICCs should not be ignored, Vivjver (2008) showed in a simulation study that ICCs between .05 and 0.15 can result in biased estimates of both the parameters and standard errors, especially when the group-to-member ratio is small as is the case with the current data set [Vijver et al., 2008]. Literature has shown ICC values between .05 and .20 to be common in cross-sectional MLM applications in social research studies. However, a non-zero ICC estimate alone does not necessarily indicate the need for multilevel analyses [Muthen, 1994; Peugh, 2010].

The design effect quantifies the effect of independence violations on standard error estimates and is an estimate of the multiplier that needs to be applied to standard errors to correct for the negative bias that results from nested data [Masood et al., 2014; Muthen, 1994; Peugh, 2010].

2.6.3.3 Adding Level-1 Explanatory Variable

After confirming the significance of the variance of the random terms, which helps to verify the importance of the levels, the model can then be extended by including other independent variables which are thought to have potential effects on the response variable. As a next step, we introduce a level-1 explanatory variable, X_{ij} (e.g. Gender) in the intercept only model (equation 1, 2 and 3) [Albandar and Goldstein, 1992], which takes the value zero if the respondent is female and one if the respondent is male. Now we can rewrite the model given in Equations 1, 2 and 3, a separate individual level regression equation is defined for each group to predict the outcome variable Y_{ij} using the explanatory variables X_{ij} as follows:

$$Y_{ij} = \beta_{0j} + \beta_{ij}\,X_{ij} + e_{ij} \qquad (2.6)$$

$$\beta_{0j} = \beta_{00} + u_{0j} \qquad (2.7)$$

Combined equations: $$Y_{ij} = \underbrace{\beta_{00} + \beta_{10}X_{ij}}_{\text{Fixed part}} + \underbrace{u_{0j} + e_{ij}}_{\text{Random Part}} \qquad (2.8)$$

$$e_{ij} \sim N(0, \sigma_e^2)\ ;\ u_{0j} \sim N(0, \sigma_{u0}^2) \qquad (2.9)$$

Where Y_{ij} is the outcome variable for i^{th} individual in j^{th} group and X_{ij} the individual-level variable for i^{th} individual in j^{th} group. In this regression equation, β_{0j} is the intercept, β_{1j} is the regression coefficient (regression slope) for the dichotomous explanatory variable gender and e_{ij} is the usual residual error term. Individual-level errors (e_{ij}) within each group are assumed to be independent and normally distributed with a mean of 0 and a variance of σ_e^2 [Diez-Roux, 2000]. The difference with the usual regression model is that we assume that each group/cluster has a different intercept[8] coefficient β_{0j},. This is indicated in equations by attaching a subscript *j* to the regression coefficients [Hox, 2010].

[8] This is the random intercept model, which means that only intercept β_{0j} varies among groups but the slop β_{1j} remains constant for each group.

In these equations, the specific values for the intercept and the slope coefficients are group characteristics. This model implies that, within a given group, the mean BMI for females is β_{0j}, and the mean BMI for males is β_{0j} + β_{1j} . Thus, the mean difference in BMI between males and females in this neighborhood is β_{1j} [Bingenheimer and Raudenbush, 2004]. In general, a group with a high intercept is predicted to have a higher mean BMI than a group with a low value for the intercept. [Bingenheimer and Raudenbush, 2004].

The variance-covariance structure given in Equation 2.9 is similar to that in equation 2.4. In this model, β_{0j} regression coefficient of each of the group or context as defined in Equation 2.5 is modeled as a function of group-level variables. Across groups, the mean BMI is β_{00} for females and $\beta_{00} + \beta_{10}$ for males, and the mean difference is thus β_{10}. Again, substitution is used to combine Equations 2.6 and 2.7 into a single combined model equation 2.8 [Bingenheimer and Raudenbush, 2004].

2.6.3.4 Adding Level-2 Explanatory Variable

Alternatively, we might choose to add a level-2 explanatory variable to the model given by Equations 2.2 and 2.3. Suppose, for instance, that W_j is an explanatory variable taking the value one if the *j*th neighbourhood contains a gymnasium, and value zero if it does not[9]. Because W_j characterizes neighbourhoods rather than individuals, we include it in the level-2 model

$$Y_{ij} = \beta_{0j} + e_{ij} \qquad (2.10)$$

$$\beta_{0j} = \beta_{00} + \beta_{01} W_j + u_{0j} \qquad (2.11)$$

Combined equations:
$$Y_{ij} = \underbrace{\beta_{00} + \beta_{01} W_j}_{\text{Fixed part}} + \underbrace{u_{0j} + e_{ij}}_{\text{Random part}} \qquad (2.12)$$

$$e_{ij} \sim N(0, \sigma_e^2) \; ; \; u_{0j} \sim N(0, \sigma_{u0}^2) \qquad (2.13)$$

[9] In this mode there is no level 1 explanatory variable therefore this equation will be written same for both random intercept and random slop models.

Now the model has the same variance-covariance structure as given in Equation 2.4 and 2.13. The level-1 model in Equation 2.10 imply that within each neighbourhood. BMI follows a normal distribution with neighbourhood-specific mean β_{0j} and variance σ_e^2. The level-2 model characterizes the distribution of these neighbourhood-specific means. For neighbourhoods without a fast-food restaurant, these means vary around β_{00}; but for neighborhoods with a fast-food restaurant, they vary around $\beta_{00} + \beta_{01}$. If neighborhoods were randomly assigned to W_j, then we would have a cluster-randomized trial with the experimental condition being the presence of a fast-food restaurant, and β_{01} would be interpreted as the average treatment effect.

2.6.3.5 Full Model with Level-1 and Level-2 Explanatory Variables

Consider a model that includes explanatory variables at level 1 and level 2. Again, we let X_{ij}= 1 if the individual is male and W_j = 1 if the neighbourhood contains a gymnasium. Then we write the following model:

$$Y_{ij} = \beta_{0j} + \beta_{ij} X_{ij} + e_{ij} \qquad (2.14)$$

$$\beta_{0j} = \beta_{00} + \beta_{01} W_j + u_{0j} \qquad (2.15)$$

In this case, substitution of Equations 2.15 into 2.15 gives the following combined model:

Combined equations: $Y_{ij} = \beta_{00} + \beta_{10} X_{ij} + \beta_{01} W_j + u_{0j} + e_{ij}$ (2.16)

$$e_{ij} \sim N(0, \sigma_e^2)\ ;\ u_{0j} \sim N(0, \sigma_{u0}^2) \qquad (2.17)$$

Equation 2.14 is same as equation 2.6 and can be interpreted in the same manneras equation 2.6. The level 2 models (equation 2.15) are to explain the variation of the regression coefficient β_{0j} introducing explanatory variable W_j at the group level. Equation 2.15 predicts the average BMI in a class (the intercept β_{0j}) by the presence of gymnasium (W_j). Thus, if β_{01} is negative, the BMI is lower in neighbourhoods with a gymnasium.

The combined formulation of the model given in Equation 2.16, the segment $\beta_{00} + \beta_{10} X_{ij} + \beta_{01} W_j$ contains fixed coefficients. It is often called the fixed (or deterministic) part of the model. The segment $[u_{0j} + e_{ij}]$ contains the random error terms, and it is often called the random (or stochastic) part of the model. The errors in the group-level equation (u_{0j}), are assumed to be normally distributed with mean 0 and variances σ_{u0}^2. The error term u_{0j} measures the unique deviation of the intercept (β_{0j}) of each group from the overall intercept, β_{00}, after accounting for the effect of W_j (see equation 16). σ_{u0}^2 is the variance of the group intercepts (after accounting for the group-level variable W_j).

Thus, multilevel models allow separation of the effects of context (i.e. group characteristics) and of composition (characteristics of the individuals in groups): Do groups differ in average outcomes after controlling for the characteristics of the individuals within them? Are group-level variables related to outcomes after controlling for the individual-level variables? Multilevel models can also be used to examine whether the effects of individual-level variables differ across groups: Do individual-level associations vary from group to group, and is this partly a function of group-level variables? Do group level variables modify the effects of individual-level variables?

2.6.3.6 Random Slope Models

So far, all the previous models have been random intercept models where the overall level of the BMI has been allowed to vary across different countries when controlling for all the covariates. However, it is possible that the effects of some of the individual variables also vary across countries. For instance, the effect of household wealth on BMI might vary across countries. The random slope model is an extension of the random intercept model in which some or all of the independent variables are also regarded as random between groups [Snijders and Bosker, 2012]. This method is also high demanding in computational effort due to the large covariance matrix involved. Rabe-Hesketh and Skrondal (2008) warned researchers to be extremely cautious when fitting random coefficient models since the number of parameters for the random part of the model increases dramatically with the number of random slopes. They suggested the use of random intercept model only be fitted when focus of the study is to assess the differential effects of individual level variables on higher level variables [Rabe-Hesketh and Skrondal, 2006]. The focus of this thesis is to investigate the effect of country level factors on BMI and the individual level variables have been treated as control variables. Therefore, the random slope model is not to be considered in this study; only a brief introduction to the random slope model will be given here.

$$Y_{ij} = \beta_{0j} + \beta_{ij} X_{ij} + e_{ij} \quad (2.18)$$

$$\beta_{0j} = \beta_{00} + \beta_{01} W_j + u_{0j} \quad (2.19)$$

$\beta_{1j} = \beta_{10} + u_{1j}$ (2.20)

with the variance-covariance structure given in Equation 2.22 In this case, substitution of Equations 2.19 and 2.20 into 2.18 gives the following combined model:

Combined equations $Y_{ij} = \beta_{00} + \beta_{10}X_{ij} + \beta_{01}W_j + u_{1j}X_{ij} + u_{0j} + e_{ij}$ (2.21)

$e_{ij} \sim N(0, \sigma_e^2)$; $u_{0j} \sim N(0, \sigma_{u0}^2)$; ; $u_{1j} \sim N(0, \sigma_{u1}^2)$ (2.22)

Interpretation of equations 2.18 and 2.19 is same as equations 2.14 and 2.15 respectively. The difference from the random intercept model is that we assume that each group/cluster has a different slope coefficient β_{1j} too in addition to different intercept coefficient β_{0j} [Hox, 2010]. β_{0j} denotes the mean slop of the level 1 variable for the *j*-th group, which consists of a fixed part β_{10}, denoting the overall mean of the slop, and a random part u_{1j} as shown in equation.

2.6.3.7 Cross Level Interaction

This model adds cross-level interactions between explanatory group-level variables and individual-level explanatory variables. This leads to the full model:

$Y_{ij} = \beta_{0j} + \beta_{ij}\, X_{ij} + e_{ij}$ (2.23)

$\beta_{0j} = \beta_{00} + \beta_{01}W_j + u_{0j}$ (2.24)

$\beta_{1j} = \beta_{10} + \beta_{11}W_j + u_{1j}$ (2.25)

with the variance-covariance structure given in Equation 2.27 In this case, substitution of Equations 2.25 and 2.26 into 2.23 gives the following combined model:

Combined equations: $Y_{ij} = \beta_{00} + \beta_{10}X_{ij} + \beta_{01}W_j + \beta_{11}W_jX_{ij} + u_{1j}X_{ij} + u_{0j} + e_{ij}$ (2.26)

$e_{ij} \sim N(0, \sigma_e^2)$; $u_{0j} \sim N(0, \sigma_{u0}^2)$; ; $u_{1j} \sim N(0, \sigma_{u1}^2)$ (2.27)

An important feature of this model, namely the presence of a cross-level interaction is represented by the term $\beta_{11}W_jX_{ij}$. This interaction can be interpreted in two ways. First, the average difference in BMI between males and females depends upon whether or not a gymnasium is present in the neighbourhood (β_{10} in neighborhoods without a gymnasium; β_{10}+

β_{11} in those with a gymnasium). Alternatively, the difference between neighbourhoods with and without gymnasium depends upon the sex of the individual. For females, the average difference is β_{01}, whereas for males the average difference is β_{01}+ β_{11} [Bingenheimer and Raudenbush, 2004]. Rest of the equation and equation 2.27 can be interpreted similar to equation 2.21 and 2.22.

2.7 Aim and Objectives

2.7.1 Aim

The aim of this thesis was to investigate the effect of country level cultural and economic macro-environmental determinants on individual level BMI.

2.7.2 Objectives

1. To quantify global variation in BMI in 70 low, middle and high-income countries.
2. To determine the relationship of national income and national income inequality with BMI in low, middle and high income countries using multilevel analysis.
3. To identify the cross level interaction of national income and individual level wealth on individual level BMI.
4. To determine the relationship of countries' cultural dimensions with BMI in low, middle and high income countries using multilevel analysis.
5. To discuss the implications of national income, national income inequality and culture differences on obesity prevention policy implications.

CHAPTER 3: Methods

This chapter includes the description of datasets and the variables included in this thesis and the analytical methods used in this thesis. Seventy-three different datasets were used to address the objectives of this thesis, seventy World Health Survey (WHS) datasets form 70 countries, two datasets from World Bank Database, one dataset form Hofstede cultural dimensions. The outcome variable (BMI) and all individual level explanatory variables (Age, gender, marital status, education level, household wealth, occupation, living in urban or rural area) were derived from WHS. Country level variables, national income and income inequality were derived from World Bank Datasets [World Bank, 2003a, b]. Other country level variables i.e. uncertainty avoidance, individualism, power distance and masculinity were collected from Hofstede cultural dimensions Data [Hofstede, 2001a]. The main reason for using WHS datasets for this study was that these are unique comparable datasets available for 70 countries representing the countries from a range of low, middle and high-income countries.

3.1 World Health Survey (WHS)

The World Health Survey (WHS) was a large cross-sectional study, conducted between 2002 and 2004 in 70 Countries. Table 3.1 presents the list of the 70 countries included in WHS. The survey covered a large proportion of the world's population, and geographically represented the six WHO regions countries [WHO, 2003]. The aim of the WHS was to provide low cost, valid, reliable and comparable information on health, associated risks and to monitor whether health systems achieve their desired goals [Ustun TB, 2003]. Nationally comparable and representative samples of adults, male and female over 18 years, were chosen through stratified, multistage cluster random sampling in 55 countries[10] and simple random sampling in the other 15 countries[11].

[10] Australia, Bangladesh, Bosnia and Herzegovina, Brazil, Burkina Faso, Chad, China, Comoros, Congo Rep., Coted'Ivoire, Croatia, Czech Republic, Dominican Republic, Ecuador, Estonia, Ethiopia, Georgia, Ghana, Guatemala, Hungary, India, Kazakhstan, Kenya, Lao PDR, Latvia, Malawi, Malaysia, Mali, Mauritania, Mauritius, Mexico, Morocco, Myanmar, Namibia, Nepal, Pakistan, Paraguay, Philippines, Russian Federation, Senegal, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, Swaziland, Tunisia, Turkey, Ukraine, United Arab Emirates, Uruguay, Vietnam, Zambia, Zimbabwe.

[11] Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Luxembourg, Netherlands, Norway, Portugal, Sweden, united kingdom.

Data was collected at both the individual and household level by utilizing two types of questionnaires: the household questionnaire and the Individual questionnaire [WHS, 2002a, b, c, d]. Individual and household questionnaires used in WHS data collection are available in appendices A and B. These questionnaires were used to assess healthcare expenditure, adult mortality, birth history, risk factors, chronic health conditions, and the coverage of health interventions. Questionnaires were translated into countries' official languages using a standard WHO protocol with both translation and back-translation of the instrument to improve its comprehensibility for the local people. Translations were reviewed and verified by independent bilingual experts prior to field implementation [WHO, 2002a]. Three interview methods: 90-minute face-to-face interview (FTF) in 53 countries[12]; 30-minute brief face-to-face interview (BFTF) in 13 countries[13]; and 30-minute computer assisted telephone interview (CATI) in 4 countries[14], were used for WHS data collection, each country selected the interview method appropriate for that country [WHO, 2002b]. Quality assurance procedures were implemented at all stages, ranging from the selection of survey institutions to data analysis [Ustun TB, 2003].

The first section, the Individual Questionnaire (Appendix A), collected the data about socio-demographic factors (Gender, age, marital status, education level, occupation etc.). This questionnaire also collected data on self-reported body height and weight[15]. Self-assessed health levels were elicited for each of the eight domains of health—mobility, self-care, pain and discomfort, cognition, interpersonal activities, vision, sleep, and energy and affect. Data on various risk factors including tobacco use, alcohol consumption, fruit and vegetable intake, physical activity, water and sanitation, and indoor air pollution, was also collected. These risks have been selected taking into account the risk factors that are the largest worldwide and for which self-report is a reasonable method of data collection [WHS, 2002c, d].

Data on coverage of health interventions, such as immunization was collected. Assessment of coverage requires information on who received the immunization. For interventions directed at

[12] Bangladesh, Bosnia and Herzegovina, Brazil, Burkina Faso, Chad, China, Comoros, Congo Rep., Coted'Ivoire, Croatia, Czech Republic, Dominican Republic, Ecuador, Estonia, Ethiopia, Georgia, Ghana, Guatemala, Hungary, India, Kazakhstan, Kenya, Lao PDR, Latvia, Malawi, Malaysia, Mali, Mauritania, Mauritius, Mexico, Morocco, Myanmar, Namibia, Nepal, Pakistan, Paraguay, Philippines, Russian Federation, Senegal, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, Swaziland, Tunisia, Turkey, Ukraine, United Arab Emirates, Uruguay, Vietnam, Zambia, Zimbabwe.

[13] Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Sweden, United Kingdom.

[14] Australia, Israel, Luxembourg, and Norway.

[15] This data on self-reported height and weight was used for BMI calculation for each participant in this study

particular diseases, the coverage questions collected information on the prevalence or incidence of a condition and whether the respondent received treatment or not. Questions were included on treatment of childhood illnesses, safe motherhood interventions, DOTS for tuberculosis, STD and HIV/AIDS prevention, and treatment of angina, asthma, arthritis, depression, road traffic injuries, and others. Questions on health system responsiveness gathered basic information on health care utilization for inpatient and outpatient services. Two items were collected on the eight domains of responsiveness—autonomy, dignity, communication, confidentiality, basic amenities, prompt attention, choice, and social support [Ustun TB, 2003].

Health system goals and social capital data was collected because many health systems performance assessment schemes have a composite measure combining different aspects of health systems such as health of the population, responsiveness, and financing of the system [Ustun TB, 2003; WHO, 2000b]. WHS modules asked about the relative importance of the key goals of a health system: level and distribution of health, level and distribution of responsiveness and fairness in financial contribution. In addition, given the importance of interdependencies between social capital and health, this module included a range of questions on social capital, e.g. relating to stress, security, and participation in community, plus corresponding anchoring vignettes to enhance the cross-population comparability of these data.

The second section, the Household Questionnaire (Appendix B) provides important information on household composition and characteristics. It included the information on members of the household, their relationship to the informant, age, education, marital status, and whether they have worked in a health occupation. The adult member of the household, who was interviewed as the primary respondent for the individual questionnaire, was selected. This questionnaire collected data on household health intervention coverage, for example, use of insecticide impregnated bed nets for children and pregnant women in the household. Health insurance data was collected for each household member. The informant was asked whether he or she is covered by a health insurance plan and what are the various characteristics of this plan, including premiums. In selected countries, this module was extended to collect detailed information on participation in community health insurance schemes. Information on total expenditure broken down into food, housing, education, health care, and all other expenditures was collected in this questionnaire. It also collected information on the household ownership of selected assets such as houses, cars, radios, televisions, refrigerator, computer, washing machines for cloths, washing machine for dishes, chairs and tables as well as access to household services such as electricity, running water, and sewerage [Ferguson, 2003; Filmer and Pritchett, 2001]. The exact set of items is adjusted to national levels of income per capita. Health occupations for any household member identified as having worked in a health related occupation, a series of items on the type of employment and employer, educational experience, and compensation mechanism was collected [WHS, 2002a, b].

3.1.1 Quality Assurance in World Health Survey

To implement the WHS with high quality, intensive consultations with survey countries were undertaken to understand and improve survey implementation. A large-scale exercise was built with participation of countries, international survey experts, and regional advisors on WHS Quality Assurance Standards & Guidelines. This exercise has led to the examination of country needs and survey procedures to ensure appropriate sampling, efficient survey implementation, high quality data management, and analysis strategies. The WHS Quality Assurance Standards & Guidelines identify explicitly the operational criteria as quality standards [Ustun TB, 2003]. These guidelines were implemented locally by national institutions and monitored through external peer reviews. Each step of the survey production process involved a certification of quality. The instrument design required careful consideration to ensure that the questions were easily understood, the concepts were transferable across languages, and the measurement properties could remain stable across populations and over time. Attention was paid to the design and implementation of the survey with adequate supervision and training of interviewers. Troubleshooting on-site with actual observations of the implementation was a prerequisite. In large multi-country surveys like WHS, uniform procedures for data entry, cleaning, and archiving are necessary. Therefore, monitoring of the process during the data collection phase, with a regular feedback loop from the site to the central monitoring center and back, ensures that all analytical strategies can be executed with minimal error.

3.1.2 Sampling strategy in World Health Survey

Surveys for 59 countries[16] in the WHS employed a stratified multistage cluster probability sampling design[17] and 11 countries[18] employed a simple random sampling design. The WHS

[16] Australia, Bangladesh, Bosnia and Herzegovina, Brazil, Burkina Faso, Chad, China, Comoros, Congo Rep., Coted'Ivoire, Croatia, Czech Republic, Dominican Republic, Ecuador, Estonia, Ethiopia, Georgia, Ghana, Guatemala, Hungary, India, Israel, Kazakhstan, Kenya, Lao PDR, Latvia, Luxembourg, Malawi, Malaysia, Mali, Mauritania, Mauritius, Mexico, Morocco, Myanmar, Namibia, Nepal, Norway Pakistan, Paraguay, Philippines, Russian Federation, Senegal, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, Swaziland, Tunisia, Turkey, Ukraine, United Arab Emirates, Uruguay, Vietnam, Zambia, Zimbabwe, Finland, France, Ireland, Portugal, Sweden.

sampling frame covered 100% of the eligible population in the surveyed country. This means that every eligible person in the country has a chance of being included in the survey sample regardless of ethnic group or geographical area [WHO, 2002b].

3.1.2.1 Stratification

Stratification refers to the process of independent sampling from mutually exclusive sub-populations, or strata, which when combined make up the full population. Because the sample variation within sub-populations is lower than that for the whole population, stratified sampling improves the precision of estimates [Cochran, 1977]. The sample size from each strata is also pre-specified ensuring that sup-population estimates can be made with known precision [Deaton, 2000]. In WHS, stratification was done at the first stage of the sampling. Once the strata was chosen and justified, all stages of sample selection were conducted separately in each stratum. The strata chosen varied by country and reflected local conditions. Some examples of the factors that were used for stratification were geography (e.g. North, Central, South), level of urbanization (e.g. urban, rural), socio-economic zones, provinces (especially if health administration is primarily under the jurisdiction of provincial authorities), or presence of health facility in area. For example, in a country X stratification was done on three factors: 1) Region: North/ Center /South, 2) Socio-economic status: High/ Low, 3) Presence of health care facility: Yes/ No.

3.1.2.2 Clustering

A cluster is a naturally occurring unit or grouping within the population (e.g. cities, universities, provinces, hospitals etc.); it is a unit for which the administrative level has clear, non-overlapping boundaries. Cluster sampling is useful because it avoids having to compile exhaustive lists of every single person in the population. Clusters should be as heterogeneous as possible within and as homogenous as possible between. Clusters should be as small as possible (i.e. large administrative units such as Provinces or States are not good clusters) but not so small as to be homogenous. In cluster sampling, a number of clusters are randomly selected from a list of clusters. Then, either all members of the chosen cluster or a random selection from among them are included in the sample. Multistage sampling is an extension of cluster sampling where a hierarchy of clusters is chosen going from larger to smaller as illustrated in the following example and figure.

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[17] Stratified multistage cluster probability sampling design employed stratification, clustering at various stages of sampling.
[18] Austria, Belgium, Denmark, Germany, Greece, Guatemala, Italy, Netherlands, Slovenia, united kingdom, Zambia.

For example in WHS, stratification can be done at province level followed by selection of clusters in each strata, where Primary Sampling Unit (PSU) was a country, Secondary Sampling Unit (SSU) was an Enumeration Area, Elementary Unit (EU) was a Households and Final Unit was a Person.

3.1.2.3 Sampling Weights

In WHS, the probability of selection into the survey sample for each cluster was proportional to its relative size.

$$\text{Probability selection (Cluster A)} = \frac{\text{Population (Cluster A)}}{\text{Total Population (All clusters)}} \qquad (3.1)$$

This is called probability proportional to size sampling (PPS). By way of illustration let us take a case where:
A PPS was done for Country X that has 11,000,000 inhabitants. The primary sampling unit is chosen to be Counties and it has been decided that 4 PSUs out of 8 will be chosen for the sample. Therefore, the probability of selection of county 1 with population 900000 will be 900000/11000000= 0.08. In PPS random sampling, the probabilities of selection of each cluster were weighted by the relative size of each cluster. These weighted probabilities were entered into a computer program (a PPS algorithm) which then randomly chose 4 from the 8 PSUs. Note that every cluster (county) in the above example had a known and non-zero probability of being selected to the survey sample and sampling units with larger populations have a greater chance of being included. This same methodology was then applied to each stage of the multi-stage cluster sampling process: SSUs, elementary units etc. were all randomized using probability proportional to size sampling.

All the countries provided WHO the population sizes, probabilities of selection and sampling weights of all sampling units for each stage of the sampling process. Since clusters are often of unequal size, sampling weights are necessary to be able to reconstruct population estimates from sample estimates.

$$\text{Weight (Cluster A)} = 1/\text{Probability selection (Cluster A)} \qquad (3.2)$$

The weights of each sampling unit in cluster one in the example above would be 1/0.08=12.5. The weights essentially describe the number of persons in the sampling frame represented by each person in the cluster (i.e. each person in County one represents 12.5 people etc.). Weights for SSUs were calculated in the same way. The probability of selection of the elementary unit, the household, was not proportional to the number of people in the household. Rather, the household level weights were generated at the time of respondent selection within the household. The number of households selected within each chosen sampling unit was proportional to the total number of households in that sampling unit.

All members of each household selected into the survey sample were enumerated on the household roster. A member of the household is defined as someone who usually stays in the household, sleeps and shares meals, who has that address as primary place of residence, or who spends more than 6months a year living there. The respondent for the survey was selected among all eligible members of the household. It is a method by which each eligible person in a household has an equal probability of selection into the survey sample. The sampling weight for each person was calculated by multiplying the weight at each stage of sampling.

Personal weight= Weight(PSU) X Weight (SSU) X Weight (EU) (3.3)

3.1.3 Sample Size

The combined data of 70 countries represents a sample size of 274,482 individuals. Table 3.1 shows list of countries and sample size for each country. This table also shows the list of countries included for the cultural dimensions and BMI analysis. All samples were selected from nationally representative frames with a known probability in order to obtain estimates based on general population parameters. The eligible population from each country was included in the sampling frame and final sample size varied by country from 1,000-10,000 (except in Luxembourg, which included a sample of 600) [Salomon JA, 2003]. Countries that used face-to-face interview method generally had sample sizes between 5,000 and 10,000, based on feasibility and survey costs. The countries that used brief face-to-face and CATI interviews generally had between 1,000 and 1,500 respondents (except in Luxembourg, which included a sample of 600). Details of WHS sampling methods and sample size are documented on the WHS website [WHO, 2003].

Table 3.1 Initial and final sample size after excluding values on height, weight and BMI variables.

	Participants surveyed	Missing values	Participants included in analysis	Response rate*	Countries included in 53 countries analysis$^{\Psi}$
Australia	3600	685	2915	81.0	Yes
Austria	1055	107	948	89.9	Yes
Bangladesh	5552	4696	856	15.4	Yes
Belgium	1012	56	956	94.5	Yes
Bosnia and Herzegovina	1028	6	1022	99.4	No
Brazil	5000	557	4443	88.9	Yes
Burkina Faso	4825	3100	1725	35.8	Yes
Chad	4661	1132	3529	75.7	No
China	3993	10	3983	99.7	Yes
Comoros	1759	37	1722	97.9	No
Congo, Rep.	2497	304	2193	87.8	No
Cote d'Ivoire	3184	330	2854	89.6	No
Croatia	990	10	980	99.0	Yes
Czech Republic	935	22	913	97.6	Yes
Denmark	1003	29	974	97.1	Yes
Dominican Republic	4534	1423	3111	68.6	Yes
Ecuador	4660	600	4060	87.1	Yes
Estonia	1012	14	998	98.6	Yes
Ethiopia	4938	3967	971	19.7	Yes
Finland	1013	9	1004	99.1	Yes
France	1008	57	951	94.3	Yes
Georgia	2755	14	2741	99.5	No
Germany	1259	79	1180	93.7	Yes
Ghana	3938	264	3674	93.3	Yes
Greece	1000	39	961	96.1	Yes
Guatemala	4770	1577	3193	66.9	Yes
Hungary	1419	20	1399	98.6	Yes
India	9994	726	9268	92.7	Yes
Ireland	1014	104	910	89.7	Yes
Israel	1236	51	1185	95.9	Yes
Italy	1000	42	958	95.8	Yes
Kazakhstan	4496	387	4109	91.4	No
Kenya	4417	129	4288	97.1	Yes
Lao PDR	4889	23	4866	99.5	No
Latvia	856	121	735	85.9	Yes
Luxembourg	700	8	692	98.9	Yes
Malawi	5306	121	5185	97.7	Yes
Malaysia	6040	1051	4989	82.6	Yes

Mali	4285	3740	545	12.7	No
Mauritania	3842	733	3109	80.9	No
Mauritius	3888	1379	2509	64.5	No
Mexico	38746	15266	23480	60.6	Yes
Morocco	5000	2959	2041	40.8	Yes
Myanmar	5886	5	5881	99.9	Yes
Namibia	4250	484	3766	88.6	Yes
Nepal	8688	5522	3166	36.4	Yes
Netherlands	1091	6	1085	99.5	Yes
Norway	984	26	958	97.4	Yes
Pakistan	6379	2930	3449	54.1	Yes
Paraguay	5143	491	4652	90.5	No
Philippines	10078	1929	8149	80.9	Yes
Portugal	1030	134	896	87.0	Yes
Russian Federation	4422	921	3501	79.2	Yes
Senegal	3226	1545	1681	52.1	Yes
Slovak Republic	2519	726	1793	71.2	Yes
Slovenia	585	14	571	97.6	Yes
South Africa	2352	892	1460	62.1	Yes
Spain	6364	203	6161	96.8	Yes
Sri Lanka	6732	1069	5663	84.1	Yes
Swaziland	3121	1287	1834	58.8	No
Sweden	1000	25	975	97.5	Yes
Tunisia	5069	845	4224	83.3	No
Turkey	11220	3071	8149	72.6	Yes
Ukraine	2855	1081	1774	62.1	No
United Arab Emirates	1180	48	1132	95.9	Yes
United Kingdom	1200	141	1059	88.3	Yes
Uruguay	2991	26	2965	99.1	Yes
Vietnam	3492	17	3475	99.5	Yes
Zambia	3812	1600	2212	58.0	Yes
Zimbabwe	4100	1590	2510	61.2	No
Total	278878	72612	206266	74.0	

*Response rate after excluding missing and invalid values for height, weight and BMI.

$^{\Psi}$Yes=data was available for Hofstede cultural dimensions, therefore were included in analysis for cultural dimensions and BMI; No= data was not available for Hofstede cultural dimensions, therefore were not included in analysis for cultural dimensions and BMI

3.2 Outcome Variable

In epidemiological studies, to date, overweight and obesity have almost universally been measured in population groups using body mass index (BMI) [Garrow and Webster, 1985]. BMI is used in epidemiologic surveys to track change in the overall incidence and prevalence of obesity, by identifying the proportion of people who have an excess storage of body fat. It classifies adults into underweight, overweight and obese according to sex and age independent of cut-off points (WHO, 1995). Table 3.2 summaries the details of the international classification of adult underweight, ideal range, overweight and obese. There is less clarity whether these criteria are applicable for all racial groups across the countries. Therefore, additional cutoff points were given for the Asian communities [Mahmood and Arulkumaran, 2013]. The basis for this recommendation of using different cut-off points for Asian population was based on the observation that they consistently manifested metabolic problems at a lower BMI. New studies have also proposed different values for different ethnic groups such as Chinese [Mahmood and Arulkumaran, 2013; Misra, 2003]. These different cutoff points make multicountry comparison of overweight and obesity more challenging. The evidence indicates that using the same cutoff points for all the countries will be misleading and will produce biased results [Mahmood and Arulkumaran, 2013; Misra, 2003]. On the other hand the country (or ethnic) specific cutoff points for all countries (or ethnic groups) are not available to get correct overweight and obesity prevalence for each country [Mahmood and Arulkumaran, 2013]. Therefore, in contrast to the previous assessments that have focused exclusively on obesity or overweight, we chose Body Mass Index (BMI) as a continuous outcome variable in this study. Additionally, it captures the entire nutritional spectrum of energy intake in a population as opposed to an exclusive focus on the high-risk group. Although, choosing mean BMI has some advantages over obesity prevalence but the relationship between mean BMI and prevalence is incredibly tight so the advantages and disadvantages are very similar.

BMI was calculated from weight (in kilograms) divided by height (in meters) squared. Self-reported height and weight responses from the WHS were used to estimate individual level BMI, and hence mean BMI and the proportion of overweight and obesity in each country. Respondents who did not provide data on weight or height, miscoded responses or provided out-of-range codes were removed from the analysis, and were not included in the estimation of the BMI (*See. Missing data Section*). For some countries, data height and weights were measured in Kilogram and meters, whereas for some countries it was measured in Pound and feet/inches. All the pound and feet/inches values were converted to kilogram and meters before merging the data from all the countries. Following values were used for this conversion

1 Kilogram = 2.204 pounds

1 Meter = 39.37 Inches

1 Foot = 12 Inches

Since BMI does not measure body fat directly but is rather calculated from an individual's weight that includes both muscle and fat, it may not correspond to the same degree of fatness in different populations. For instance, the correlation between BMI and body fatness is stronger in young and middle aged adults than it is in older adults [Villareal et al., 2005b]. At the same BMI, women tend to have more body fat than men; on the other hand, both athletic men and women may have an excess body weight due to increased muscle mass rather than fat mass, a body form known as hyper-muscular obesity [Chamieh, 2013; Reidpath et al., 2014]. However, research has shown that it effectively captures obesity in the general population, correlates fairly strongly with body fatness even though this correlation might vary by gender, ethnicity, and age [Gallagher et al., 1996; Mei et al., 2002]. Despite these limitations, international health organizations agreed that BMI is a simple and inexpensive tool that provides a reasonable approximation of obesity at the population level, and estimation of the relative risk of disease in most people [Glasgow et al., 1995].

Table 3.2 The World Health Organization International Classification of adult underweight, overweight and obesity according to BMI.

Classification	BMI(kg/m²)	
	Principal cut-off points	Additional cut-off points
Underweight	<18.50	<18.50
Severe thinness	<16.00	<16.00
Moderate thinness	16.00 - 16.99	16.00 - 16.99
Mild thinness	17.00 - 18.49	17.00 - 18.49
Ideal range	18.50 - 24.99	18.50 - 22.99
		23.00 - 24.99
Overweight	≥25.00	≥25.00
Pre-obese	25.00 - 29.99	25.00 - 27.49
		27.50 - 29.99
Obese	≥30.00	≥30.00
Obese class I	30.00 - 34-99	30.00 - 32.49
		32.50 - 34.99
Obese class II	35.00 - 39.99	35.00 - 37.49
		37.50 - 39.99
Obese class III	≥40.00	≥40.00

3.3 Explanatory Variables

3.3.1 Individual Level Variables

The first set of explanatory variables were related to demographic backgrounds including gender, age, and marital status; socioeconomic status including education level, household wealth and occupation; and household setting whether rural or urban. All these are each discussed in turn.

3.3.1.1 Gender

Gender is an important demographic variable that influences BMI and obesity. Different studies have found different prevalence of obesity in men and women. In WHS individual questionnaire, question q1001 contains data on gender. Original datasets coded Female=1 and Male=2, I recoded a dummy variable for Gender, with female coded as “1” and male coded as “0”.

3.3.1.2 Age

Age is a key demographic indicator for obesity. In the WHS individual questionnaire, question q1002 collected data on age of participants in years. Age was used as a continuous variable rather than age categories. However, this makes regression intercept of age variable uninterruptable. Therefore, grand mean centring of age variable was performed[19]. Since previous literature documented the non-linear age effect on BMI and obesity prevalence varies by age cohort [Ogden et al., 2010; Rzehak and Heinrich, 2006], I include a quadratic term of age in the analysis. The continuous age and age square terms were used in the modelling.

3.3.1.3 Marital Status

One's marital status has been found to be closely related to the obesity risk [Sobal et al., 1992]. Marital status was recorded in question q1008 in individual questionnaire "What is your current marital status?", responses were coded as 1-Never married, 2-Currently married, 3-Separated, 4-Divorced, 5-Widoved and 6-Cohabiting. In this analysis all these responses were grouped in 1-Never Married (Never married), 2- Married (Currently married and cohabitant) and 3-Previously married (Separated, divorced and widowed).

The second set of independent variables was individual-level socioeconomic status. To investigate socioeconomic status disparities in obesity, I assessed three dominant components of socioeconomic status: Educational level, household wealth and occupational status.

3.3.1.4 Educational Attainment

Individual questionnaire of WHS measured education level using question "q1009 - What is the highest level of education that you have completed?" which were measured by 1. No formal schooling, 2. Less than primary school, 3. Primary school completed, 4. Secondary school completed, 5. High school (or equivalent) completed, 6. College / pre-university / University completed, 7. Postgraduate degree completed. Following the methods used in previous literature, I created three categories: "primary education" representing one less than primary school and primary school, "intermediate education" representing secondary school completed and high school completed, and "higher education" representing College / pre-university / University completed and Post graduate degree completed [Masood et al., 2015c; Viacava et al., 2005].

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[19] Centering procedure has been discussed in the following section "data cantering".

3.3.1.5 Household Wealth

Household wealth is an indicator of overall economic well-being of a household and is relatively less sensitive to short-term income such as the annual household income. Past studies attempted to measure household wealth by an index of composite assets representing the living standard of a household. The household wealth index has been found to be a good proxy for household wealth in both developed and developing countries [Bollen et al., 2002; Rutstein and Johnson, 2004]. The household wealth index based on household asset and wealth information is useful because annual household net income per capita does not really reflect one's economic well-being. Following the household index approach, I measured household wealth by constructing a wealth index for each household using assets data collected with WHS household questionnaire [Vyas and Kumaranayake, 2006]. Principle component analysis was used to construct a wealth index. Seventy separate principle component analyses were performed for each country to calculate the country specific index for all the 70 countries.

The Household Questionnaire assessed each household on the household's ownership of a number of consumer items and other characteristics that are related to wealth status. I incorporated the following consumer items from household questionnaire: how many rooms there are in your home, how many cars are there in your household, how many chairs are there in your home, how many tables are there in your home, does your home have electricity, and household ownership of the following items: Bicycle, bucket, washing machine for clothes, washing machine for dishes, refrigerator, fixed line telephone, mobile / cellular telephone, television, computer and clock. Using principal components analysis, a weight or factor score was assigned to each asset variable. I normalized these scores to a standard normal distribution with a mean of zero and a standard deviation of one. With these scores, I created four break points that define wealth quintiles as: Quintile 1(poorest), Quintile 2 (lower-middle), Quintile 3 (middle), Quintile 4 (higher-middle), and Quintile 5 (wealthiest). With this approach, I have the wealth quintile rank from 1 to 5, with 1 representing the lowest and 5 representing the highest level of wealth. Then I created dummy variables for household wealth, with the lowest quintile set as the reference. The distributions of wealth scores among each wealth quintile category are: poorest; poor; middle; rich and richest. Principal component analysis and quintile divisions were done for seventy countries separately and later, data for all the countries was merged to get a single variable for household wealth. The wealth quintiles were calculated separately for each country. This independent calculation of wealth quintile only allows for within country comparison. Separate analysis for each country was necessary because a person in poorest quintile of a wealthy country may be in the richest quintile of a poor country.

3.3.1.6 Occupation

The WHS individual questionnaire contained 10 categories of primary occupation for the question “q1013” “During the last 12 months, what has been your main occupation?” 1. Legislator, Senior Official, or Manager 2. Professionals (engineer, doctor, teacher, clergy, etc.) 3.Technician or Associate Professional (inspector, finance dealer, etc.) 4. Clerk (secretary, cashier, etc.) 5. Service or sales worker (cook, travel guide, shop salesperson, etc.) 6. Agricultural or fishery worker (vegetable grower, livestock producer, etc.) 7. Craft or trades worker (carpenter, painter, jewelry worker, butcher, etc.) 8. Plant/machine operator or assembler (equipment assembler, sewing-machine operator, driver, etc.) 9. Elementary worker (street food vendor, shoe cleaner, etc.) 10. Armed forces (government military). I adopted a sociological view by following the Goldthorpe schema [Goldthorpe et al., 1987] to group the primary occupations into four categories: High (1. Legislator, Senior Official, or Manager 2. Professional and 10.armed forces), medium (3.Technician or Associate Professional 4. Clerk 5. Service or sales worker), low (6. Agricultural or fishery worker 7. Craft or trades worker 8. Plant/machine operator or assembler) and elementary (elementary workers).

3.3.1.7 Household Setting Rural/Urban

The question q0104 in household questionnaire collected data for the location of household either in 1=urban, 2=peri-urban or 3=rural settings. In this analysis, I merged the peri-urban category with rural category and defined the categories as 1=urban, 2=rural/peri-urban.,

3.3.2 Country Level Variables

The second set of explanatory variables was related to the country level economic macro-environmental factors including national income and national income inequality. And the third set of explanatory variable was related to country level cultural macro-environmental factors including cultural dimensions. All these are each discussed individually.

3.3.2.1 National Income

The World Bank website provides international country-level income data on Gross National income per capita (GNI pc) in purchase power parity (PPP) in US dollars on an annual basis from 1970 for 232 countries, including all 70 WHS countries [The world Bank, 2014]. According to the definition from the Human Development Report 2001 [United Nations, 2001], GNI represents the final product of total goods and service at market value for an economy shared by its population, including the residents and foreign labor within the territory for a period of time. PPP is a rate of exchange that accounts for price differences across countries allowing international comparisons at the PPP US$ rate. A PPP US$1 has the same purchasing power in the domestic economy as $1 has in the United States. This is clearly an ideal source for country specific data on absolute income for a comparative analysis [Firebaugh, 2003]. In this thesis, I included the GNI-PPP data for year 2003 matching the year of WHS data collection. Table 3.3 presents the GNI-PPP values for all the 70 WHS countries.

Some authors have suggested a non-linear association between obesity and national income, indicating that at the lower range of national income, increasing national income is associated with increasing obesity prevalence. However, this association attenuates at a higher national income of the countries [Egger et al., 2012]. Therefore, in this thesis the assumption of linearity for the relationship between GNI-PPP and BMI was formally tested using residuals versus fitted plots. Residual plot revealed no significant departures from the assumption of linearity in this data. Therefore GNI-PPP was not transformed. Appendix C shows the residual verses fitted plots [Wells et al., 2012] to test the linear relationship of BMI and GNI-PPP. Possible reasons for this linear relationship are the inclusion of selected countries in WHS and using BMI rather obesity prevalence as an outcome variable. Previous studies for example Egger et. al. (2012) included 176 countries whereas this study used only 70 countries[20].

3.3.2.2 Income Inequality

Social scientists have developed many different dimensions for income inequality, which can be measured through various indicators[21] including the Gini index, coefficient of variation (CV), decile ratios, generalized entropy (GE) index, Kakwani progressivity index, Proportion of total income earned, Robin Hood index and Sen Poverty measure [De Maio, 2007; Evans et al.,

[20] Assumption for linearity for GNI-PPP with BMI was formally tested using residuals verses fitted plots. Residual plot revealed no departures from the assumption of linearity in this data. Therefore GNI-PPP was not transformed. Appendix C shows the residual verses fitted plots Wells JC, Marphatia AA, Cole TJ, McCoy D: Associations of economic and gender inequality with global obesity prevalence: Understanding the female excess. Soc Sci Med 2012;75:482-490..

[21] These inequality measurements could differ in three approaches: shares of income, such as the percentage of total income held by the top quartile of the income distribution; percentile ratios, such as the 90/10 ratio, and one-number summary statistics such as the Gini coefficient. The first two measures give the point-specific income inequality, whereas the third common measure gives the inequality throughout the complete income distribution.

2004; Judge et al., 1998]. While choices are many, the selection of an indicator should be guided by the theoretical considerations rather than merely data considerations. It has been suggested by various authors that the selection of the measure alone should not make a huge difference in the results as most of these measures are highly correlated to each other. Researchers have compared the Gini index with the alternative measures of income inequality such as the Decile ratio, the proportions of total income earned by the bottom 50%, 60%, and 70% of households, the Robin Hood Index, the Atkinson Index and Theil's entropy measure, and found that these measures were highly correlated to each other, with Pearson's r>0.94 [Kawachi et al., 1997]. In another study, Evans et. al. found that the one-number summary statistics of the Gini index, and Robin Hood indexes and the share of income for the top quartile were highly correlated to each other [Evans et al., 2004].

In this thesis, I have chosen the Gini index to depict the overall effect of income inequality on BMI because it is a single number measure of income inequality for each country and the data is available for all the 70 WHS countries. Additionally, since the Gini index is the most commonly used measure of income inequality, using Gini index in this study makes this study consistent with a large number of previous studies on income inequality and health. The Gini index can be derived from Gini coefficient after multiplying it by 100. The Gini coefficient is derived from the associated Lorenze curve[22]. On the graph[23], equally distributed income is represented with a diagonal, and percentage of the total income earned by cumulative percentage of the population is represented by the Lorenze curve. The farther the curve is from the diagonal, the greater is the degree of inequality. The Gini coefficient is a single summary statistic of the income distribution, which is the size of the area between the Lorenze curve and the 45° line of equality divided by the total area under the 45° line of equality. The Gini coefficient of 1 represents perfect inequality, and a Gini coefficient of 0 represents perfect equality [Cowell, 1995; Cowell, 2011]. Therefore the Gini index varies from 0 (perfect equality) to 100 (perfect inequality).

[22] A disadvantage of this method of income inequality calculation reflects all persons' experiences without stratifying individuals into social classes, therefore, Gini coefficient failed to capture the different kinds of inequalities, as different shape of Lorenz curve could result in similar Gini coefficient values.

[23] An example of Lorenz curve is given in Appendix D. De Maio FG: Income inequality measures. Journal of epidemiology and community health 2007;61:849-852.

Table 3.3 National income (GNI-PPP) and national income inequality (Gini index) for 70 countries

Country	GNI-PPP	Gini index
Australia	28960	35.19
Austria	31020	29.15
Bangladesh	1040	33.46
Belgium	30760	32.97
Bosnia and Herzegovina	5530	28.03
Brazil	7270	59.42
Burkina Faso	940	39.6
China	3180	42.59
Croatia	12980	31.1
Czech Republic	18110	25.8
Denmark	30250	24.7
Dominican Republic	5180	50.12
Ecuador	5830	55.06
Estonia	12710	36.81
Ethiopia	480	30
Finland	27420	26.88
France	27470	32.7
Georgia	2960	40.31
Germany	28120	28.31
Ghana	1060	42.8
Greece	22400	34.27
Guatemala	3730	59.19
Hungary	14640	26.82
India	1830	33.38
Ireland	29740	34.28
Israel	21350	39.2
Italy	27090	36.03
Kazakhstan	6530	34.95
Latvia	10590	35.91
Luxembourg	47060	30.76

Malaysia	9970	37.91
Mali	870	40.01
Mexico	10080	49.68
Morocco	3080	40.63
Netherlands	32070	30.9
Norway	38520	25.79
Pakistan	1870	30.39
Philippines	2650	44.48
Portugal	19280	38.5
Russian Federation	8970	35.7
Slovak Republic	12930	29.08
Slovenia	20370	29.15
South Africa	7320	57.77
Spain	24480	34.66
Sri Lanka	3030	41.06
Sweden	30810	25
Turkey	8760	42.71
Ukraine	4450	28.28
United Arab Emirates	66140	33.7
United Kingdom	30150	36
Uruguay	7700	46.66
Vietnam	1750	37.55
Zambia	1000	42.08
Zimbabwe	1547	50.1

3.3.2.4 Cultural Dimensions

Data on cultural dimensions (Uncertainty Avoidance, Individualism, Masculinity and Power Distance) was obtained from Hofstede's book "Cultural Consequences", 2nd edition [Hofstede et al., 2010]. Initially, Hofstede derived indexes for each dimension from questionnaires of carefully matched samples of employees in different national subsidiaries of the same multinational corporation IBM, between 1967 and 1973[24]. Later additions used a simplified questionnaire, the Values Survey Module 1994 [Hofstede, 2001b]. It consisted of 14 content questions, scored on a five-point scale. The mean score for each country has been calculated, giving the index-value per country. The most recently published lists contain index values on these four dimensions for 103 countries and regions. Indexes refer to relative differences between countries not an absolute value for a particular country. In the original study, they varied between 0–100. But later, countries were added with higher scores e.g. Guatemala with an uncertainty avoidance of 101. These findings have been replicated in a number of successive studies by different researchers using a variety of other matched samples of respondents. Data on Uncertainty Avoidance, Individualism, Masculinity and Power Distance was available only for 53 WHS countries. Therefore, the remaining 17 countries[25] were excluded from this analysis. Scores for the 53 included countries in this analysis are presented in table 3.4.

[24] Some researchers have claimed that these cultural dimensions are too old to be of any modern value, particularly with today's rapidly changing global environments, internationalization and convergence. Hofstede argued that the cross-cultural outcomes were based on centuries of indoctrination and recent replications have supported the fact that culture will not change overnight. Studies correlating the old country scores with related variables available on a year-by-year basis in many cases find no weakening of the correlations. A good reason for this is that the country scores on the dimensions do not provide absolute country positions, but only their positions relative to the other countries in the set. Influences, such as globalization and new technologies tend to affect all the countries without necessarily changing their relative position or ranking; if their cultures change, they change together. Only, when based in a specific dimension one country leapfrogs over others, the validity of the original scores will be reduced. But this remains to be demonstrated in carefully designed research.

[25] Bosnia and Herzegovina, Chad, Comoros, Congo Rep., Cote d'Ivoire, Georgia, Kazakhstan, Lao PDR, Mali, Mauritania, Mauritius, Myanmar, Paraguay, Swaziland, Tunisia, Ukraine, Zimbabwe.

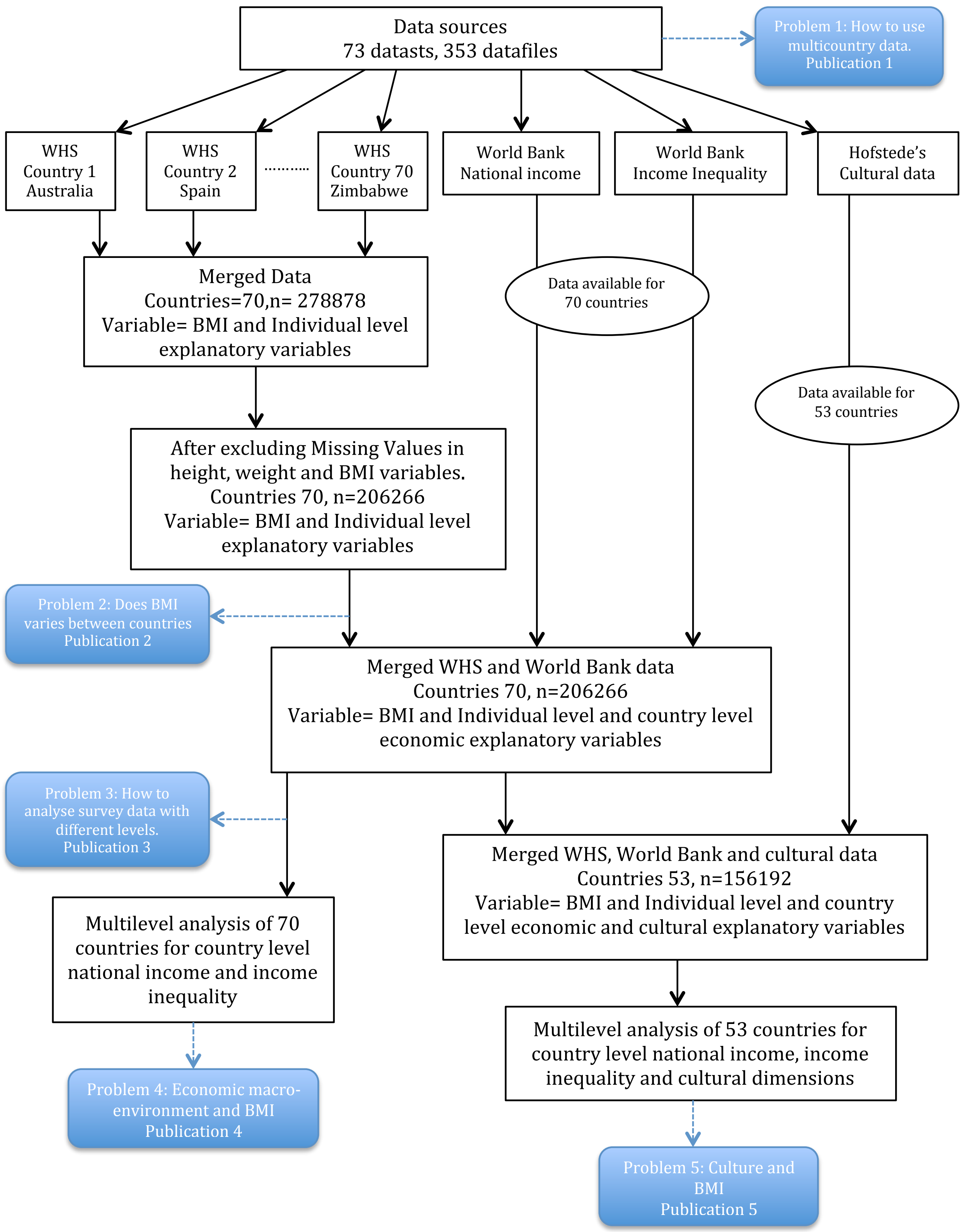
Table 3.4 Hofstede cultural dimensions for 53 country included in the culture and BMI analysis

Country	Uncertainty avoidance (UAI)	Individualism (IDV)	Power Distance (PDI)	Masculinity (MAS)
Australia	51	90	36	61
Austria	70	55	11	79
Bangladesh	60	20	80	55
Belgium	94	75	65	54
Brazil	76	38	69	49
Burkina Faso	55	15	70	50
China	30	20	80	66
Croatia	80	33	73	40
Czech Republic	74	58	57	57
Denmark	23	74	18	16
Dominican Republic	45	30	65	65
Ecuador	67	8	78	63
Estonia	60	60	40	30
Ethiopia	55	20	70	65
Finland	59	63	33	26
France	86	71	68	43
Germany	65	67	35	66
Ghana	65	15	80	40
Greece	112	35	60	57
Guatemala	101	6	95	37
Hungary	82	80	46	88
India	40	48	77	56
Ireland	35	70	28	68
Israel	81	54	13	47
Italy	75	76	50	70
Kenya	50	25	70	60
Latvia	63	70	44	9
Luxembourg	70	60	40	50
Malawi	50	30	70	40
Malaysia	36	26	104	50
Mexico	82	30	81	69
Morocco	68	46	70	53
Namibia	45	30	65	40
Nepal	40	30	65	40
Netherlands	53	80	38	14
Norway	50	69	31	8
Pakistan	70	14	55	50
Philippines	44	32	94	64
Portugal	104	27	63	31
Russian Federation	95	39	93	36
Senegal	55	25	70	45

Slovak Republic	51	52	104	110
Slovenia	88	27	71	19
South Africa	49	65	49	83
Spain	86	51	57	42
Sri Lanka	53	28	72	35
Sweden	29	71	31	5
Turkey	85	37	66	45
United Arab Emirates	80	25	90	50
United Kingdom	35	89	35	66
Uruguay	100	36	61	38
Vietnam	30	20	70	40
Zambia	50	35	60	40

3.4 Data Management

Analysis involving 73 different datasets (WHS datasets from 70 countries) creates challenges for data merging and cleaning. Merging and cleaning WHS was especially challenging as the WHS data for all the 70 countries is available in more than 353 different files. In this section, I am presenting the details about how I merged and cleaned the WHS data to make my methods more reproducible by others in the future. The various stages of data inclusion from WHS datasets have been presented as a flowchart in Figure 3.1.


Data sources
73 datasts, 353 datafiles
Problem 1: How to use multicountry data. Publication 1
WHS Country 1 Australia
WHS Country 2 Spain
....
WHS Country 70 Zimbabwe
World Bank National income
World Bank Income Inequality
Hofstede's Cultural data
Merged Data Countries=70,n= 278878 Variable= BMI and Individual level explanatory variables
Data available for 70 countries
Data available for 53 countries
After excluding Missing Values in height, weight and BMI variables. Countries 70, n=206266 Variable= BMI and Individual level explanatory variables
Problem 2: Does BMI varies between countries Publication 2
Merged WHS and World Bank data Countries 70, n=206266 Variable= BMI and Individual level and country level economic explanatory variables
Problem 3: How to analyse survey data with different levels. Publication 3
Merged WHS, World Bank and cultural data Countries 53, n=156192 Variable= BMI and Individual level and country level economic and cultural explanatory variables
Multilevel analysis of 70 countries for country level national income and income inequality
Multilevel analysis of 53 countries for country level national income, income inequality and cultural dimensions
Problem 4: Economic macro-environment and BMI Publication 4
Problem 5: Culture and BMI Publication 5

3.4.1 Data Merging

WHO provides WHS data in 70 different folders, each folder containing the data for a country. Each country data folder contains data in four (high income countries) or five (low or middle income countries) different STATA files. STATA file named “Country-ID” e.g. “Belgium-ID” contains data on identification number and survey design characteristics i.e. stratification, PSU and weights. STATA file named “WHS-Country_F2” e.g. “WHS-Belgium_F2” contains data on household variables (from WHS household questionnaire) including household assets and it also contains data on household setting (Urban/ Rural). Individual variables (from WHS individual questionnaire) height, weight, age, gender, marital status, education level, occupation were included in STATA File named “WHS-Country_F4” for high income countries and in STATA File named “WHS-Country_F5” for low and middle income countries. STATA Files “WHS-Country_F3” included data on household roster and health insurance for each household member but the data from this file was not needed in this thesis. There were a few other files in low and middle-income countries folders that were not used in this thesis, STATA File “WHS-Country_F4” included data on health occupation of household members. “WHS-Country_F6” and “WHS-Country_F7” included data on Mortality.

Data from STATA files “Country-ID” for all 70 countries were imported to “R-project software” using a package named “foreign” and were combined into a single dataframe using “smartbind” command in “gtools” package of R. This data on id, PSU, strata, and psweignts was saved in a single R.DATA file named ID.Rdata. Data from STATA files “WHS-Country_F2” for all 70 countries were imported to “R-project software” and were merged into single dataframe. Household variables of interest id, q0104 (Urban or rural setting), q0700 to q0719 on household ownership on selected assets were extracted from main dataframe and saved as household.Rdata. STAT files “WHS-Country_F4” from high income countries and “WHS-Country_F5” from low and middle income countries were imported to “R-project software” and were merged into single dataframe. Individual level variables of interest id, q1001 (sex), q1002 (age), q1004(weight in kilos), q1005 (eight in pounds),q1006 (high in centimetres), q1007a (height in feet), q1007b (height in inches), q1008 (marital status), q1009 (education level), q1013 (occupation) were extracted from these dataframes and saved as file “individual.Rdata”. Later these three R.DATA files ID, household and individual variables were merged together using the “merge” command, and all the variables were matched by the common variable named “id” from each dataset. Merge command combines different datasets with different variables of same “id” into a single dataset. It also keeps all the cases in the final dataset even if values are missing in any of the merging datasets. The final merged dataset was saved as WHS.Rdata.

Data on GNI-PPP and Gini index was imported from World Bank data portal using WDI package in R [R-Team, 2012]. The WDI package is a tool to search, extract and format data from the World Bank's World Development Indicators. In essence, it is an R-based wrapper for the World Bank Economic Indicators Data. When used in combination with the information on the World Bank data portal, it provides easy access to thousands of global datapoints. GNI-PPP and Gini index data for all 70 WHS countries were extracted and merged with WHS.Rdata file. It added more variables named GNI-PPP and Gini index to the file WHS.Rdata. This merging process provided a specific value for GNI-PPP and Gini index for each country. Data on all Hofstede dimensions (Uncertainty avoidance, individualism, power distance and masculinity) were collected from Hofstede book "Cultural Consequences" and merged with WHS. Rdata. This merging process provides a specific value for uncertainty avoidance, individualism, power distance and masculinity for each country.

3.4.2 Data Cleaning

Data cleaning was carried out on all variables to verify that the data values are correct and valid. Outliers were explored for outcomes and all explanatory variables to identify invalid and incorrect values in the variable. All categorical variables such as sex, marital status, education level, occupation and household setting rural/urban were screened for invalid values using "table" command in R. "table" command shows all the values entered for that particular variable.

Valid values for sex variable were 1 and 2, data was valid for all countries except Portugal and Zambia. In Portugal, the data values were entered as "Male" and "Female" and in Zambia the values were entered as "male" and "female". Values for these two countries were recoded as 1 for Female or female and 2 for Male or male. Similar pattern was seen for these two countries for rest of the variables i.e. marital status, education level and occupation. Table 3.5 shows valid and invalid data for these variables and how invalided values were recoded to valid values.

Table 3.5 Variables with valid and invalid values and recoding.

Variable	Valid values	Invalid values in the variable	Recoding
Sex	1 and 2	Male	Male→2
		Female	Female→1
		Male	Male→2
		female	female→1
Marital Status	1, 2, 3, 4, 5 and 6	never married	never married→1
		currently married	currently married→2
		separated	separated→3
		divorced	divorced→4
		widowed	widowed→5
		cohabiting	cohabiting→6
Education	1, 2, 3, 4, 5, 6 and 7	No formal schooling	No formal schooling→1
		no formal schooling	no formal schooling→1
		less than primary school	less than primary school→2
		primary school completed	primary school completed→3
		secondary school completed	secondary school completed→4
		high school completed	high school completed→5
		college completed	college completed→6
		post graduate degree completed	post graduate degree completed→7
Occupation	1, 2, 3, 4, 5, 6, 7, 9 and 10	Legislator, Senior Official, or Manager	Legislator, Senior Official, or Manager→1
		legislator, senior official, or manager	legislator, senior official, or manager→1
		Professional	Professional→2
		professional	professional→2
		Technician or Associate Professional	Technician or Associate Professional→3
		technician or associate professional	technician or associate professional→3
		Clerk	Clerk→4
		clerk	clerk→4
		Service or sales worker	Service or sales worker→5
		service or sales worker	service or sales worker→5
		Agricultural or fishery worker	Agricultural or fishery worker→6
		agricultural or fishery worker	agricultural or fishery worker→6
		Craft or trades worker	Craft or trades worker→7
		craft or trades worker	craft or trades worker→7
		Plant/machine operator or assembler	Plant/machine operator or assembler→8
		plant/machine operator or assembler	plant/machine operator or assembler→8

		Elementary worker elementary worker armed forces Armed forces	Elementary worker→9 elementary worker→9 armed forces→10 Armed forces→10
Setting	1, 2, 3	Urban Peri-urban / semi urban Rural	Urban→1 Peri-urban or semi urban→2 Rural→3
Age	18 years to 120 years	<18 years >120 years	<18 years → missing value >120 years →missing vale
Height	1.2 meter to 2.2 meter	<1.2 meter >2.2 meter	<1.2 meter → missing value >2.2 meter→ missing value
Weight	30 Kg to 400 Kg	<30 Kg >400 Kg	<30 Kg → missing value >400 Kg → missing value
BMI	14 kg/m^2 to70 kg/m^2	<14 kg/m^2 >70 kg/m^2	<14 kg/m^2 →missing value >70 kg/m^2 →missing value

For cleaning outcome variable BMI, I first screened height and weight variables for biologically implausible values (BIV). I followed the criteria given by Booth et. al. for biologically implausible values for BMI. Values were considered biologically implausible values if weight was less than 30 kg or more than 400 kg, height was less than 1.2 meters and more than 2.2 meters and BMI was less than 14 kg/m^2 or more than 70 kg/m^2. The “table” command was used for these variables to screen the values falling outside these cutoff points. A total of 2065/278878 (0.74%) participants reported a weight between 0kg to 29 kg, these values were categorized as biologically implausible values for weight and excluded from further analysis and BMI calculation. There were no biologically implausible values at the higher end of weight i.e. more than 400 kg. A total of 5427/278878 (2.09%) participants reported height less than 1.2 meters and more than 2.2, these values were categorized as biologically implausible values for height and excluded from further analysis and BMI calculation [Booth et al., 2013].

Apart from the outliers, a special problem was the “erroneous inliers”, i.e., data points generated by error but falling within the expected range. Though one can also identify some erroneous inliers by examining the history of each data point or by remeasurement, such examination was not feasible for such a big dataset. Erroneous inliers will often escape detection. Sometimes, these inliers are discovered during further analysis, or consistency checks [Van den Broeck et al., 2005]. I checked the potential erroneous inliers by screening BMI for biologically implausible values. After the exclusion of biologically implausible inliers a total of 272693 (272693/278878) participants were retained. I calculated the BMI scores for all 272693 participants and screened for any biologically implausible values for BMI. A total of 383/272693 (0.14%) participants reported a BMI above 70 Kg/m^2, these values were categorized as biologically implausible values and excluded from the further analysis. Exclusion of BIV values for BMI makes the sample size as 272310.

3.4.3 Missing Data

I first screened the dataset for the missing data on height, weight and BMI variables. There were 58559/272310 (21.5%) observations that had the missing values in height variable and 51680/272310 (19.0%) with missing weight variable. After calculating BMI from height and weight variable, 66044/272310 (24.2%) observation in BMI were missing. As BMI is used as an outcome variable in this thesis, all these missing observations were not included in the analysis. Exclusion of BMI missing values left a sample size of 206266.

For explanatory variables, two primary issues emerge in dealing with missing values. The first is the random or non-random distribution of missing values and the second issue involves deciding on the appropriate imputation procedure [Roth and Switzer, 1995]. With these issues in mind, I handled missing data by retaining as many observations as possible without biasing results.

For the individual-level variables, I addressed missing data starting with the variable that had the least number of missing observations, and then proceeded to the variable with the second smallest number of missing observations, and so on (Table 3.6). There were 35 individual records with missing data for the sex variable (0.01% of the sample) and 286 records with missing data for the age variable (0.1% of the sample). For these variables, there were very few missing values and consequently not enough power to detect the relationships between missing values and other model variables. Therefore for the gender variable, I generated a random value from a uniform distribution (range [0,1]), and compared the random value to the probability of each categorical outcome. For age, simple random imputation was performed using values between 18 and 120 years [Dong and Peng, 2013]. In the urban/rural setting variable 6425 (3.1%) observations were missing , 5529 out of these 6425 were due to completely missing data on urban/rural setting variable for Australia, Netherlands, Norway and Slovenia. It was not reasonable to impute data for the completely missing groups. Therefore we coded these values as missing values and modeled these missing values in regression models. Rest of the missing values in other countries were imputed with random values from uniform distribution (range [0,1]), and compared the random value to the probability of each categorical outcome.

For the education level variable, 1062 individual records (0.5% of sample) had missing information. Data on education variable was completely missing for Turkey. WHS also collected data on the number of school years. This data on the number of school years for Turkey was converted to education level variable. After combining data on education level and number of schools for Turkey, a majority of the data in education level was missing i.e. 982 out of 1062 missing cases. As majority of the data was missing for Turkey, a separate imputation process was done for Turkey and the rest of the countries. For Turkey, I used deterministic imputation. First, I assessed whether values were missing at random by creating a binary variable (not missing = 0, missing = 1) to reflect whether individual observations had a missing value on education level in Turkey. Then I regressed this variable on the other model variables, using multivariate logistic modeling. Four significant relationships were found between observations with missing values and other model variables: age, occupation, household wealth and rural/urban setting. I regressed the outcome variable (reflecting missing data on education in Turkey) again but only on the four variables listed above to confirm that they were significant predictors. All predictors remained significant at the $p<.01$ level. This procedure assumed that the pattern of relationships among education and the model variables for those with responses holds for those with education missing. Later, the same significant predictors were used to impute missing values in education variables using deterministic imputation method suggested by Gellman and Hill [Gelman and Hill, 2007]. For rest of the missing data from all other countries, I generated a random value from a uniform distribution (range [0,2]), and compared the random value to the probability of each categorical outcome.

Marital status had 8610 (4.2%) missing values. Majority of this data in marital status variable was missing for Turkey i.e. 8149 out of 8610 missing cases. As a majority of the marital status data for Turkey was missing, I coded Turkey as a missing value and used it as missing values in the regression model as missing values. The remaining 461 missing values in marital status variable for other countries were imputed with random values from uniform distribution (range [0,2]), and I compared the random value to the probability of each categorical outcome.

Data on household wealth was missing for 12734 (5.9%) cases. I first assessed whether values were missing at random or non-random by first creating a binary variable (not missing = 0, missing = 1) to reflect whether individual observations had a missing value on household wealth. Then I regressed this variable on the other model variables, using multivariate logistic modeling. Three significant relationships were found between observations with missing values and other model variables: age, occupation and rural /urban setting. I regressed the outcome variable (reflecting missing data on household wealth) again but only on the three variables listed above to confirm that they were significant predictors. All predictors remained significant at the $p<.01$ level. This procedure assumed that the pattern of relationships among household wealth and the model variables for those with responses holds for those with household wealth missing. Later, the same significant predictors were used to impute missing values in household wealth variables using deterministic imputation method suggested by Gellman and Hill [Gelman and Hill, 2007].The occupation variables had missing data for the largest number of observations (n=99468 cases, 48.2%). I coded Turkey as missing value and used them in regression model as missing values.

For the country level variables, the World Bank data is very comprehensive and available for more than 200 countries including all 70 WHS countries. Therefore, no data was missing for GNI-PPP and Gini index. Hofstede's Cultural consequences book provides data for 103 countries (on power distance, individualism, uncertainty avoidance and masculinity) that includes only 53 countries. Therefore the 17 countries[26] with missing data were not included in the analysis with cultural dimensions.

[26] Bosnia and Herzegovina, Chad, Comoros, Congo Rep., Coted'Ivoire, Georgia, Kazakhstan, Lao PDR, Mali, Mauritania, Mauritius, Paraguay, Swaziland, Tunisia, Ukraine, Zimbabwe.

Table 3.6 List of variables with percentage of missing data and missing data handling methods

Variable		Percentage of missing cases	Treatment of missing cases
Outcome variables			
Height	Continuous	58559/272310 (%)	Not included in the analysis
Weight	Continuous	51680/272310 (%)	Not included in the analysis
BMI	Continuous	66044/272310 (24.2%)	Not included in the analysis
Individual level explanatory variable			
Sex	Categorical	35/206266 (0.01%)	Imputation using [0,1] uniform distribution
Age	Continuous	286/206266 (0.1%)	Random imputation with values from 18 to 100 years
Setting	Categorical	6425/206266 (3.1%)	Imputation using [0,1] uniform distribution
Education	Categorical	1061/206266 (0.51%)	Imputation using [0,1,2] uniform distribution
Marital Status	Categorical	8610/206266 (4.2%)	Missing values were treated as a category in regression models.
Household wealth	Categorical	12734/206266 (5.9%)	Deterministic imputation
Occupation	Categorical	99469/206266 (48.2%)	Missing values were treated as a category in regression models.
Country level explanatory variables			
PDI	Continuous	16/70 (23%)	Excluded from analysis
PDV	Continuous	16/70 (23%)	Excluded from analysis
MAS	Continuous	16/70 (23%)	Excluded from analysis
UAI	Continuous	16/70 (23%)	Excluded from analysis
GNI-PPP	Continuous	0.0%	
Gini index	Continuous	0.0%	

3.4.5 Data Centering

In this dataset, age, national income, national income inequality and cultural dimensions variables do not have a readily interpretable zero value. Therefore, using these variables without centering may lead to a misinterpretation of the intercept, which is the expected value of the BMI, when all the independent variables equal zero, for example at the age of zero. The zero value was not practically possible. Therefore, for correct interpretation of the intercept, it is needed to centre the age variable.

Centering involves simple linear transformations of the predictor variables by subtracting a constant such as the mean from each observation in the data [Hox, 2010; Ka-yan, 2011]. In multilevel models, two main centering options are available: grand-mean centering and group-mean centering. The grand-mean centering involves subtracting the overall mean, or the pooled average, from each observation in the data. The subtracted mean, then, becomes the new zero point so that the positive values represent scores above the mean and negative values represent scores below the mean [Johnson, 2010]. Grand-mean centering only affects the parameter estimates for the model intercept. In this data, by centering the age, the intercept can be taken as the expected value of the BMI at the average age of the respondents. In-group mean centering, the group's mean is subtracted from the corresponding individual scores. Group-mean centering is more complicated than grand-mean centering because it fundamentally alters the meaning and interpretation of both the parameter estimates and the variance components in the multilevel model [Johnson, 2010].

Enders and Tofighi (2007) recommended that the selection of centering approach to be adopted should depend on the interpretation wanted, whether the inference is made on the upper or the lower level. If the former is of more interest, grand mean centering would be a better choice, otherwise, group mean is preferable [Enders and Tofighi, 2007]. Many authors have suggested using group mean centering only if there are strong theoretical reasons to do so [Hox, 2010; Luke, 2004]. As the main inference in this thesis is made at the country level, the grand mean centering is preferred for age variable centering. For country level variables; national income, national income inequality and cultural dimensions group mean centering was not an option because each member of a given country shares the same value at the country level. Grand mean centering was used to centre age at mean age 41.11 years, national income at mean GNI-

PPP 8840 USD, national income inequality at Gini index 42.38, mean power distance at 58.59, mean individualism at 47.1, mean uncertainty avoidance at 65.5 and mean masculinity at 48.7.[27]

3.5 Analytical Strategy and Models

A descriptive analysis for all the 70 countries together and for each country separately was performed. All the analysis was done using R-project statistical software [R-Team, 2012]. A designed based descriptive analysis was performed using survey package in R software. I fitted multilevel regression models for continuous BMI outcome, using lmer command in lme4 package of R statistical software [Bates, 2012; Bates et al., 2014]. I examine bivariate and multivariate associations between the BMI and country level national income, income inequality and cultural dimensions after controlling individual level variables. Estimation methods, model comparison and model diagnostics used in this analysis are discussed in the following section. I performed a review on the analytical methods of multicountry survey with the aim of reviewing the types of approaches currently utilized in the analysis of multi-country survey data, specifically focusing on design and modeling issues with a focus on analyses of significant multi-country surveys published in 2010 (Appendix E) [Masood and Reidpath, 2014]. This review provided me an overview of the methodological approaches researchers use to analyse the multicountry complex survey data.

3.5.1 Design Based Descriptive Analysis

The purpose of the descriptive analysis was to produce unbiased estimates of population parameters, such as totals, means and proportions. To account for the complexities of complex survey data, two approaches are commonly used: (i) model-based approaches and (iii) design-based approaches. The model-based methods ignore the complex survey design features, clustering, stratification and unequal probability of selection (weights). The sample observations, in a model-based approach, are assumed to be generated by a random process. Therefore, using model based analysis for complex survey sampling will result in biased estimates of parameters and inconsistent variance estimates. The design-based approach is the best method for descriptive analysis for survey data as it accounts for the complexities arising due to the sampling scheme (stratification, clustering and unequal probability of selection) [Ghosh, 2007; Lumley, 2010]. Therefore, I performed design based descriptive analysis for the BMI and all

[27] Centering was done separately for the 53 countries; age was centered at 41.98 years, national income at mean GNI-PPP 9041 USD, national income inequality at Gini index 41.33.

individual-level variables for each country and for all the countries together. I also analysed and plotted the design based distribution of the BMI by all individual level variables for each country. The “survey” package of R software was used to include design features (Sampling weights, stratification and clustering) of the WHS survey in the design based analysis [Lumley, 2010, 2012]. The design based mean and proportion in survey package of r software are obtained by estimating the population equation using the Horvitz-Thompson estimator. Standard errors for these estimates can be obtained with replicate weights simply by repeating the estimation for each set of replicates. Standard errors based on design information use an approach called linearization to translate the Horvitz-Thompson standard error estimator for the estimated population equation into a standard error for the estimates [Lumley, 2010].

3.5.2 Choice of Modeling Methods

A significant methodological challenge arises about how these data sets should be analysed for the investigation of country level effects. I performed a separate analysis using Spanish WHS data to identify the best analytical method for country level effect (Appendix F).

If one considers typical regression analysis, the unequal probability of selection and the multilevel nature of the data could lead to four possible approaches to the analysis of data collected using a complex survey design. The first approach is to analyse the data as if it was derived from a simple random sample of the population – a “model based analysis” e.g., Harling et. al., [Harling et al., 2010]. In the analysis of predictors of a continuous outcome, this typically involves a straightforward application of ordinary least squares regression. The second approach is to take account of the unequal probability of selection, stratification and the clustering in the data, while still treating all predictors as if they are measured at the lowest (individual) level – a “design-based analysis” e.g., Merikangas et.al., [Merikangas et al., 2011]. The design-based estimators using the weighted sample provide an unbiased estimate of the independent variables in the regression model [Diez-Roux, 2000; Ghosh and Pahwa, 2006; Reiter et al., 2005]. The third approach is an unweighted, multilevel analysis e.g., Subramanian et. al., [Subramanian et al., 2011]. The unequal probability of selection is ignored, and the hierarchical nature of the data becomes an explicit focus of the analysis, allowing interpretations of individual and area level effects on individual outcomes. The purpose of the analysis is to explain variation in the dependent variable at one level as a function of variables defined at other levels, plus interactions within and between levels [Diez-Roux, 2000]. In our developing nomenclature, this could be described as a "multilevel, model based analysis". Like its non-multilevel counterpart, the model-based analysis may lead to biased estimates when employed in samples that include unequal probability of selection [Carle, 2009]. Finally, the fourth approach is a weighted, multilevel analysis in which the unequal probability of selection is taken into account, and the hierarchical nature of the data becomes an explicit focus of the analysis – a "multilevel, design-based analysis" e.g., Antai et. al., [Antai and Moradi, 2010] and Goldhaber-Fiebert et. al., [Goldhaber-Fiebert et al., 2011].

I empirically tested the results of these four analytical methods using WHS Spanish data in a scientific paper (Appendix F). Metabolic Equivalent of Task (METs) was the outcome variable modelled against various explanatory variables using Model Based Analysis, Design Based Analysis, Multilevel Model Based Analysis, and Multilevel Design Based Analysis strategies to measure the differences in the model estimates and model fit. Regression coefficients, standard errors and AICs from all the four models were compared to analyze the extent of differences in the estimates of these strategies. Design based analysis showed highest estimates among the four models for most of the variables. Design based analysis estimates showed consistently higher standard errors than the other models. It showed higher standard errors when compared with the Model based analysis by 20% to 48%, with the multilevel design based analysis by 10% to 37% and with the multilevel design based analysis by 23% to 35%. Multilevel design based analysis had consistently higher standard error by 2.5% to 13% from multilevel model based analysis in level 1 predictors, but standard error in multilevel model based analysis was higher by 18% in level 2 predictor. Model fit index (AIC) showed multilevel design based analysis was the best fitted model and design based analysis was the least fitted model.

Although, this paper provides evidences in support of using Multilevel Design Based Analysis approach to address the research question of this thesis, this approach requires that the clusters used for the random effects (e.g. country level) are the same as (or nested in) the clusters used for sampling (personal communication with Professor Thomas Lumley)[28]. This means that if districts have been used as clustering unit in the sampling procedure, it is impossible to include countries as a level for Multilevel Design Based Analysis. The Multilevel Design Based Analysis can only incorporate the design features and multilevel in a single model if both clustering in sampling and level in the analysis are the same (e.g. district) (personal communication with

[28] Professor Thomas Lumley, Department of Biostatistics, University of Auckland.

Professor Thomas Lumley). Therefore for regression analysis, I have adopted Multilevel Model Based Analysis (i.e. multilevel modeling without sampling design) in this thesis.

3.5.3 Multilevel Model Building

Multilevel modeling was the main analytical approach used in this thesis, as it allows the differentiation between main and interaction effects for group and individual level variables, and also allows simultaneous analysis at a number of levels. The data used in this thesis was based on two levels: individuals at level one were nested within countries at level two. In order to model the individual level outcome variable (BMI), a number of predictor variables from both the individual level (age, gender, marital status, education level, household wealth, occupation and household setting rural/urban) and country level (national income, income inequality, uncertainty avoidance, individualism, power distance and masculinity) were included. The required models are complex multilevel linear regression models. Here a range of these models of increasing complexity and faithfulness to the data structure are sequentially discussed.

3.5.3.1 Model Building for National Income and Income Inequality

Model 0: I started with the basic or the least complex model the so called null model (empty, without including any predictors in the fixed part of the model). In the random part, the intercept (associated with the constant term) is allowed to vary at the country level. This model provides an estimate of the global pattern of mean BMI, the within and the between-country variations in BMI. This model was used to calculate intra-class correlation coefficient (ICC). The relative size of these higher-level variances can be compared in subsequent models as predictor variables are introduced. The model is specified as follows:

$$BMI_{ij} = \gamma_{00} + u_{oj} + r_{ij} \qquad (3.4)$$

The outcome variable BMI for individual i nested in the country j, γ_{00} is the mean BMI in the country j, u_{oj} is country level effect and r_{ij} is individual-level error.

Model 1 to model 9: These models are bivariate models to examine separately the effects of individual's gender, age, marital status, education level, household wealth, occupation and living in rural or urban areas and country level national income and income inequality on their BMI. These models are specified as follows.

$$BMI_{ij} = \gamma_{00} + \beta_1(GNIPPP)_{ij} + u_{oj} + r_{ij} \quad (3.5)$$

$$BMI_{ij} = \gamma_{00} + \beta_1(Gini)_{ij} + u_{oj} + r_{ij} \quad (3.6)$$

$$BMI_{ij} = \gamma_{00} + \beta_1(Age)_{ij} + u_{oj} + r_{ij} \quad (3.7)$$

$$BMI_{ij} = \gamma_{00} + \beta_1(Male)_{ij} + u_{oj} + r_{ij} \quad (3.8)$$

$$BMI_{ij} = \gamma_{00} + \beta_1(Married)_{ij} + \beta_2(Previously\ married)_{ij} + \beta_3(missing\ values)_{ij} + u_{oj} + r_{ij} \quad (3.9)$$

$$BMI_{ij} = \gamma_{00} + \beta_2(Intermediate\ education)_{ij} + \beta_3(Higher\ education)_{ij} + u_{oj} + r_{ij} \quad (3.10)$$

$$BMI_{ij} = \gamma_{00} + \beta_1(Quintile\ 2)_{ij} + \beta_2(Quintile\ 3)_{ij} + \beta_3(Quintile\ 4)_{ij} + \beta_4(Wealthiest)_{ij} + u_{oj} + r_{ij} \quad (3.11)$$

$$BMI_{ij} = \gamma_{00} + \beta_1(Medium)_{ij} + \beta_2(Low)_{ij} + \beta_3(Elimentery)_{ij} + \beta_4(Missing\ occupation)_{ij} + u_{oj} + r_{ij} \quad (3.12)$$

$$BMI_{ij} = \gamma_{00} + \beta_1(Rural)_{ij} + u_{oj} + r_{ij} \quad (3.13)$$

Model 10: This model builds on model 0 by including all the individual predictors in the fixed part of the model to examine the multivariate effect of all individual level variables. It models how much an individual's gender, age, marital status, education level, household wealth, occupation and living in rural or urban areas affect their BMI together. Consequently, when moving from model 1 to model 2, the contextual variation between countries in BMI was estimated before and after taking into account the compositional effect of individual level variables. The model is specified as follows:

$$\begin{aligned} BMI_{ij} = \gamma_{00} &+ \beta_1(Age)_{ij} + \beta_2(Male)_{ij} + \beta_2(Intermediate\ education)_{ij} + \beta_3(Higher\ education)_{ij} \\ &+ \beta_5(Married)_{ij} + \beta_6(Previously\ Married)_{ij} + \beta_7(missing\ values)_{ij} \\ &+ \beta_8(Quintile\ 2)_{ij} + \beta_9(Quintile\ 3)_{ij} + \beta_{10}(Quintile\ 4)_{ij} + \beta_{11}(Wealthiest)_{ij} \\ &+ \beta_{12}(Medium)_{ij} + \beta_{13}(Low)_{ij} + \beta_{14}(Elementary)_{ij} + \beta_{15}(Missing\ occupation)_{ij} \\ &+ \beta_{14}(Rural)_{ij} + u_{oj} + r_{ij} \end{aligned} \quad (3.14)$$

where the Age variable is the age for each individual centered at mean age 41.1, β_1 is the change in the individual's BMI with every year of increased in age; Gender is identifying females with a value 0, males with a value 1; β_2 is the gender gap of mean BMI; the difference between males and females. The terms; secondary education and college and above (Primary education as the base) are the education categories; $\beta_{3,}$ and β_4 are the differentials of each education category in contrast to the primary education. The categories of marital status are Married, previously married and missing values (Single as the base). Therefore, $\beta_{5,}$ $\beta_{6,}$ and β_7 define the difference for marital status in contrast to singles (the base). The terms; Quintile 2, Quintile 3, Quintile 4 and Wealthiest (poorest as the base) are the income dummies in the quintiles; $\beta_{8,}$ $\beta_{9,}$ $\beta_{10,}$ and β_{11} are the differentials of each income group in contrast to poorest. The terms; medium, low, elementary and missing occupation (High occupation as the base) are the occupation categories; $\beta_{12,}$ $\beta_{13,}$ $\beta_{14,}$ β_{15} are the differentials of each occupation category in contrast to occupation 1. Urban rural setting is identifying urban with a value 0, rural with a value 1; the difference between urban and rural. It should also be noted that the choice of reference or base group is a matter of convenience – it does not affect the estimates of the differences between the groups. While building this model with all the individual variables, bivariate relationships were first analyzed for each individual level variable separately.

Model 11: The model builds on model 10, by adding the fixed effect of a country's income on individuals' BMI at level 2. It tests the absolute income hypothesis whether or not the level of a country's wealth affects people's BMI after controlling for their individual level characteristics. The model is defined as follows:

$$\begin{aligned} BMI_{ij} = \gamma_{00} &+ \beta_1(Age)_{ij} + \beta_2(Male)_{ij} + \beta_2(Intermediate\ education)_{ij} + \beta_3(Higher\ education)_{ij} \\ &+ \beta_5(Married)_{ij} + \beta_6(Previously\ Married)_{ij} + \beta_7(missing\ values)_{ij} \\ &+ \beta_8(Quintile\ 2)_{ij} + \beta_9(Quintile\ 3)_{ij} + \beta_{10}(Quintile\ 4)_{ij} + \beta_{11}(Wealthiest)_{ij} \\ &+ \beta_{12}(Medium)_{ij} + \beta_{13}(Low)_{ij} + \beta_{14}(Elementary)_{ij} + \beta_{15}(Missing\ occupation)_{ij} \\ &+ \beta_{16}(Rural)_{ij} + \beta_{17}(GNIPPP)_{ij} + u_{oj} + r_{ij} \end{aligned} \tag{3.15}$$

Where GNI-PPP refers to the countries' national income which has been centered around a mean value of USD 8840. The term β_{17} estimates the effect of increasing by ten thousand dollar a country's average income on people's BMI after controlling for individual level variables.

Model 12: This builds on model 11, by considering the fixed effect of the contextual variable, country income inequality on individual's BMI and the extent to which it explains the country-level differences. The model can be specified as follows:

$$
\begin{aligned}
BMI_{ij} = \gamma_{00} &+ \beta_1(Age)_{ij} + \beta_2(Male)_{ij} + \beta_2(Intermediate\ education)_{ij} + \beta_3(Higher\ education)_{ij} \\
&+ \beta_5(Married)_{ij} + \beta_6(Previously\ Married)_{ij} + \beta_7(missing\ values)_{ij} \\
&+ \beta_8(Quintile\ 2)_{ij} + \beta_9(Quintile\ 3)_{ij} + \beta_{10}(Quintile\ 4)_{ij} + \beta_{11}(Wealthiest)_{ij} \\
&+ \beta_{12}(Medium)_{ij} + \beta_{13}(Low)_{ij} + \beta_{14}(Elementary)_{ij} + \beta_{15}(Missing\ occupation)_{ij} \\
&+ \beta_{16}(Rural)_{ij} + \beta_{17}(GNIPPP)_{ij} + \beta_{18}(Gini)_{ij} + u_{oj} + r_{ij}
\end{aligned}
\tag{3.16}
$$

where Gini index means the country's income inequality centered on the mean value 42.38. The term β_{18} estimates the effect of increasing by one unit a country's income inequality on people's BMI after controlling for individual level variables and the national income. Here, the base category is the group of respondents who are 41.1-year-old single females with primary education, low income, professional occupation, living in an urban area, who live in a country with average income USD 8840 and its national income inequality is 42.48.

Model 13: This model builds on Model 12 but includes the cross-level interaction of country income and household wealth groups. This will provide not only the relationship between national income and BMI, but will also show the differential impact that national income has on BMI of individuals who are on different incomes. The model is specified as follows:

$$
\begin{aligned}
BMI_{ij} = \gamma_{00} &+ \beta_1(Age)_{ij} + \beta_2(Male)_{ij} + \beta_2(Intermediate\ education)_{ij} + \beta_3(Higher\ education)_{ij} \\
&+ \beta_5(Married)_{ij} + \beta_6(Previously\ Married)_{ij} + \beta_7(missing\ values)_{ij} \\
&+ \beta_8(Quintile\ 2)_{ij} + \beta_9(Quintile\ 3)_{ij} + \beta_{10}(Quintile\ 4)_{ij} + \beta_{11}(Wealthiest)_{ij} \\
&+ \beta_{12}(Medium)_{ij} + \beta_{13}(Low)_{ij} + \beta_{14}(Elementary)_{ij} + \beta_{15}(Missing\ occupation)_{ij} \\
&+ \beta_{16}(Rural)_{ij} + \beta_{17}(GNIPPP)_{ij} + \beta_{18}(Gini)_{ij} + \beta_{19}(GNIPPP)_{ij} * (Quintile\ 2)_{ij} \\
&+ \beta_{20}(GNIPPP)_{ij} * (Quintile\ 3)_{ij} + \beta_{21}(GNIPPP)_{ij} * (Quintile\ 4)_{ij} \\
&+ \beta_{22}(GNIPPP)_{ij} * (Wealthiest)_{ij} + u_{oj} + r_{ij}
\end{aligned}
\tag{3.17}
$$

where there are four more cross-level interaction terms between a country's income and each category of household wealth except "poorest", which has been treated as base. The terms β_{19} to β_{22} show the difference among different level of household wealth groups and the differences between means over different levels of a country's income.

3.5.3.2 Model Building for Cultural Dimensions

Model building for models 0a, model 14 and model 15 were corresponding to the model 0, model 1 and model 2, except that these models were built for 53 countries which were included for cultural dimensions analysis.

Model 16 to model 19: These models are bivariate models to examine separately the effects of country level cultural dimensions; uncertainty avoidance, individualism, power distance and masculinity on BMI. These models are specified as follows.

$$BMI_{ij} = \gamma_{00} + \beta_1(UAI)_{ij} + u_{oj} + r_{ij} \quad (3.18)$$

$$BMI_{ij} = \gamma_{00} + \beta_1(IDV)_{ij} + u_{oj} + r_{ij} \quad (3.19)$$

$$BMI_{ij} = \gamma_{00} + \beta_1(PDI)_{ij} + u_{oj} + r_{ij} \quad (3.20)$$

$$BMI_{ij} = \gamma_{00} + \beta_1(MAS)_{ij} + u_{oj} + r_{ij} \quad (3.21)$$

Model 20 to Model 26: were similar to the model 3 to model 9, except these models were built for 53 countries which were included for cultural dimensions analysis.

Model 27: was similar to the model 12, except these models were built for 53 countries which were included for cultural dimensions analysis.

Model 28: This model builds on model 27, by considering the fixed effect of a cultural factor, the uncertainty avoidance on individual's BMI and the extent to which it explains the country-level differences after controlling individual level factors and country level national income and income inequality. This model can be specified as follows:

$$\begin{aligned} BMI_{ij} = {} & \gamma_{00} + \beta_1(Age)_{ij} + \beta_2(Male)_{ij} + \beta_2(Intermediate\ education)_{ij} + \beta_3(Higher\ education)_{ij} \\ & + \beta_5(Married)_{ij} + \beta_6(Previously\ Married)_{ij} + \beta_7(missing\ values)_{ij} \\ & + \beta_8(Quintile\ 2)_{ij} + \beta_9(Quintile\ 3)_{ij} + \beta_{10}(Quintile\ 4)_{ij} + \beta_{11}(Wealthiest)_{ij} \\ & + \beta_{12}(Medium)_{ij} + \beta_{13}(Low)_{ij} + \beta_{14}(Elementary)_{ij} + \beta_{15}(Missing\ occupation)_{ij} \\ & + \beta_{16}(Rural)_{ij} + \beta_{17}(GNIPPP)_{ij} + \beta_{18}(Gini)_{ij} + \beta_{19}(UAI)_{ij} + u_{oj} + r_{ij} \end{aligned} \quad (3.22)$$

Where UAI refers to the countries' uncertainty avoidance score which has been centered around a mean value of 65.5. The term β_{19} estimates the effect of increasing, by one unit, uncertainty avoidance on people's BMI after controlling for individual level variables and country level national income and income inequality.

Model 29: This model builds on model 28, by considering the fixed effect of the Individualism on individual's BMI and the extent to which it explains the country-level differences after controlling individual level factors and country level national income and income inequality. The model can be specified as follows:

$$\begin{aligned} BMI_{ij} = \gamma_{00} &+ \beta_1(Age)_{ij} + \beta_2(Male)_{ij} + \beta_2(Intermediate\ education)_{ij} + \beta_3(Higher\ education)_{ij} \\ &+ \beta_5(Married)_{ij} + \beta_6(Previously\ Married)_{ij} + \beta_7(missing\ values)_{ij} \\ &+ \beta_8(Quintile\ 2)_{ij} + \beta_9(Quintile\ 3)_{ij} + \beta_{10}(Quintile\ 4)_{ij} + \beta_{11}(Wealthiest)_{ij} \\ &+ \beta_{12}(Medium)_{ij} + \beta_{13}(Low)_{ij} + \beta_{14}(Elementary)_{ij} + \beta_{15}(Missing\ occupation)_{ij} \\ &+ \beta_{16}(Rural)_{ij} + \beta_{17}(GNIPPP)_{ij} + \beta_{18}(Gini)_{ij} + \beta_{19}(IDV)_{ij} + u_{oj} + r_{ij} \end{aligned} \tag{3.23}$$

Where IDV refers to the countries' individualism score which has been centered around a mean value of 47.1. The term β_{19} estimates the effect of increasing, by one unit, individualism on people's BMI after controlling for individual level variables and country level national income and income inequality.

Model 30: The model builds on model 29, by considering the fixed effect of the power distance on individual's BMI and the extent to which it explains the country-level differences after controlling individual level factors and country level national income and income inequality. The model can be specified as follows:

$$\begin{aligned} BMI_{ij} = \gamma_{00} &+ \beta_1(Age)_{ij} + \beta_2(Male)_{ij} + \beta_2(Intermediate\ education)_{ij} + \beta_3(Higher\ education)_{ij} \\ &+ \beta_5(Married)_{ij} + \beta_6(Previously\ Married)_{ij} + \beta_7(missing\ values)_{ij} \\ &+ \beta_8(Quintile\ 2)_{ij} + \beta_9(Quintile\ 3)_{ij} + \beta_{10}(Quintile\ 4)_{ij} + \beta_{11}(Wealthiest)_{ij} \\ &+ \beta_{12}(Medium)_{ij} + \beta_{13}(Low)_{ij} + \beta_{14}(Elementary)_{ij} + \beta_{15}(Missing\ occupation)_{ij} \\ &+ \beta_{16}(Rural)_{ij} + \beta_{17}(GNIPPP)_{ij} + \beta_{18}(Gini)_{ij} + \beta_{19}(PDI)_{ij} + u_{oj} + r_{ij} \end{aligned} \tag{3.24}$$

Where PDI refers to the countries' power distance score which has been centered around a mean value of 58.59. The term β_{19} estimates the effect of increasing, by one unit, power distance on people's BMI after controlling for individual level variables and country level national income and income inequality.

Model 31: This model builds on model 30, by considering the fixed effect of the masculinity on individual's BMI and the extent to which it explains the country-level differences after controlling individual level factors and country level national income and income inequality. The model can be specified as follows:

$$
\begin{aligned}
BMI_{ij} = \gamma_{00} &+ \beta_1(Age)_{ij} + \beta_2(Male)_{ij} + \beta_2(Intermediate\ education)_{ij} + \beta_3(Higher\ education)_{ij} \\
&+ \beta_5(Married)_{ij} + \beta_6(Previously\ Married)_{ij} + \beta_7(missing\ values)_{ij} \\
&+ \beta_8(Quintile\ 2)_{ij} + \beta_9(Quintile\ 3)_{ij} + \beta_{10}(Quintile\ 4)_{ij} + \beta_{11}(Wealthiest)_{ij} \\
&+ \beta_{12}(Medium)_{ij} + \beta_{13}(Low)_{ij} + \beta_{14}(Elementary)_{ij} + \beta_{15}(Missing\ occupation)_{ij} \\
&+ \beta_{16}(Rural)_{ij} + \beta_{17}(GNIPPP)_{ij} + \beta_{18}(Gini)_{ij} + \beta_{19}(MAS)_{ij} + u_{oj} + r_{ij}
\end{aligned} \tag{3.25}
$$

Where MAS refers to the countries’ masculinity score which has been centered around a mean value of 48.7. The term β_{19} estimates the effect of increasing masculinity, by one unit, on people’s BMI after controlling for individual level variables and country level national income and income inequality.

Model 32: The model builds on model 31, by considering the fixed effect of all the cultural dimensions together on individual’s BMI and the extent to which it explains the country-level differences after controlling individual level factors and country level national income and income inequality. The model can be specified as follows:

$$
\begin{aligned}
BMI_{ij} = \gamma_{00} &+ \beta_1(Age)_{ij} + \beta_2(Male)_{ij} + \beta_2(Intermediate\ education)_{ij} + \beta_3(Higher\ education)_{ij} \\
&+ \beta_5(Married)_{ij} + \beta_6(Previously\ Married)_{ij} + \beta_7(missing\ values)_{ij} \\
&+ \beta_8(Quintile\ 2)_{ij} + \beta_9(Quintile\ 3)_{ij} + \beta_{10}(Quintile\ 4)_{ij} + \beta_{11}(Wealthiest)_{ij} \\
&+ \beta_{12}(Medium)_{ij} + \beta_{13}(Low)_{ij} + \beta_{14}(Elementary)_{ij} + \beta_{15}(Missing\ occupation)_{ij} \\
&+ \beta_{16}(Rural)_{ij} + \beta_{17}(GNIPPP)_{ij} + \beta_{18}(Gini)_{ij} \\
&+ \beta_{19}(UAI)_{ij} + \beta_{20}(IDV)_{ij} + \beta_{21}(PDI)_{ij} + \beta_{22}(MAS)_{ij} + u_{oj} + r_{ij}
\end{aligned} \tag{3.26}
$$

Table 3.7 Description of models and explanatory variables

Model	Explanatory variable
Analysis of 70 countries	
Model 0	-
Model 1	National Income
Model 2	Income Inequality
Model 3	Age
Model 4	Gender
Model 5	Marital Status
Model 6	Education Level
Model 7	Household wealth
Model 8	Occupation
Model 9	Setting
Model 10	Age+Gender+Marital Status+ Education Level+Household Wealth+Occupation+Setting
Model 11	Age+Gender+Marital Status+ Education Level+Household Wealth+Occupation+Setting+National Income
Model 12	Age+Gender+Marital Status+ Education Level+Household Wealth+Occupation+Setting+Natioanl Income+Income Inequality
Model 13	Age+Gender+Marital Status+ Education Level+Household Wealth+Occupation+Setting+Natioanl Income*Income Inequality

Analysis of 53 countries	
Model 0a	-
Model 14	National Income
Model 15	Income Inequality
Model 16	Uncertainty Avoidance
Model 17	Individualism
Model 18	Power Distance
Model 19	Masculinity
Model 20	Age
Model 21	Gender
Model 22	Marital Status
Model 23	Education Level
Model 24	Household wealth
Model 25	Occupation
Model 26	Setting
Model 27	Age+Gender+Marital Status+ Education Level+Household Wealth+Occupation+Setting+Natioanl Income+Income Inequality

Model 28	Age+Gender+Marital Status+ Education Level+Household Wealth+Occupation+Setting+Natioanl Income+Income Inequality+ Uncertainty avoidance
Model 29	Age+Gender+Marital Status+ Education Level+Household Wealth+Occupation+Setting+Natioanl Income+Income Inequality+ Individualism
Model 30	Age+Gender+Marital Status+ Education Level+Household Wealth+Occupation+Setting+Natioanl Income+Income Inequality +Power Distance
Model 31	Age+Gender+Marital Status+ Education Level+Household Wealth+Occupation+Setting+Natioanl Income+Income Inequality + Masculinity
Model 32	Age+Gender+Marital Status+ Education Level+Household Wealth+Occupation+Setting+Natioanl Income+Income Inequality + Uncertainty avoidance+Individualim+Power Distance

3.5.4 Estimation Method

There are various estimation methods that have been used in multilevel modeling ; Maximum likelihood (ML), generalized least squares (GLS), generalized estimating equations (GEE), and Bayesian methods such as Markov chain Monte Carlo (MCMC) [Hox, 2010; Hox and Roberts, 2011]. Among these, Maximum Likelihood is the most commonly used estimation method in multilevel modeling. It is a general estimation procedure, which produces estimates for the population parameters that maximize the probability of observing the data that is actually observed.

In this thesis, I have used ML methods for the following reasons. An advantage of the ML estimation method is that it is generally robust, and produces estimates that are asymptotically efficient and consistent. With large samples, ML estimates are usually robust against mild violations of the assumptions, such as having non-normal errors. I have presented the results for distribution of residual errors of my data analysis in Appendix G. The data utilized in this thesis violates the assumption of normal distribution of residual error. However, considering very large sample size, I selected ML method for the analysis in this thesis.

Two different ML functions are used in multilevel regression modeling. Full maximum likelihood (FML): in this method, both the regression coefficients and the variance components are included in the likelihood function. Restricted maximum likelihood (RML): here only the variance components are included in the likelihood function, and the regression coefficients are estimated in a second estimation step. In practice, with large sample sizes the differences between the two methods are usually small [Kreft and Leeuw, 1998]. FML still continues to be used because it has two advantages over RML. First, the computations are generally easier, and second, since the regression coefficients are included in the likelihood function, an overall chi-square test based on the likelihood can be used to compare two models that differ in the fixed part (the regression coefficients). With RML, only differences in the random part (the variance components) can be compared with this test. Since FML and RML do not produce significantly different results with large sample sizes, I used FML in this thesis due ease of its computation [Hox, 2010], and the possibility of comparing nested models.

GLS is an extension of the standard estimation ordinary least squares (OLS) method that allows for heterogeneity and observations that differ in sampling variance. However, simulation research shows that, in general, GLS estimates are less efficient, and the GLS-derived standard errors are rather inaccurate (see Hox, 1998; Kreft, 1996; van der Leeden, Meijer, & Busing, 2008). GEE [Zeger and Liang, 1986] estimates the variances and covariances in the random part of the multilevel model directly from the residuals, which makes them faster to compute than full ML estimates. A drawback of the GEE approach is that it only approximates the random effects structure, and therefore the random effects cannot be analyzed in detail. So, most softwares will estimate a full unstructured covariance matrix for the random part, which makes it impossible to estimate random effects for the intercept or slopes. Bayesian methods can provide accurate estimates of the parameters and the uncertainty associated with them [Goldstein, 2011]. However, they are computationally demanding, and the simulation procedure must be monitored to ensure that it is working properly. Therefore, in general, ML estimation is preferred and used in this thesis.

3.5.5 Coefficient of Determination (R^2)

An important statistic in ordinary multiple regression analysis is the coefficient of determination or R^2, which is interpreted as the proportion of variance modelled by the explanatory variables. In multilevel models, the issue of explained variance is a complex one due to the several levels involved in the analysis. In lme4 package, R^2 is not reported automatically. However it can be computed by using the formula that is suggested by Rabe-Hesketh and Skrondal (2008) and Hox 2010 [Hox, 2010; Rabe-Hesketh and Skrondal, 2005]. To calculate multiple R^2, we must express this difference as a proportion of the total error variance. To calculate the explained variance at both the levels separately, two different formulas were used. R_1^2 represents the explained variance at the individual level and R_2^2 represents explained variance at the country level. For the proportion of variance explained at the individual level, I used:

$$R_1^2 = \frac{\sigma_{eb}^2 - \sigma_{em}^2}{\sigma_{eb}^2} \quad (3.27)$$

σ_{eb}^2 is the individual-level residual variance for the baseline model, which is the intercept-only model, and σ_{em}^2 is the individual-level residual variance for the comparison model.

For the proportion of variance explained at the country level, I used:

$$R_2^2 = \frac{\sigma_{ub}^2 - \sigma_{um}^2}{\sigma_{ub}^2} \quad (3.28)$$

Where σ_{ub}^2 is the country-level residual variance for the baseline model, which is the intercept-only model, and σ_{um}^2 is the country-level residual variance for the comparison model [Hox, 2010; Raudenbush and Bryk, 2002].

3.5.6 Model Fit/Comparison

When fitting several models to the same dataset, we need to compare them using summary measures of fit. Therefore, several model fit indices, deviance, log likelihood, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to compare the fitted models. The maximum likelihood procedure also produces a statistic called the deviance, which indicates how well the model fits the data. The deviance is defined as -2 ×ln (Likelihood) [Goldstein, 2011; Hox, 2010]. If two models are nested, i.e. one model contains the other, the deviances of the two models can be used to compare their fit statistically. For nested models, the difference in deviance has a chi-square distribution with degrees of freedom equal to the difference in the number of parameters that are estimated in the two models. The deviance test can be used to perform a formal chi-square test, in order to test whether the more general model fits significantly better than the simpler model.

However, deviance is also sensitive to the number of observations and the number of parameters in the model, and that is the reason lme4 computes AIC and BIC [Bates et al., 2014; Gelman and Hill, 2007].

AIC= deviance + 2 X number of parameters (3.29)

BIC= deviance + number of parameters X ln (number of observations) (3.30)

When the deviance goes down, indicating a better fit, both the AIC and the BIC also tend to go down. However, both AIC and the BIC include a penalty function based on the number of estimated parameters or observations. As a result, when the number of estimated parameters goes up, AIC and BIC also tend to go up. For most sample sizes, BIC places a larger penalty on complex models, which leads to a preference for smaller models. Since multilevel data has different sample sizes at different levels, AIC is more straightforward than BIC, and is therefore the recommended choice. While AIC helps to choose the best model among the models available, BIC tries to select the true model, assuming that it is among the models adopted.

3.5.7 Model Diagnostics

Model diagnostics based on residual analysis were also conducted before finally building multilevel models in lme4. I examined the distribution of residuals by using QQ plot (quintile) and residual verses fitted plot (Appendix G). Results of model diagnostics show slight deviation from the assumptions of normal distribution of residuals. I used log transformation on all the country level variables such as GNI-PPP, Gini index, individualism, uncertainty avoidance, power distance and masculinity in order to account for the non-normality and skewness. Log transformation of these variables, adding quadric term for age and GNI-PPP, excluding the outlying countries South Africa, Swaziland and UAE didn't improve the residual plot and other diagnostic plots. In the preliminary analysis, I use collinearity diagnostics to test the potential multicollinearity between outcome variables and country level variables. I calculated bivariate correlations among variables. The absolute values of correlations ranged from 0.00 to 0.65, which is good evidence suggesting sufficient independent variance to estimate stable effects [Wolch et al., 2011]. These diagnostics results indicate that multicollinearity is not a problem in this study.

3.5.8 Stratified Analysis

All the 70 countries were divided into three (low, middle and high income countries) groups according to the national income (GNI-PPP) of the countries. Countries with GNI-PPP under US$ 3,035 are classified as low income group; GNI-PPP between US$ 3,036 to US$ 9385 as middle income group; and GNI-PPP US$ 9386 and above as high income group [World Bank, 2005]. This grouping divided all the 70 countries into 30 high income, 19 middle income and 21 low-income countries. Stratified multilevel regression analysis was performed separately for each group to observe the relationship of BMI and explanatory variables (Appendix H).

CHAPTER 4: Results

The presentation of the results in this thesis is separated into three sections. In the first section, the descriptive results of the 70 countries' data are presented. In the second section, the results of the relationship of BMI and national income and income inequality based on all 70 countries' data are presented. And in the third section, results for the relationship between BMI and country level cultural dimensions based on 53 countries[29] are presented.

4.1 Descriptive Analysis

A sample of 206,266 people from 70 countries was included in this study. Sample size and response rate for each country is given in Table 3.1 in the methods section. Initial sample size for each country ranged from 585 for Slovenia to 38,576 for Mexico. Analytical sample sizes ranged from 545 for Mali to 23,480 for Mexico with response rate ranging from 12.7% to 99.9% (Table 3.1).

Weighted and unweighted descriptive analysis of individual level variables for 70 countries is presented in the table 4.1. Here, I will discuss the descriptive analysis for 70 countries. The weighted mean BMI and standard error (SE) in these 70 countries was 23.90 (0.07). The weighted mean age (SE) of the participants in all of the included countries was 41.1 (0.17). A nearly equal weighted percentage of females (50.7%) and males (49.2%) were included in this study. More than half of the people (59.8%) were currently married, 20.7% of people were not married and 15.9% were divorced/widowed. Nearly half of the participants had primary or lower education (46.4%), people with intermediate education were 38.8% and only 14.3% had higher education (completed college/university or above education). Household wealth quintiles had nearly 19% of people in each quintile and 5.7% of the data was missing on household wealth. In occupation variables, nearly quarter of the people were from low occupation (agriculture/fishery/ Craft or trades worker/ plant/machine operator or assembler), 14.1% were from medium occupation (Technician/ Associate Professional/ Clerk/ Service/ sales worker), 7.6% from high occupation (Legislator/Senior Official/ Manager/ professionals/ armed forces) and 5.0% were elementary workers. Nearly fifty percent of the data in the occupation variable was missing.

[29] Data on cultural dimensions was not available for 17 countries.

Nearly half of the participants were from rural (50.8%) and 46.0% from rural setting and 3.2% of the data was missing.

Table 4.1 Model based and design based descriptive analysis of outcome variable (BMI) and individual level explanatory variables in the 70 WHS countries.

	70 countries for national income and income inequality analysis	
	Model Based	Design Based
	n=206266	N= 885431753
	Mean ± SD	Mean ± SE
Outcome variable		
BMI	24.02(4.84)	23.90(0.07)
Explanatory Variables		
Age	41.19(16.5)	41.11(0.17)
	n(%)	N(%)
Gender		
Female	110778(53.7)	449234978(50.7)
Male	95453(46.3)	436174517(49.2)
Missing values	35(0.016)	22256 (0.1)
Marital Status†		
Never Married	40663(19.7)	183696842(20.7)
Married	117864(57.1)	529457230(59.8)
Previously married	39129(19.0)	140656180(15.9)
Missing values	8610(4.17)	31621501(3.6)
Education		
Primary	101347(49.1)	410420475(46.4)
Intermediate	81964(39.7)	342786029(38.8)
Higher	21894(10.61)	127976371(14.3)
Missing values	1061(0.51)	4248878(0.5)
Household Income		
1^{st} Quintile (Poorest)	40145(19.46)	181004197(20.4)
2^{nd} Quintile	40312(19.54)	175298294(19.8)
3^{rd} Quintile	37709(18.28)	158155749(17.9)
4^{th} Quintile	38032(18.43)	160158090(18.1)
5^{th} Quintile (Wealthiest)	37334(18.09)	142770575(16.1)
Missing values	12734(6.17)	68044846(7.7)

Occupation‡		
High	15491(7.5)	67380934(7.6)
Medium	26948(13.1)	119950548(13.5)
Low	53894(26.1)	250461529(28.2)
Elementary	10464(5.1)	46019304(5.2)
Missing values	99469(48.2)	401619438(45.4)
Setting¥		
Urban	105066(50.93)	406861657(46.0)
Rural	94775(46.25)	450418126(50.8)
Missing values	6425(3.11)	28151969(3.2)

†All data in this variable was missing for Turkey; ‡All data in this variable was missing for Turkey and Norway; ¥ All data in this variable was missing for Australia, Netherlands, Norway and Slovenia;

$^{\Psi}$Occupation categories: High (1. Legislator, Senior Official, or Manager 2. Professional and 10.armed forces), medium (3.Technician or Associate Professional 4. Clerk 5. Service or sales worker), low (6. Agricultural or fishery worker 7. Craft or trades worker 8. Plant/machine operator or assembler) and elementary (elementary workers)

Design based descriptive analysis was also performed for each country separately. Figure 4.1 to figure 4.7 present the data for all individual level explanatory variables for each country. To make these graphs more informative, I have colour coded the countries in these graphs according to their economic classification (High, middle and low income country). All the countries were classified into tertiles based on GNI-PPP; under US$ 3,035 (low income); US$ 3,036 to US$ 9385 (middle income); and US$ 9386 and above (high income) [30] [World Bank, 2005]. Figure 4.1 presents the distribution of sex variable in 70 countries. Most of the countries had 40-60% females (weighted percentage). Seven countries had more than 60% males (weighted percentage); these countries being mainly low-income countries. Ten countries were at the other end of the distribution with more than 60% females (weighted percentage), all these countries were high or middle-income countries. Low percentages of female participants from Muslim majority countries like Bangladesh, Mali, Ethiopia, Pakistan and Morocco might be due to lower participation of females in surveys.

Marital status data did not show any particular distribution pattern associated with country income groups. All the countries except Namibia and South Africa had a higher weighted percentage of married participants than never married and widowed/separated participants. Nearly 50% of participants from Namibia and South Africa were never married (Figure 4.2). Marital status data was completely missing for Turkey.

Education level had a clear pattern. A greater percentage of people with higher education occurred in high-income countries (Figure 4.3). Generally, high-income countries had most participants with intermediate and higher education and a lower percentage with primary level education. On the other hand, low and middle-income countries had a higher percentage of participants with primary education. For example, Malawi and Chad had more than 80% of the participants from primary education category. Norway, Portugal, and Mauritius were exceptions and had a higher percentage from primary education level group. This pattern of education was similar as discussed in the literature review chapter; the average education level in high-income countries is higher as compared to the low and middle-income countries.

Household wealth quintiles for 70 countries are presented in Figure 4.4. All the countries had less than 20% of the data missing in the household wealth quintile variable except Comoros, Ecuador, Congo and Ukraine. 80% of the data for Comoros and nearly 50% of the data for

[30] This grouping divided all the 70 countries into 30 high income, 19 middle income and 21 low-income countries.

Ecuador was missing. A majority of the countries had equal distribution of participants in each quintile except for a few low-income countries (such as Bangladesh, Ethiopia, Nepal) which had more participants in the lowest quintile[31].

Occupation data was completely missing for two countries: Turkey and Norway. At least 30% of the data was missing in the occupation variable for each country. Low and middle-income countries had proportionally fewer high occupation (Legislator/Senior Official/ Manager/ professionals/ armed forces) and medium occupation (Technician/ Associate Professional/ Clerk/ Service/ sales worker) participants while high-income countries had a greater proportion from these occupation categories. In low and middle-income countries, most of the participants were from low occupation categories (agricultural/fishery/craft/machine operator occupation) (Figure 4.5).

Data on the rural/urban setting was completely missing for four countries (Austria, Netherlands, Norway and Slovenia) (Figure 4.6). Low and middle-income countries had proportionally fewer participants from rural areas and high-income countries had proportionally greater urban participants.

Figure 4.7 shows the weighted mean for age in the 70 countries. On average, the participants from low and middle-income countries were younger than the participants from high-income countries. Most of the middle and low-income countries had mean age less than 40 years whereas the high-income countries had mean age more than 40 years.

[31] Development of wealth quintile index and quintile using principle component analysis was done before the exclusion of the missing values. The pattern of unequal distribution of the wealth quintile represents the relatively higher percentage of missing values in one quintile than the other.

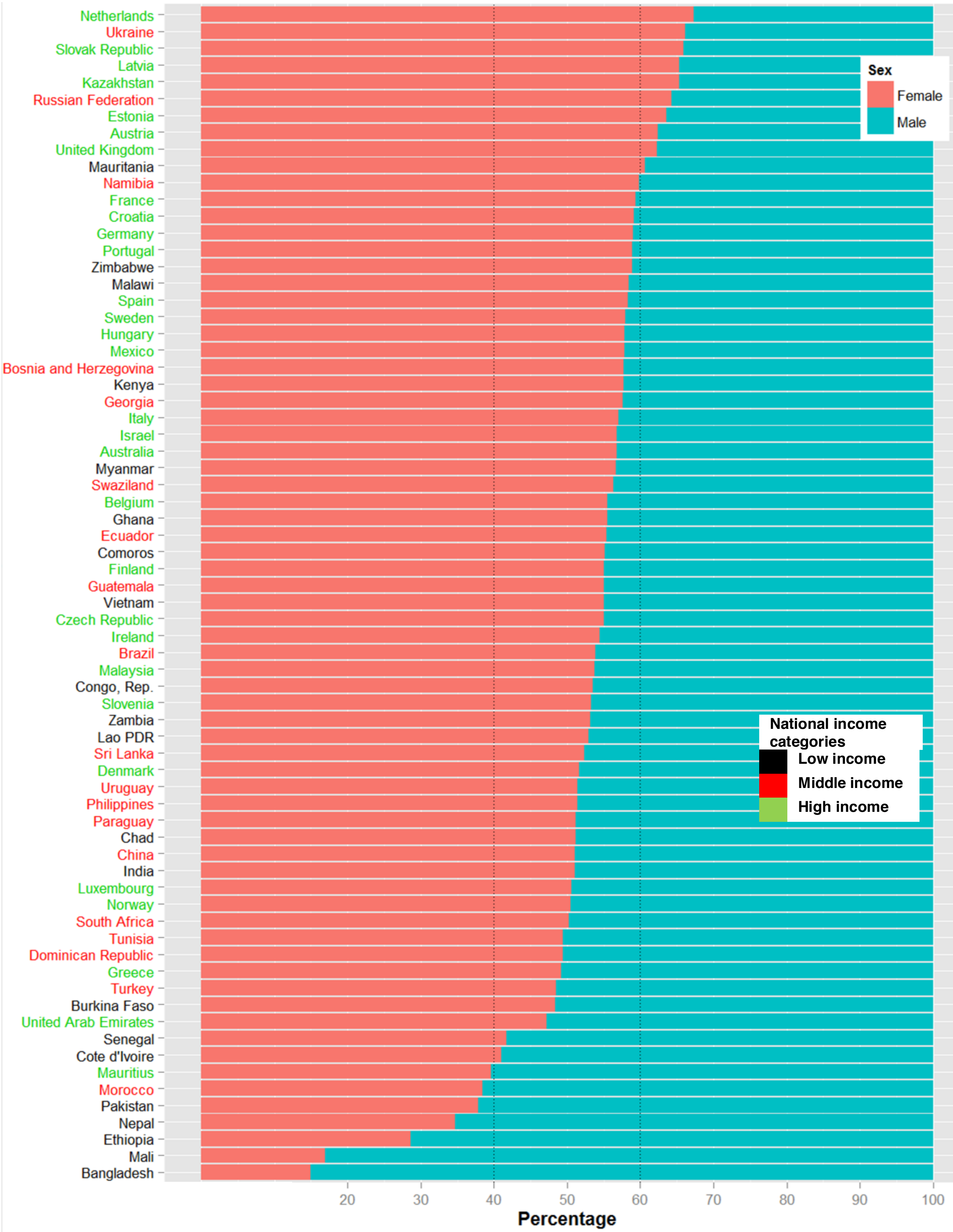


Figure 4.1 Design based distribution of gender (weighted %) in the 70 WHS countries

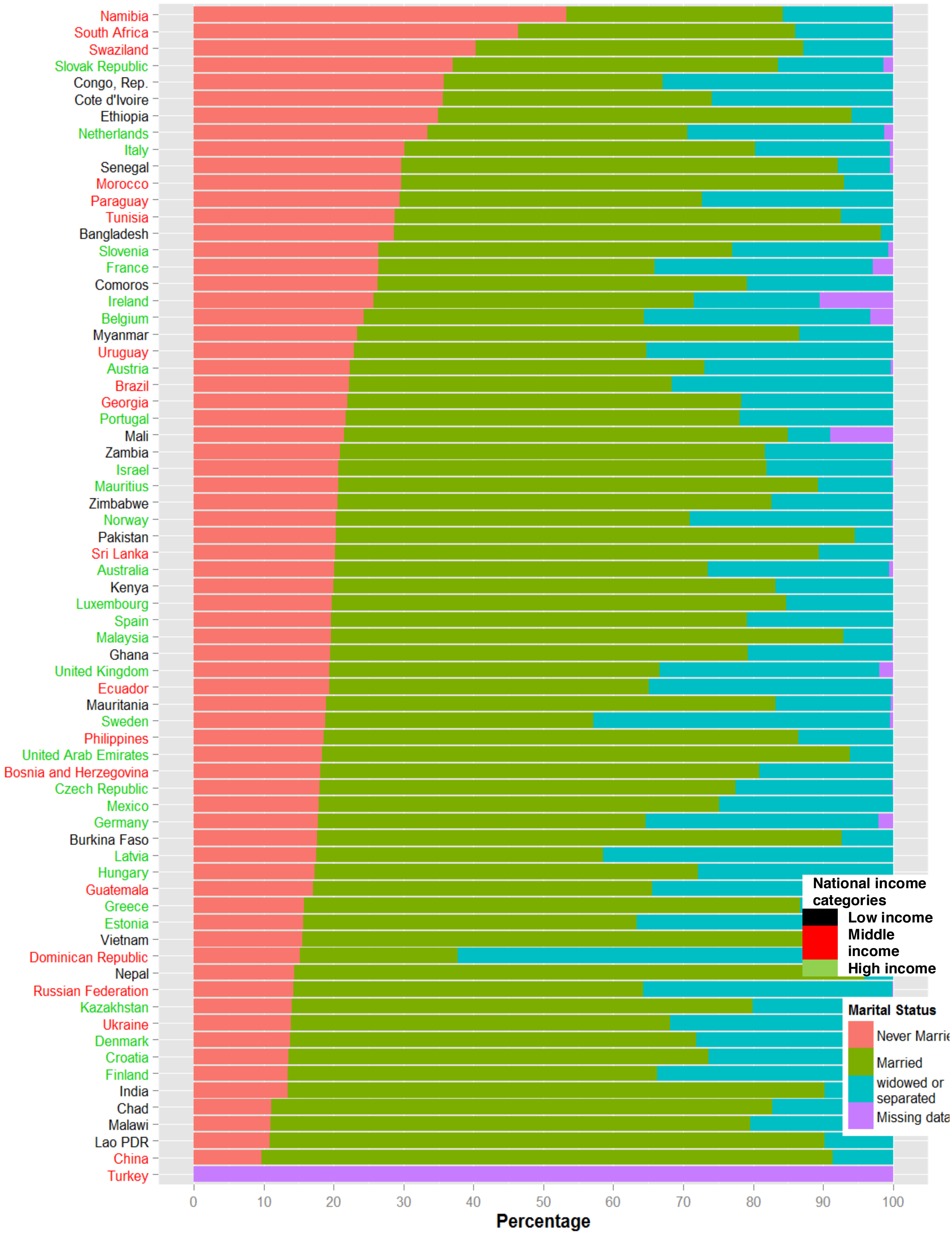


Figure 4.2: Design based distribution of marital status (weighted %) in the 70 WHS countries

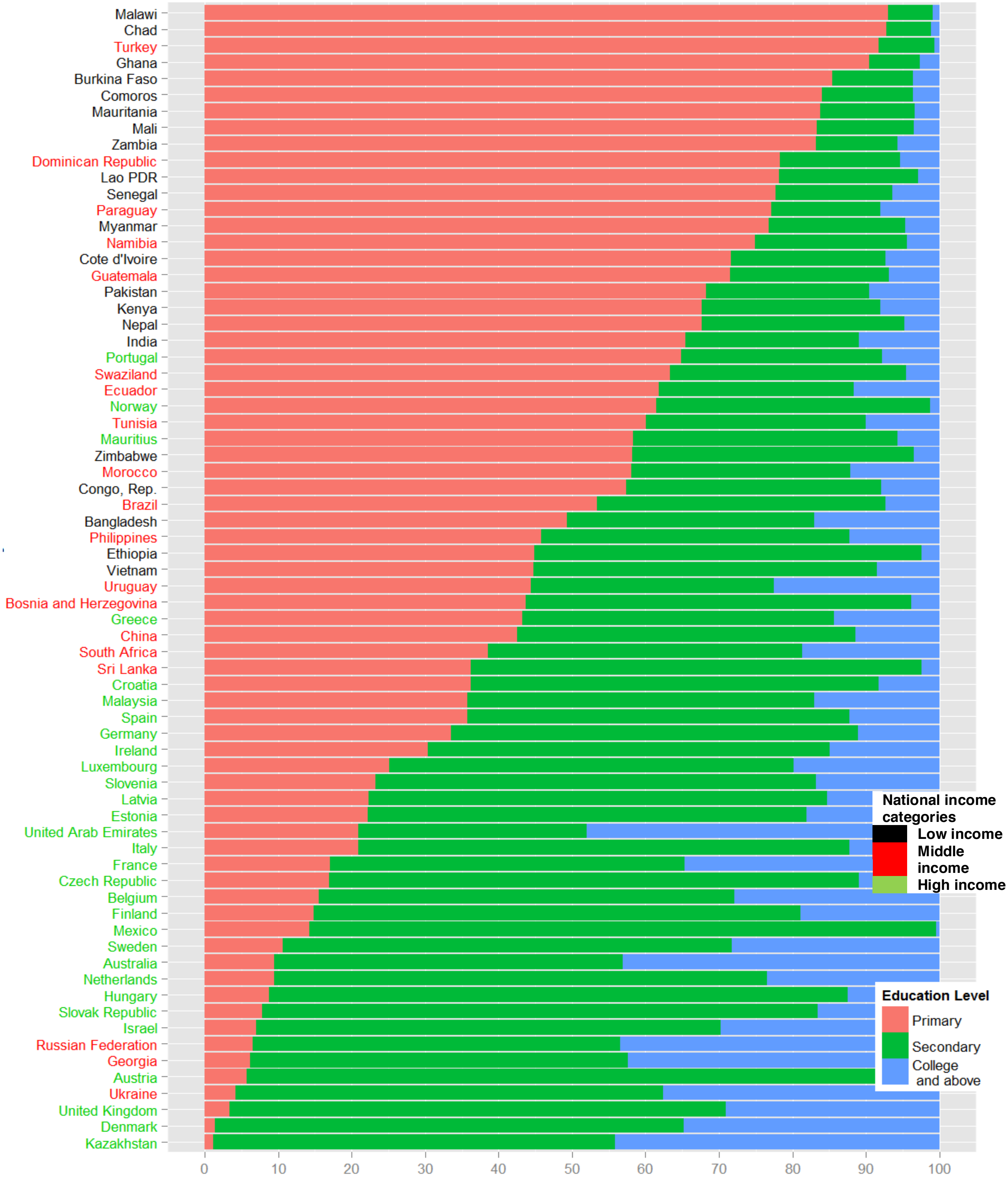


Figure 4.3: Design based distribution of education level (weighted %) in the 70 WHS countries

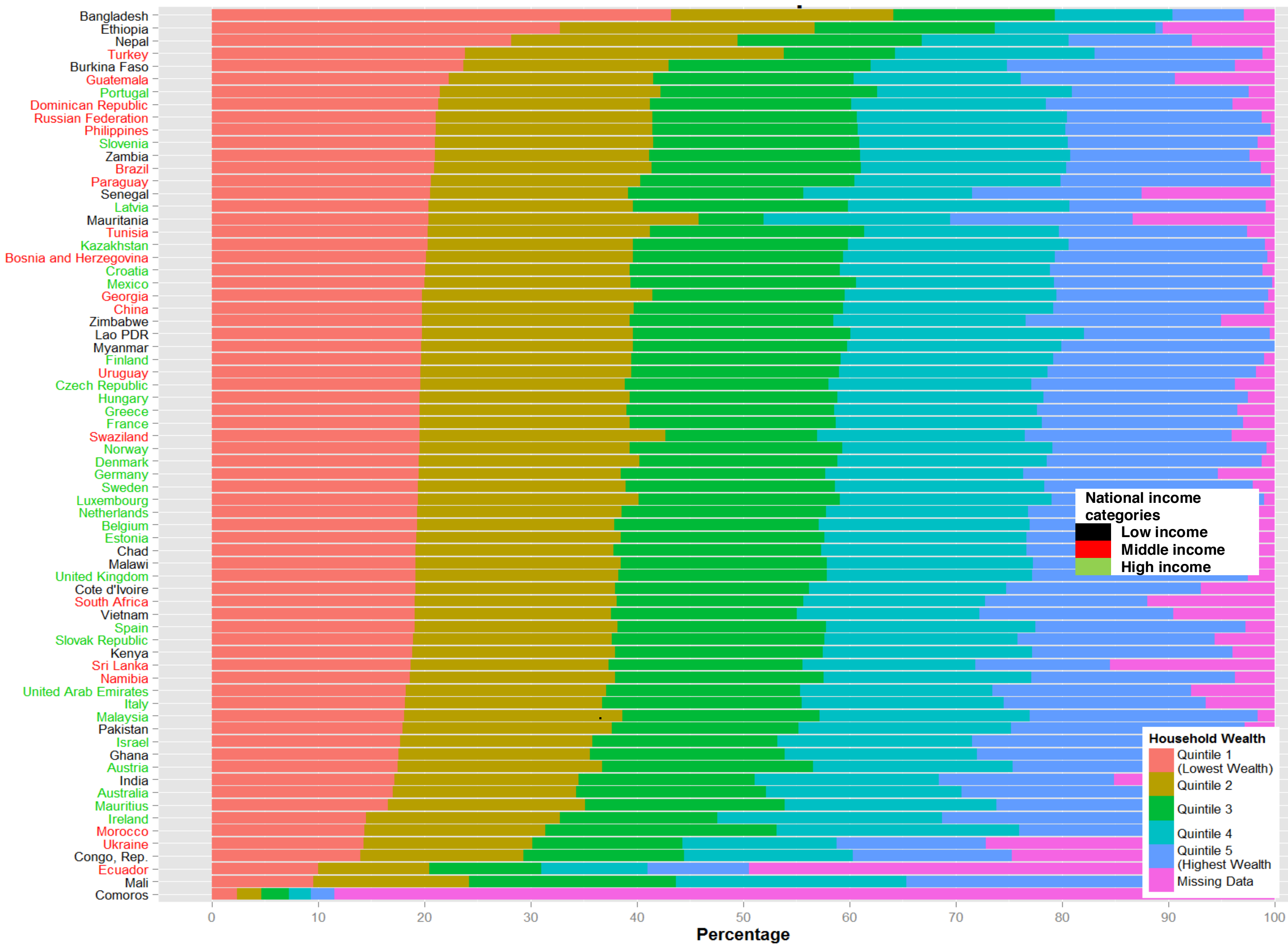


Figure 4.4: Design based distribution of household wealth (weighted %) in the 70 WHS countries

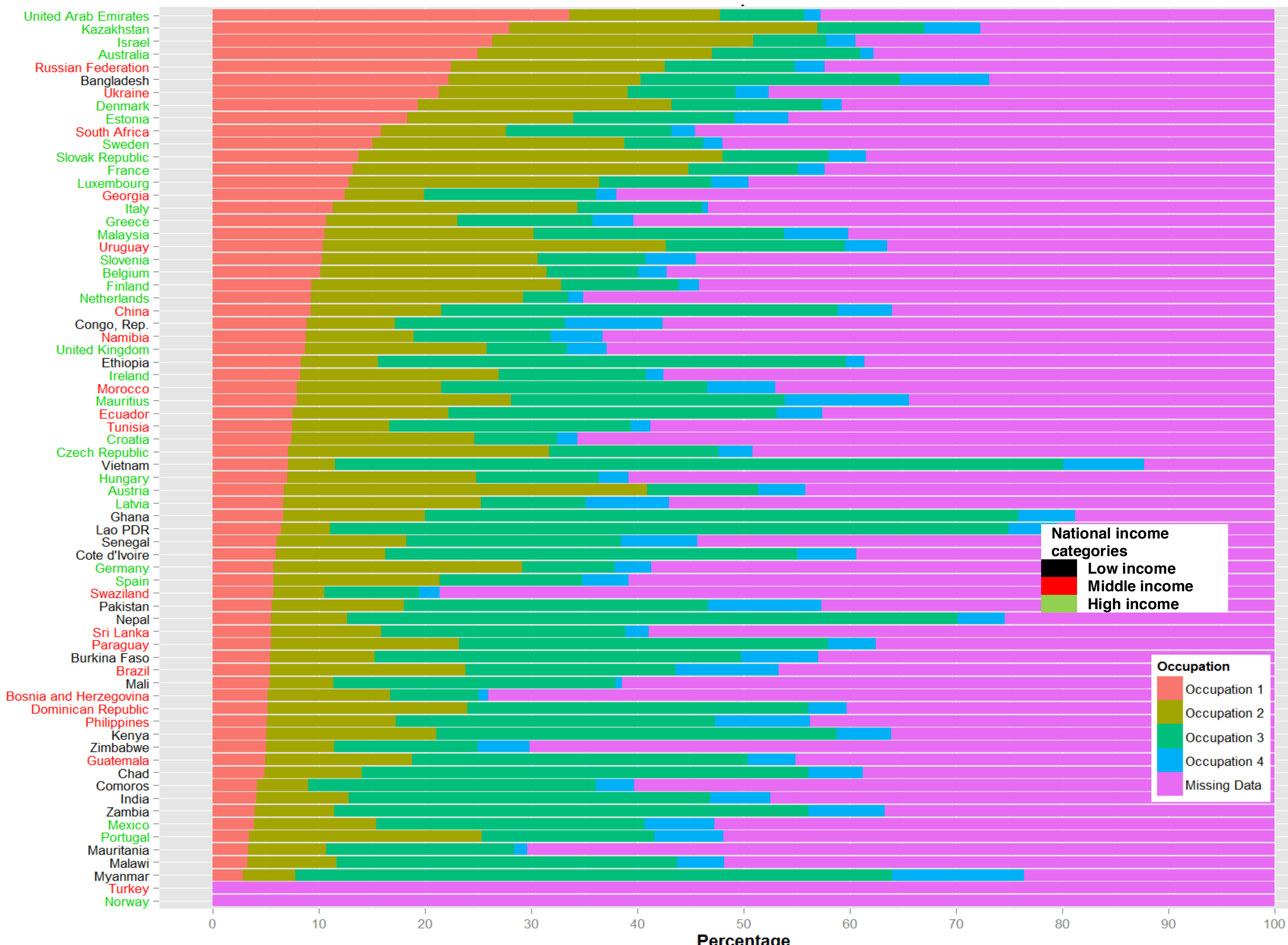


Figure 4.5: Design based distribution of occupation (weighted %) in the 70 WHS countries

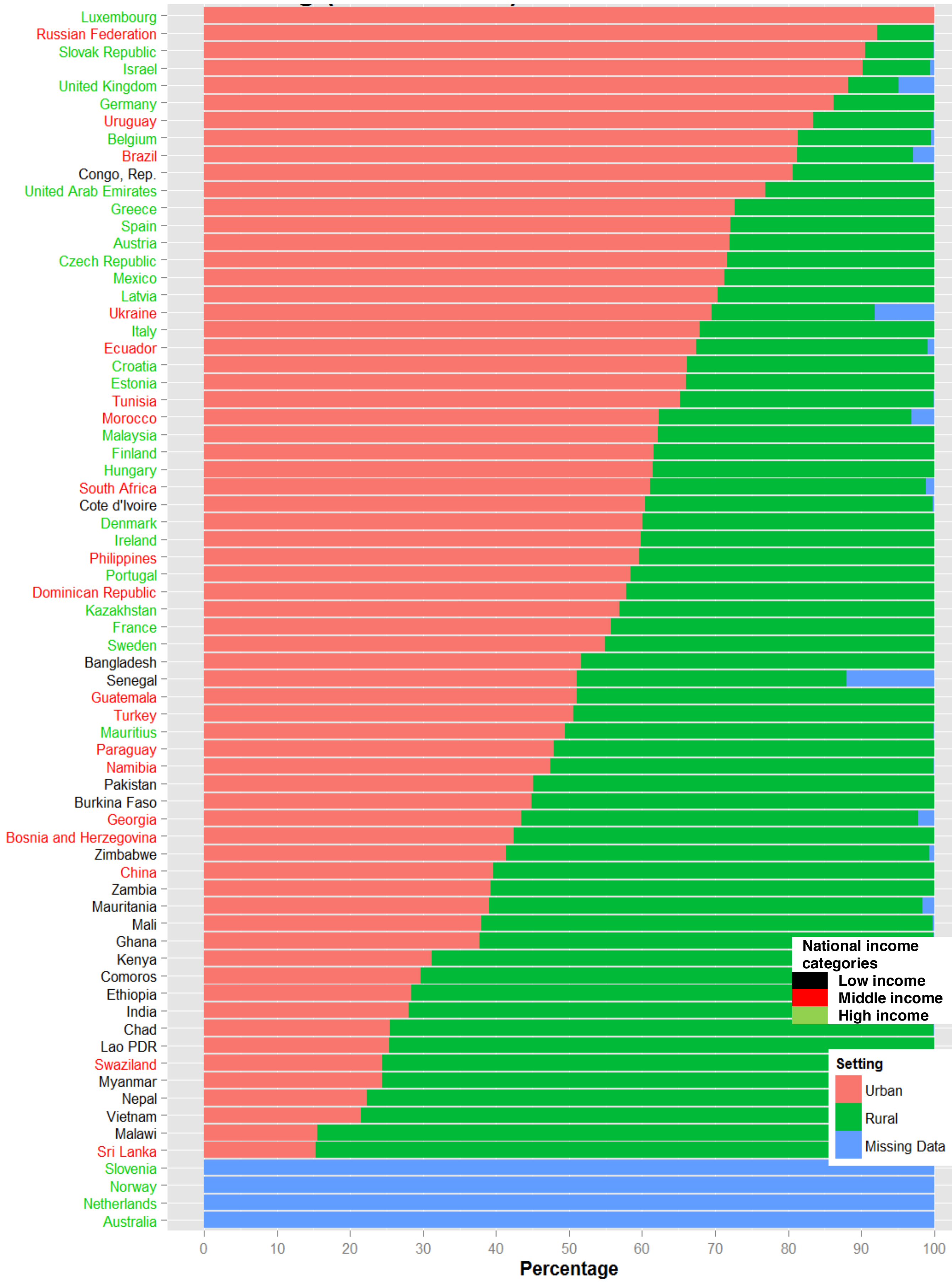


Figure 4.6: Design based distribution of rural/urban setting (weighted %) in the 70 WHS countries

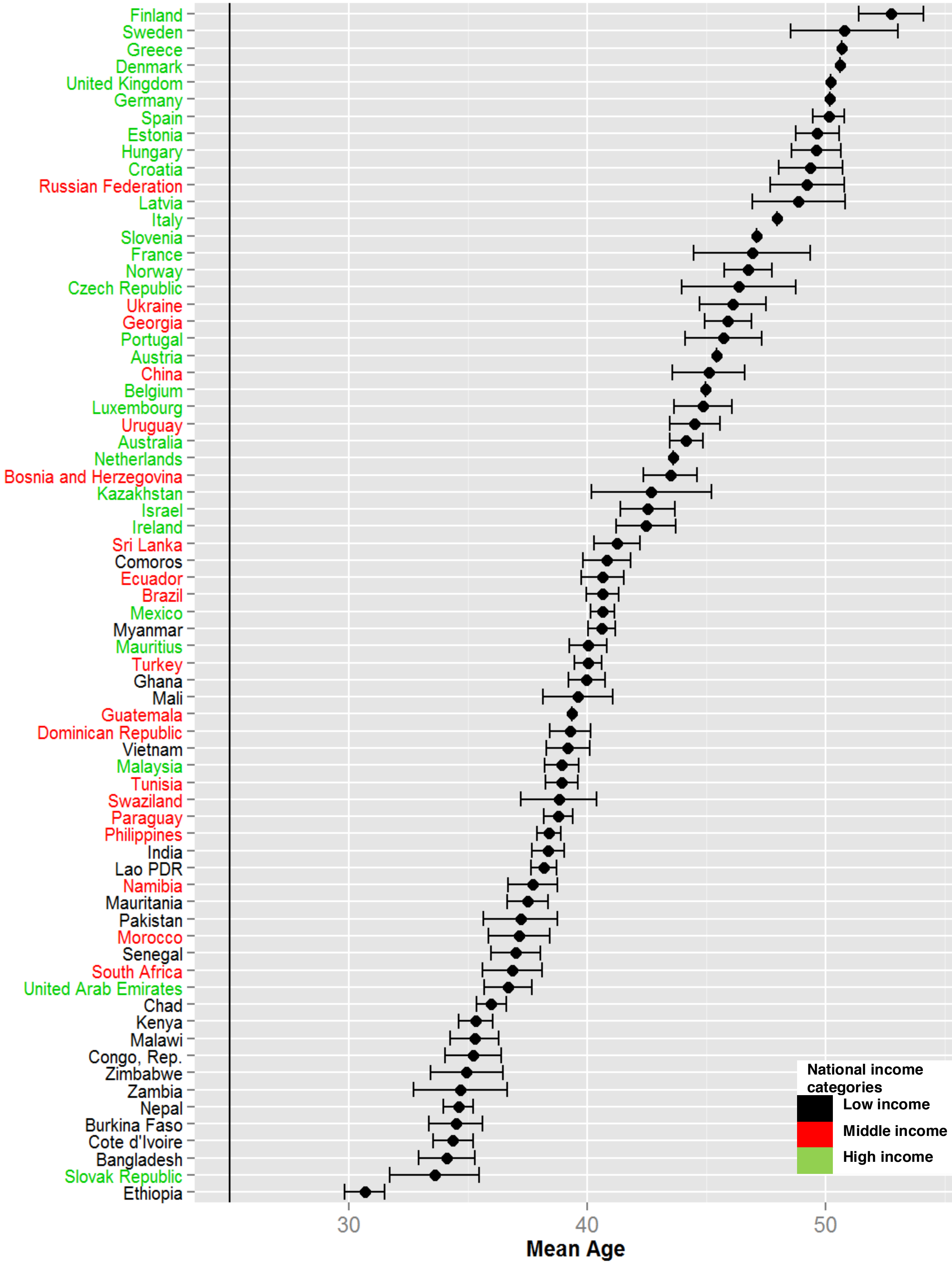


Figure 4.7: Design based mean age (weighted) and confidence interval for the 70 WHS countries.

To analyse the pattern of BMI in different countries design based mean BMI with confidence interval was calculated for all the 70 countries (Figure 4.8). Most low-income countries, such as Vietnam, India, Nepal, Myanmar, were at the lower end of the mean BMI, and high or middle-income countries, such as Australia, Finland and UAE, at the higher end of the mean BMI. All the low-income countries were below the 25.0 mean BMI level and most of the high-income countries[32] were above this mean BMI level of 25.0. Middle-income countries were scattered in this spectrum from low to high mean BMI. Swaziland and South Africa had the highest weighted mean BMI and Vietnam and India had the lowest mean BMI among the 70 countries.

[32] With some exceptions Netherlands, Austria, Belgium, Norway, Italy, France Malaysia, Mauritius and Slovak Republic.

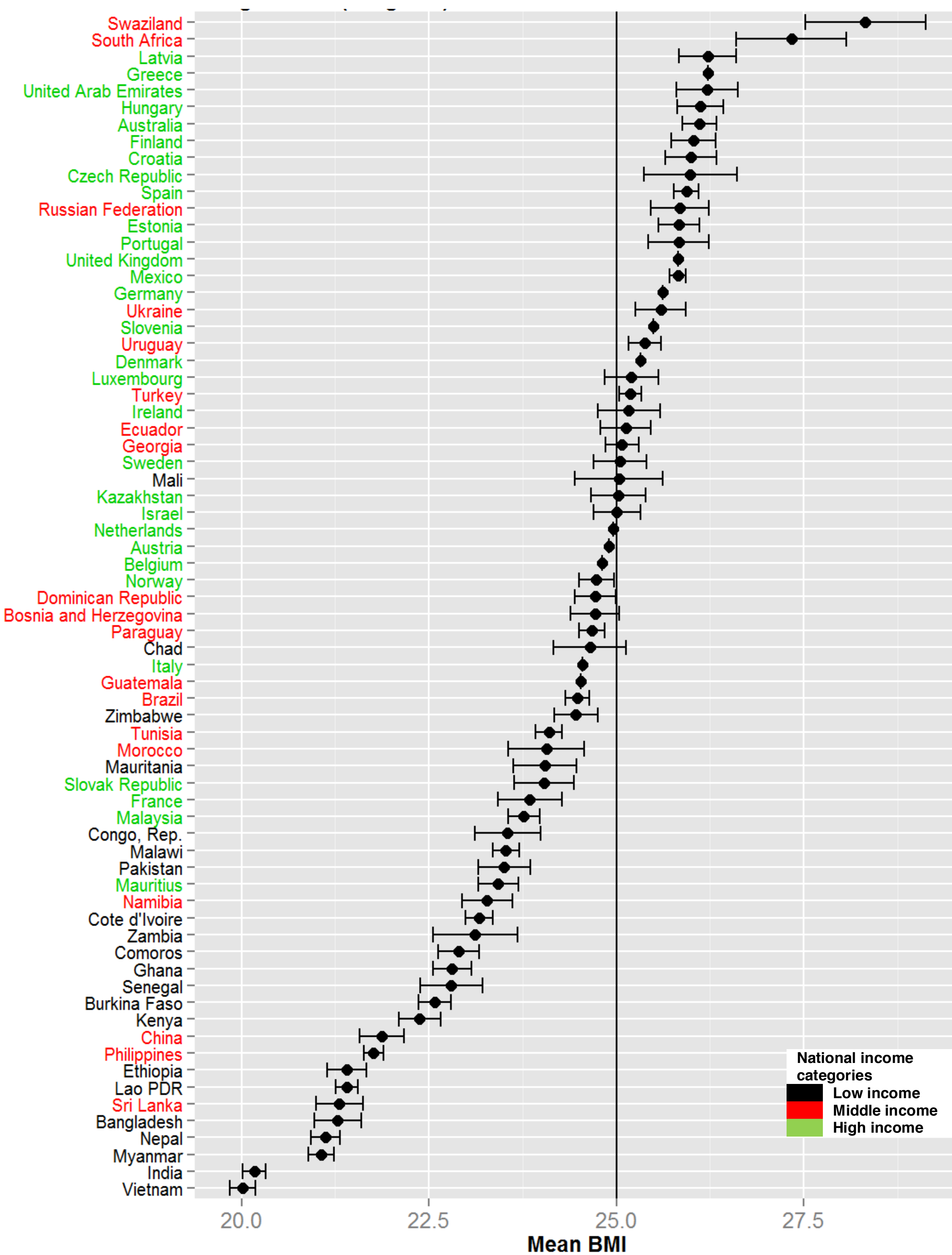


Figure 4.8: Design based mean BMI (weighted) and confidence interval for the 70 WHS

In addition to overall mean BMI it was important to analyse the pattern of BMI according to the individual level variables e.g. age, gender, education level, household wealth etc. Therefore, the pattern of mean BMI was also observed according to the individual level variables for all the 70 countries. Figures 4.9 to 4.14 describe design based (weighted) mean BMI in the 70 countries by individual level variables. Figure 4.9 shows mean BMI by gender; majority of low-income countries (especially with low mean BMI) had less difference between male and female mean BMI[33]. The difference in the mean BMI by sex was higher for majority of the high-income countries. Generally males had a higher mean BMI in high-income countries (6 out of 30 countries). In contrast, females had a higher mean BMI in the low-income countries (5 out of 21 countries) whereas the middle-income countries had a mixed picture.

Figure 4.10 shows mean BMI by the education level. In high-income countries people with lower education level had a higher mean BMI than the people with higher education level except Greece and Slovak republic. Low-income countries had contrasting pattern where people with a higher education level had a higher mean BMI than those with a lower education level, except Mauritania, Chad and Mali. In middle-income countries, people with intermediate education had the lowest mean BMI in 50% of the countries; in 25% of the countries people with a higher education level had the lowest mean BMI and in remaining 25% of the countries, people with primary education level had the lowest mean BMI. In low-income countries, people with higher education level had a higher mean BMI. This pattern showed that as the country's mean BMI increases, people with higher education had a lower mean BMI than people with lower education and vice versa.

For marital status, a nearly similar pattern was observed for all the 70 countries. Never married people had a lower mean BMI than married (currently marries/cohabitant) and previously married (widowed/separated) ones, except in Comoros and Malawi (Figure 4.11). Married people had a higher mean BMI than previously married ones in most of the countries with some exceptions e.g. Israel, Tunisia and Russian Federation. Never married people in all the countries had a mean BMI less than 25, except the three heaviest countries: Australia, South Africa and Swaziland. This relationship of mean BMI and marital status might be an artefact of age as generally never married people are younger than married and widowed/separated people[34].

[33] With some exceptions such as Mali, Mauritania, Ghana, Kenya and Bangladesh.
[34] This relationship will be tested in the multivariate logistic regression after controlling for age variable.

Mean BMI for each country by household wealth quintiles showed an interesting pattern (Figure 4.12). To improve interpretation, only poorest (quintile 1) and wealthiest (quintile 5) quintiles are plotted in the graph. This study shows a similar pattern of household wealth and BMI as established in the previous literature. In all the low-income countries, wealthy people had a higher mean BMI as compared with poor people. In most of the high income countries (20 out of 30 countries) , poor people had a higher mean BMI as compare with wealthy people. However, rest of the high-income countries had a reverse pattern where wealthy people had a higher mean BMI as compared with poor people. Majority of the middle-income countries (14 out of 19) had the same pattern as low-income countries, rest five middle countries had a pattern similar to high-income countries.

Analysis for mean BMI by occupation in the 70 countries showed pattern similar to household wealth (Figure 4.13)[35]. There were 4 categories in occupation variable but only high occupation (Legislators, Managers, Professionals) and elementary occupation (elementary workers) are plotted in this graph to improve interpretability of this graph. In majority of the low-income countries, people with high occupation (Legislators, Managers, Professionals) had higher mean BMI compared with elementary workers. An opposite pattern was observed for most of the high-income countries. Middle-income countries had mixed patterns.

People living in rural areas of the low-income countries had a lower mean BMI than people living in urban areas of the low-income countries. Mauritania was the only low-income country with an opposite pattern. The high-income countries had an opposite pattern where urban people had a mean BMI lower than that of rural people but in Sweden, Mexico, France and Slovak republic rural people had a BMI which was lower than the urban people. Similar to other variables, the middle-income countries had a mixed pattern for rural/urban setting of mean BMI.

[35] An alternate presentation of the descriptive analysis of this data has been given in Appendix I. Difference in the mean BMI of the categories for each variable was calculated and plotted against the countries.

Figure 4.9: Design based mean BMI (weighted) by gender for the 70 WHS countries

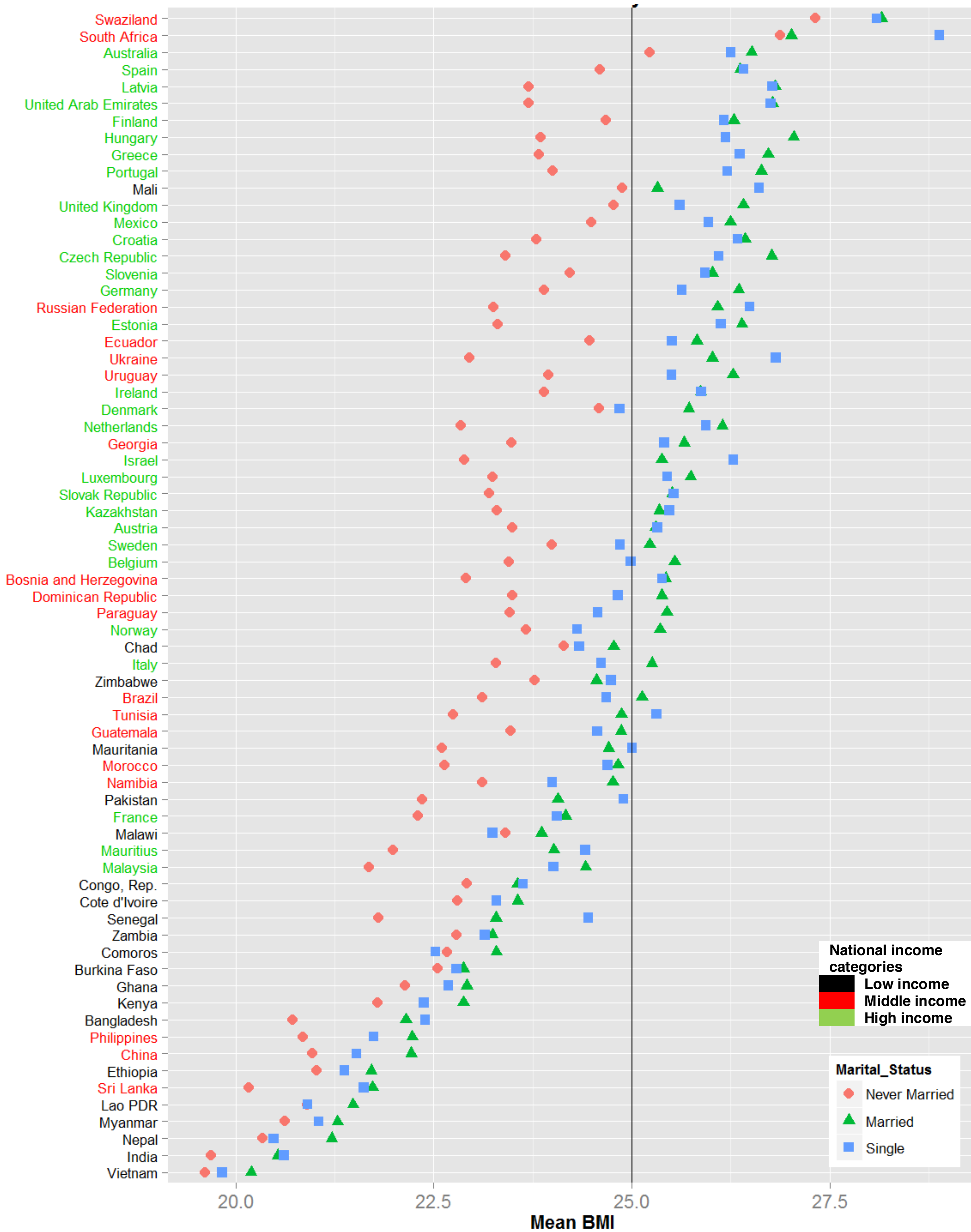


Figure 4.10: Design based mean BMI (weighted) by marital status for the 70 WHS countries

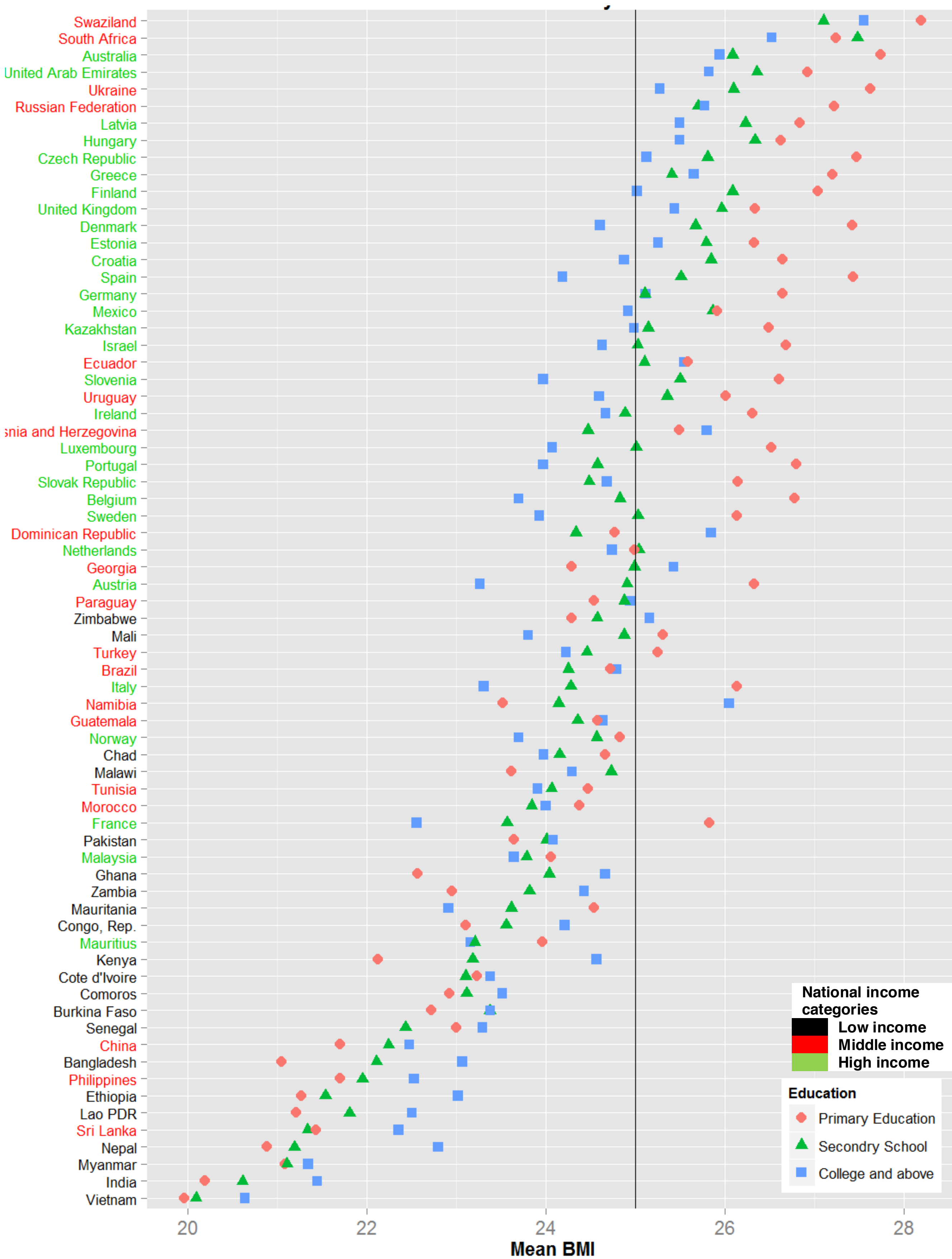


Figure 4.11: Design based mean BMI (weighted) by education level for the 70 WHS countries

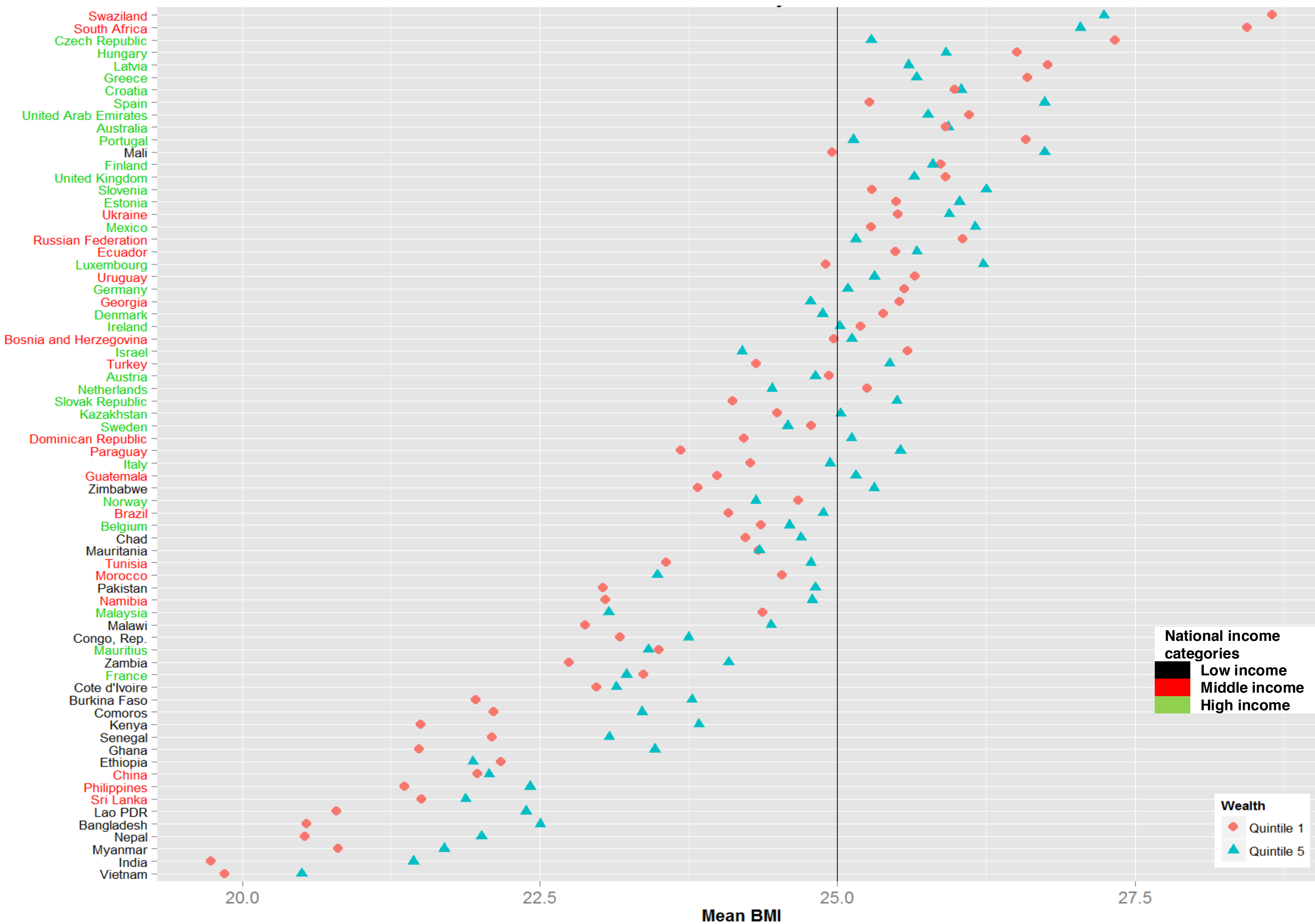


Figure 4.12: Design based mean BMI (weighted) by household wealth quintile for the 70 WHS countries. (Only poorest and wealthiest quintiles are plotted here to ease interpretation of the graph)

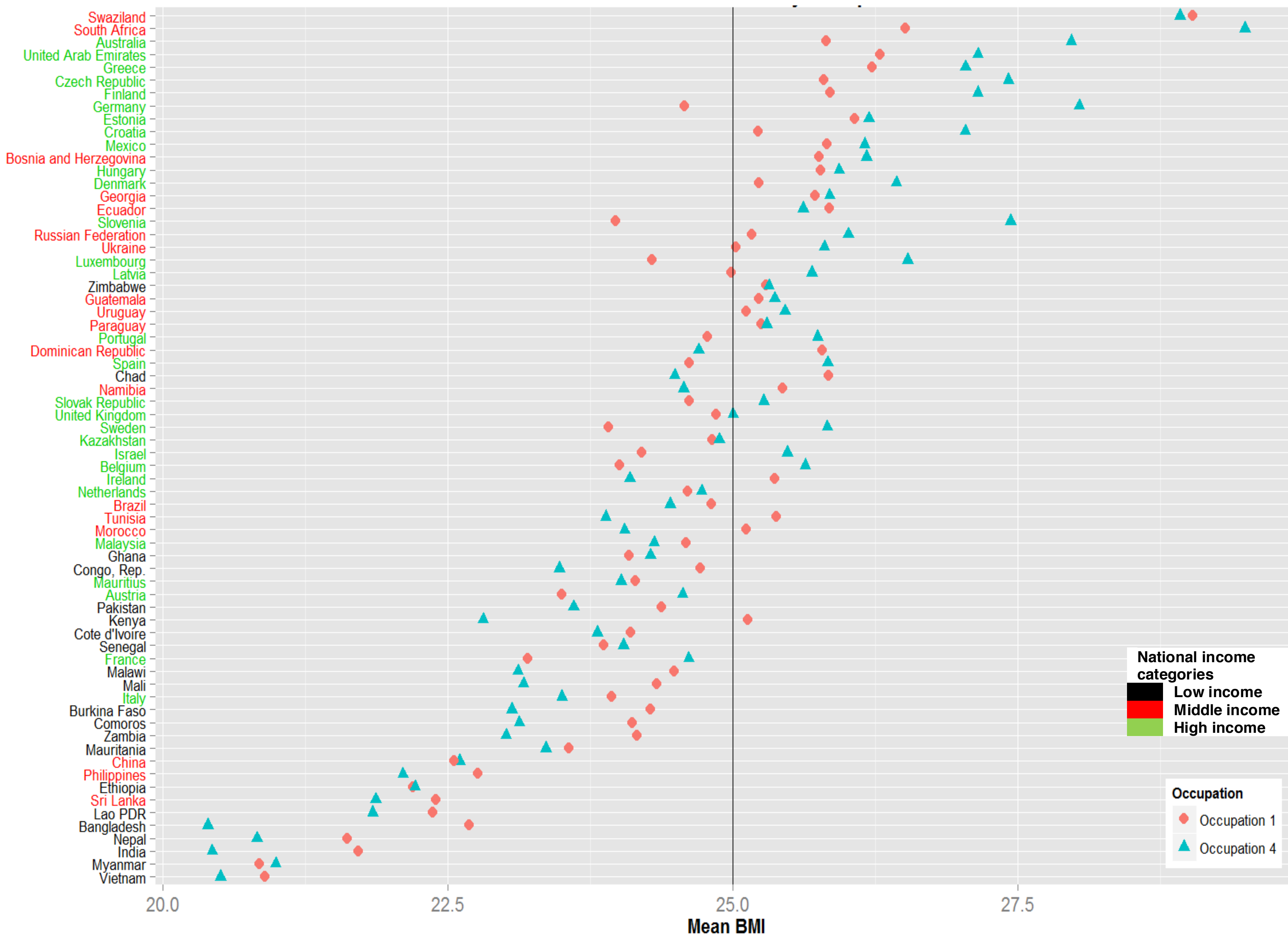


Figure 4.13: Design based mean BMI (weighted) by occupation for the 70 WHS countries. (Only occupation 1 and occupation 4 are plotted here to ease interpretation of the graph)

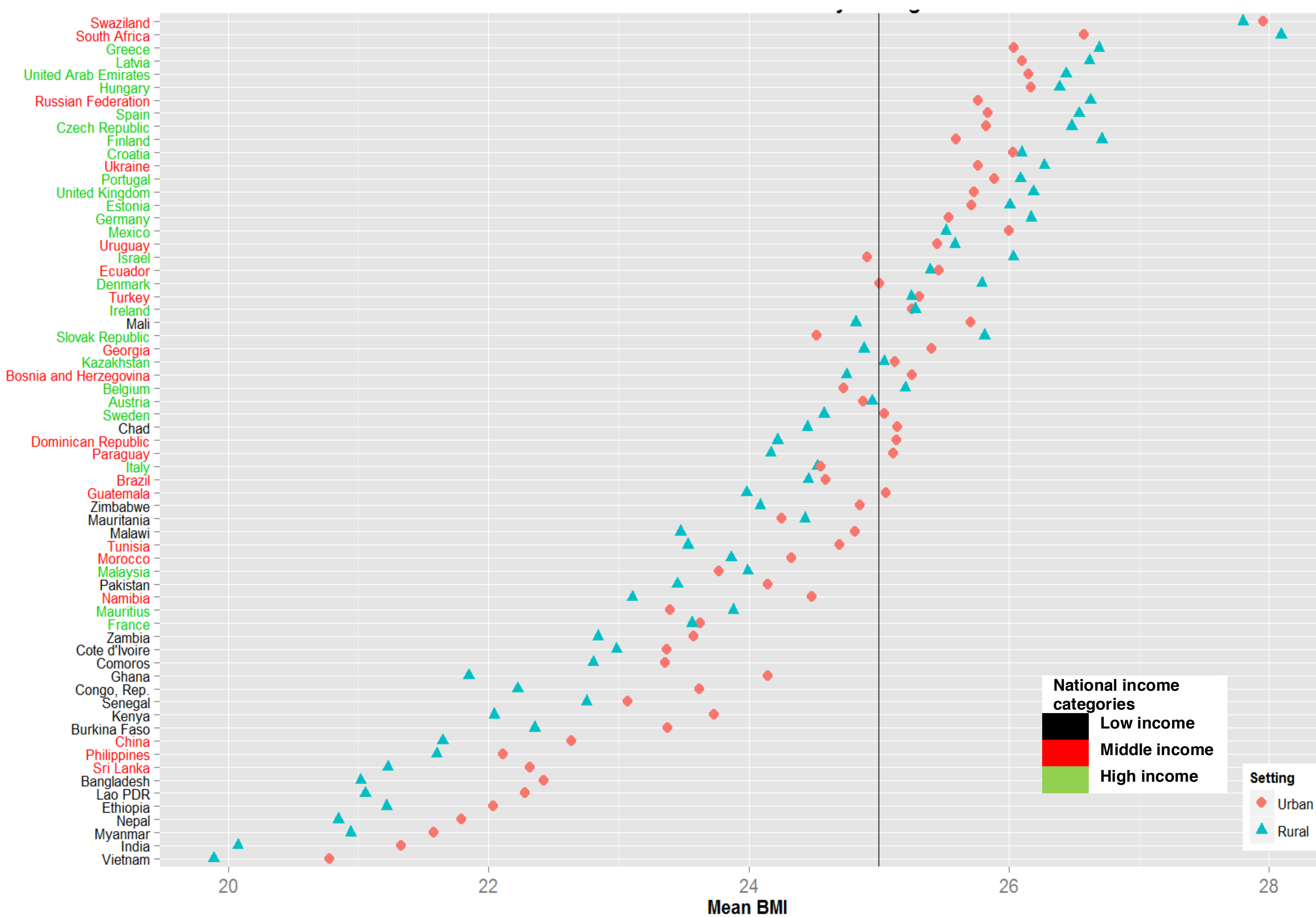


Figure 4.14: Design based mean BMI (weighted) by setting for the 70 WHS countries

The above section describes the results for low, middle and high-income countries together. However, previous literature suggests a different relationship of BMI with individual level variables for different economic levels of the countries (low, middle and high income countries). For example, the relationship between BMI and gender is different in low, middle and high-income countries. Males have a lower mean BMI as compared with females in low-income countries and females have lower mean BMI as compared with males in high-income countries. Therefore, I formally tested the difference in the relationship using a stratified analysis and I ran multilevel linear regression models separately for low, middle and high-income countries[36]. These models included BMI as an outcome variable and gender, age, education, marital status, household wealth, occupation and urban/rural setting as predictor variables. Appendix H shows the results of this stratified analysis. The relationship of BMI with individual level variables was opposite for low and high-income countries. However, low and middle-income countries have a similar relationship for most of the variables except occupation and education levels. In low-income countries, females had a higher BMI compared with males, people with higher education levels and household wealth had a higher BMI than people with lower education levels and household wealth. In contrast, in high-income countries, males had a higher mean BMI compared with females, people with lower education level had a higher mean BMI than people with a higher education level. Household wealth and occupation did not have any statistically significant relationship with BMI in high-income countries. Marital status had a similar relationship with BMI in all low, middle and high-income countries, where married people had a higher mean BMI than never married and previously married people. Urban people had higher mean BMI in low and middle-income countries and rural people had higher mean BMI in high-income countries.

4.2 National income, Income Inequality and BMI

Values for country level variables, national income and income inequality, for each country are given in the table 3.3. Figure 4.15 is a scattered plot matrix for GNI-PPP, Gini index[37] and BMI variables. Correlations coefficient for GNI-PPP and Gini index across these 70 countries was weak (-0.34). This negative direction suggests that as a country's national income increases its income inequality decreases. Correlation coefficient for BMI and Gini index was weak (-0.04), across the 70 countries, suggesting a weak correlation between BMI and country level income

[36] All the countries were classified into tertiles based on GNI-PPP; under US$ 3,035 (low income); US$ 3,036 to US$ 9385 (middle income); and US$ 9386 and above (high income) World Bank: World development indicators; in. Washington, DC, World Bank, 2005. It divides all 70 countries into 30 high income, 19 middle income and 21 low-income countries.

[37] GNI-PPP measures national income in USD and Gini is an index to measure for income inequality.

inequality. For these countries, GNI-PPP also had a weak positive correlation with BMI with a correlation coefficient measuring 0.18. This positive correlation suggested the increase in BMI with increase in national income.

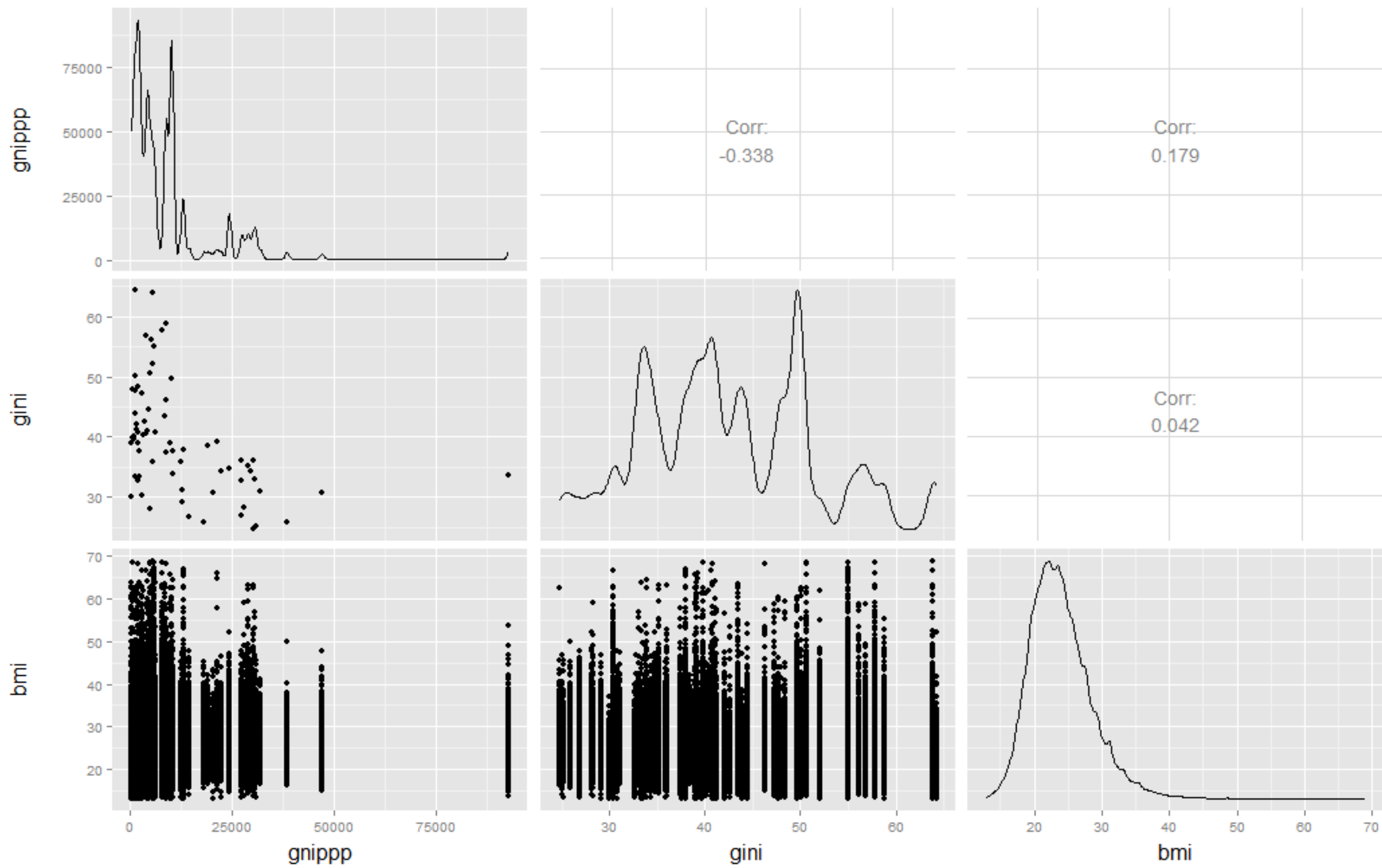


Figure 4.15: Scattered plot matrix and correlation coefficients for BMI, Gini and GNI-PPP

I started the regression analysis with bivariate multilevel linear regression analysis of the 70 countries for all individual and country level predictors with BMI as an outcome variable. Model 0 represents the null model or the variance component model for BMI. The fixed part is represented by the coefficient for the constant, which was 24.3 with a standard error of 0.20. That is to say, the estimated overall population mean for BMI is 24.3 for 70 countries. The random part is given under the heading "Random effect" for variance of level-1 residuals and "variance and covariance of random effects" for variance of the random intercept. The estimate of the between-countries variance was 2.75 and the estimate of within-countries variance was 20.07. Using equation 2.5, these estimates for random effect were used to calculate the intra-class correlation coefficient (ICC=0.125). The ICC value suggests that the proportion of total variance that occurs between these countries is 0.125. That is to say, 12.5% of the variance in the individual level BMI was between countries and remaining 87.5% of the variation in the individual level BMI was within countries. Therefore, 12.5% of the variation in the individual level BMI is due to the difference in the characteristics of the countries e.g. national income and income inequality of the countries. I have written a scientific paper to calculated ICC of BMI for each country separately using primary sampling unit (PSUs) as a clustering variable. (ICC for each country is given in Appendix J)

I tested the bivariate relationship of all the individual and the country level predictors using multilevel linear regression analysis (Table 4.2). First, I regressed the country level predictors to see their relationship with BMI. Model 1 in table 4.2 shows the bivariate relationship of country level GNI-PPP and individual level BMI. GNI-PPP was centered at USD 8840 and the intercept (22.4) was the mean BMI for the country with GNI-PPP= USD 8840. GNI-PPP[38] had significant positive relationship with BMI. With each USD 10000 increase in GNI-PPP, the BMI increased by 0.50 units. For example, after considering all other variables being equal, a person in United Kingdom (GNI-PPP=30150) would be nearly 1.50 BMI units heavier than a person in India (GNI-PPP=1830). Model with GNI-PPP was significantly better fit than the model 0 (null model) with country level R^2=0.201 and total R^2=0.024; which means that 20.1% of country level variance and 2.4% of total variance in BMI was explained by GNI-PPP alone. Model 2 tested the bivariate relationship of Gini index with BMI. Gini index was centered at the mean (42.38 units). Gini index was negatively associated with BMI but it was not significant and this model was not a better fit compared with null model. Gini index only explained 1.6% of the country level and 0.2% of the

[38] Assumption of linearity for GNI-PPP was formally tested using residuals versus fitted plots. Residual plot revealed no departures from the assumption of linearity. Therefore GNI-PPP was not transformed. Appendix C shows the residual versus fitted plots.

total variation in BMI. This indicates that a minor percentage of country level variation in BMI is explained by income inequality alone.

Next, I tested the bivariate relationship between BMI and individual level variables. All these relationships were similar to those established in previous researches. Model 3 to model 9 tested the bivariate relationship of individual level variables (age, gender, marital status, education level, household wealth, occupation and household setting) with BMI. Age was positively associated with BMI; people becomes heavier with increasing age, every 10 years increase in age was associated with a 0.4 units increase in BMI. Age was centered at 41.11 years; therefore the intercept represents the mean BMI at the age of 41.11 years. Females were on an average 0.03 BMI units higher than males but it was not significant. Education level had a negative significant association with BMI. People with intermediate and higher education had significantly lower BMI than people with primary education. Although this model was a better fit than the null model, it didn't explain any variance in individual level BMI. Descriptive analysis showed that never married people had a lower mean BMI compared with married and previously married people. Regression analysis showed that the difference was statistically significant and married people had a higher BMI than never married and previously married. A clear significant positive gradient for BMI was present for household wealth; on an average wealthier people had a higher BMI compared with poorer people. The BMI for the wealthiest people was 0.70 units higher BMI than that for the poorest people. Occupation variable shows interesting findings that people with high occupation and elementary workers didn't have a significant difference in their BMIs. However, people with medium occupation (Technician/ Associate Professional/ Clerk/ Service/ sales worker) and low occupation (agriculture/fishery/ Craft or trades worker/ plant/machine operator or assembler) had a significantly lower mean BMI than professionals. A large proportion of the data was missing for the occupation variable. Therefore, I categorized missing values as a separate category to study the effect of missing values in the regression analysis. Missing values had a significant negative effect in this relationship, which indicates that the majority of these missing values were from elementary workers. Inclusion of the missing values as elementary workers might improve the model with significant association for elementary workers. People living in the rural areas, on an average, had significantly less BMI compared with people living in the urban areas.

Table 4.2: Multilevel linear regression models showing bivariate relationship of BMI and individual level and country level explanatory variables in the 70 WHS countries.

Model		**Fixed Effect**		**Random effect**		**Fit Indices**				**Model Comparison^**	**R^2**		
		Intercept	**Estimates**	**Country**	**Residual**	**AIC**	**BIC**	**Log Likelihood**	**Deviance**		**Ind**	**Cou**	**Total**
		β(SE)	**β(SE)**	**σ(SD)**	**σ(SD)**					**Chisq(df)**			
Model 0	Null Model /Model 0	24.3(0.20)***	-	2.75(1.66)	20.07(4.48)	1204429	1204460	-602211	1204423	-	-	-	-
	Country Level												
Model 1	GNI-PPP/10000	24.2(0.18)***	0.50(0.12)***	2.2(1.48)	20.07(4.48)	1204416	1204457	-602204	1204408	15.6(1)***	-	0.201	0.024
Model 2	Gini Index	24.2(0.84)***	-0.02(0.02)	2.71(1.65)	20.07(4.48)	1204430	1204471	-602211	1204422	1.1(1)	-	0.015	0.002
	Individual Level												
Model 3	Age	24.3(1.86)***	0.04(0.006)***	2.41(1.56)	19.66(4.43)	1200131	1200172	-600061	1200123	4300(1)***	0.021	0.124	0.033
Model 4	Gender	24.4(1.20)***											
	Female		Reference category										
	Male		-0.03(0.02)	2.75(1.66)	20.07(4.48)	1204429	1204470	-602210	1204421	0.14(1)	-	-	-
Model 5	Marital Status	23.2(2.06)***											
	Never Married		Reference category										
	Married		1.56(0.03)***										
	Previously married		1.34(0.03)***	2.75(1.68)	19.73(4.44)	1200836	1200898	-600412	1200824	3593(3)***	0.017	-	0.015
	Missing Values		2.1(1.7)										
Model 6	Education	24.4(2.01)***											
	Primary		Reference category										
	Intermediate		-0.11(0.03)***										
	Higher		-0.15(0.04)***	2.71(1.68)	20.07(4.48)	1204406	1204458	-602198	1204396	26.7(2)***	-	0.015	0.002
Model 7	Household wealth	24.0(0.20)***											
	1st Quintile(Poorest)		Reference category										
	2nd Quintile		0.26(0.032)***										
	3rd Quintile		0.40(0.032)***										
	4th Quintile		0.49(0.031)***										
	5th Quintile(wealthiest)		0.70(0.031)***	2.75(1.67)	20.02(4.48)	1203884	1203956	-601935	1203870	552.9(4)***	0.002	-	0.002

Model 8	Occupation[Ψ]	24.6(0.20)***											
	High		Reference category										
	Medium		-0.17(0.046)***										
	Low		-0.40(0.042)***										
	Elementary		-0.02(0.058)	2.68(1.64)	20.06(4.48)	1204301	1204373	-602143	1204287	135.62(4)***	0.00	0.025	0.004
	Missing Values		-0.24(0.04)***										
Model 9	Setting	24.6(0.19)***											
	Urban		Reference category										
	Rural		-0.51(0.022)***	2.51(1.58)	20.02(4.48)	1203896	1203947	-601943	1203886	537.6(2)***	0.002	0.087	0.013
	Missing Values		-0.80(0.82)										

β- regression coefficient; SE- Standard Error; σ- Variance; SD: Standard Deviation; AIC- Akaike information criterion; BIC- Bayesian information criterion; Chisq- Chi Square test; df- Degree of freedom; ind- individual level, cou- country level

*pvalue≤0.05; **pvalue≤0.01; ***pvalue≤0.001; SE: Standard Error

[Ψ]Occupation categories: High (1. Legislator, Senior Official, or Manager 2. Professional and 10.armed forces), medium (3.Technician or Associate Professional 4. Clerk 5. Service or sales worker), low (6. Agricultural or fishery worker 7. Craft or trades worker 8. Plant/machine operator or assembler) and elementary (elementary workers)

^All models were compared with model 0

In the next model (model 10), I checked the combined effects of all these individual level variables. I used multivariate multilevel linear regression model using all of the above-mentioned individual level variables (Table 4.4). This model (model 10) was later used in the following models to adjust and compare the effects of country level variables (GNI-PPP and Gini index). In this multivariate model, the relationships of BMI with age, sex, marital status, household income, occupation and setting were similar to those in bivariate analysis. The relationship between age and BMI was significantly positive ($\beta=0.034$, $p<0.001$). That is to say, for every ten year increase in age, a 0.34 point increase in the BMI can be expected when holding all other variables constant. In this model (model 10), men were found to have lower BMI scores compared to women when holding all other variables constant but it was not significant. Education level was negatively associated with BMI in bivariate analysis. However, this relationship became positive for intermediate education and stayed negative but got weaker for the higher education. Household wealth was also found to be significantly related to BMI. All wealthier quintiles have higher scores in BMI compared to lower quintiles when holding all the other variables constant. Medium occupation category became non-significant in multivariate model. In this model, all these variables decreased the residual variance by 0.87. All these variables together in multivariate model explained 3.4% of the individual level, 16.4% of the country level and 5.0% of the total variance in BMI.

In order to assess the effect of country level factors on BMI, country level variables including national income (GNI-PPP) and income inequality (Gini index) were modeled after controlling all individual level variables. First, the association of GNI-PPP with BMI was tested after controlling all individual variables in model 11. This model shows a 0.4 unit increase in BMI with each $10000 increase in GNI-PPP, which was slightly less than what was observed in the bivariate model of GNI-PPP. Regression coefficients for all the individual variables remain approximately the same as in model 10. The minor changes in the individual level variables after adding national income and income inequality variable indicates a strong direct effect of these individual level variables. Model 11 was a better fit compared with model 10. This model explains 27.6% of country variance and 6.4% of total variance in BMI. Later, I fitted model 12 to see the combined effect of national income and income inequality after controlling all individual level variables. Model 12 was developed by adding Gini index in model 11. In this model, regression coefficient for GNI-PPP remains significant but the regression coefficient for Gini index was not significant. All the individual level variables had a similar relationship as in model 11. This model was not a better fit compared with model 11. This model explains 30.2% of the country level, 3.4% of the individual level and 6.7% of the total variance in BMI across the 70 countries.

Table 4.3: Multilevel multivariate linear regression analysis with individual and country level explanatory variables in the 70 WHS countries

	Model 10		Model 11		Model 12	
Fixed Effect	β	SE	β	SE	β	SE
Intercept	23.5	0.197***	23.4	0.18***	23.5	0.19***
Country Level						
GNI-PPP/10000			0.40	0.12***	0.48	0.13***
Gini index					0.03	0.02
Individual Level						
Age	0.034	0.0007***	0.034	0.0007***	0.034	0.0007***
Gender						
Female	Reference category					
Male	-0.02	0.02	-0.02	0.02	-0.02	0.02
Marital Status						
Never Married	Reference category					
Married	1.12	0.028***	1.12	0.028***	1.12	0.028***
Previously married	0.70	0.036***	0.70	0.036***	0.70	0.036***
Missing values	1.9	1.54	2.1	1.3	2.0	1.4
Education						
Primary	Reference category					
Intermediate	0.163	0.026***	0.160	0.026***	0.163	0.026***
Higher	-0.07	0.041	-0.07	0.041	-0.07	0.041
Household Income						
1st Quintile (Poorest)	Reference category					
2nd Quintile	0.21	0.031***	0.21	0.031***	0.21	0.031***
3rd Quintile	0.33	0.031***	0.33	0.031***	0.33	0.031***
4th Quintile	0.41	0.031***	0.41	0.031***	0.41	0.031***
5th Quintile (Wealthiest)	0.60	0.031***	0.60	0.031***	0.60	0.031***
Occupation$^{\Psi}$						
High	Reference category					
Medium	-0.075	0.047	-0.075	0.047	-0.075	0.047
Low	-0.307	0.046***	-0.307	0.046***	-0.307	0.046***
Elementary	0.038	0.060	0.039	0.060	0.039	0.060
Missing values	-0.295	0.043***	-0.295	0.043***	-0.30	0.043***

Setting						
Urban	Reference category					
Rural	-0.50	0.023***	-0.50	0.023***	-0.50	0.023***
Missing values	0.75	0.78	0.45	0.12	-0.14	0.70
Random effect	σ	SD	σ	SD	σ	SD
Country level	2.3	1.52	1.99	1.41	1.92	1.39
Residual	19.38	4.40	19.38	4.40	19.38	4.40
Fit Indices						
AIC	1197180.7		1197172.4		1197172	
BIC	1197385.4		1197387.4		1197397	
Log Likelihood	-598570.4		-598565.2		-598564	
Deviance	1197140.7		1197130.4		1197128	
Model Comparison	With model 0		With model 10		With model 12	
Chi-square (df)	7282.8(17)***		10.28(1)**		2.42(1)	
R^2	With model 0		With model 0		With model 0	
Country Level R^2	0.164		0.276		0.302	
Individual level R^2	0.034		0.034		0.034	
Total R	0.050		0.064		0.067	

*pvalue≤0.05; **pvalue≤0.01; ***pvalue≤0.001

β- regression coefficient; SE- Standard Error; σ- Variance; SD: Standard Deviation; AIC- Akaike information criterion; BIC- Bayesian information criterion; Chisq- Chi Square test; df- Degree of freedom.

[Ψ]Occupation categories: High (1. Legislator, Senior Official, or Manager 2. Professional and 10.armed forces), medium (3.Technician or Associate Professional 4. Clerk 5. Service or sales worker), low (6. Agricultural or fishery worker 7. Craft or trades worker 8. Plant/machine operator or assembler) and elementary (elementary workers)

Interaction effect between national income and individual level household wealth was modelled to measure the effect of national income on the relationship between individual level household wealth and BMI. Table 4.4 shows the results of the multilevel multivariate cross level interaction model. These results show a significant interaction effect between all the individual level wealth quintiles and GNIPP except quintile 2. To make the results of this model more interpretable, I graphically presented the interaction effect in figure 4.16. This graph shows that as the national income increases, people in the first four quintiles move towards higher BMIs. However, the wealthiest quintile shows a reverse pattern. The BMI of the wealthiest people decreases as the national income increases. Therefore, 80% of the people in a country move towards a higher BMI as the national income of the country increases, only 20% (i.e. wealthiest) of the people in a country show a decline in the mean BMI as the national income of the country increases.[39]

The descriptive analysis of the variables gender, education level, occupation and setting creates a compelling case for interactions. However this was not the main aim of this thesis, therefore, the results of these interaction effects has been presented in Appendix K.

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[39] The following equation was used to interpret the interaction effect and plotting the graph

$$BMI$$

In interaction analysis the value of outcome depends on the regression coefficient of explanatory variables and the interaction term. In this analysis value of BMI depends on the regression coefficient of household wealth (β_1), national income (β_2) and coefficient of interaction term (β_3). In this model the β_3 for the wealthiest category of household income was very high compared with other household wealth categories. Therefore it makes the slope of the wealthiest category negative as compared with the other household categories.

Table 4.4: Multilevel multivariate linear regression analysis with individual and country level explanatory variables with inter-level interaction between household wealth and national income (GNI-PPP)

		Model 13	
Fixed Effect		β	SE
Intercept		22.15	0.832***
Country Level			
GNI-PPP/10000		0.57	0.13*
Gini		0.03	0.02
Individual Level			
Age		0.034	0.007***
Gender			
	Female	Reference category	
	Male	-0.019	0.022
Marital Status			
	Never Married	Reference category	
	Married	1.12	0.029***
	Previously married	0.71	0.037***
	Missing values	0.345	0.234
Education			
	Primary	Reference category	
	Intermediate	0.146	0.027***
	Higher	-0.092	0.043*
Household Income			
	1st Quintile (Poorest)	Reference category	
	2nd Quintile	0.21	0.031***
	3rd Quintile	0.37	0.031***
	4th Quintile	0.41	0.031***
	5th Quintile (Wealthiest)	0.60	0.031***
Occupation$^{\Psi}$			
	High	Reference category	
	Middle	-0.067	0.048
	Low	-0.29	0.0471***
	Elementary	0.052	0.061
	Missing values	-0.29	0.044***
Setting			

Urban	Reference category	
Rural	-0.49	0.023
Missing values	-0.13	0.188
Household wealth:GNIPPP		
1st Quintile (Poorest):GNIPPP	Reference category	
2nd Quintile:GNIPPP	-0.02	0.03
3rd Quintile:GNIPPP	-0.08	0.03**
4th Quintile:GNIPPP	-0.09	0.03**
5th Quintile (Wealthiest):GNIPPP	-0.26	0.03***
Random effect	σ	SD
Country	1.93	1.39
Residual	19.37	4.40
Fit Indices		
AIC	1197166.6	
BIC	1197432.8	
Log Likelihood	-598557.3	
Deviance	1197114.6	
Model Comparison		
Chi-square(df)	105.77 (4)***	
R^2		
Country Level R^2	0.276	
Individual level R^2	0.050	
Total R	0.077	

*pvalue≤0.05; **pvalue≤0.01; ***pvalue≤0.001; SE: Standard Error.

β- regression coefficient; SE- Standard Error; σ- Variance; SD: Standard Deviation; AIC- Akaike information criterion; BIC- Bayesian information criterion; Chisq- Chi Square test; df- Degree of freedom.

ΨOccupation categories: High (1. Legislator, Senior Official, or Manager 2. Professional and 10.armed forces), medium (3.Technician or Associate Professional 4. Clerk 5. Service or sales worker), low (6. Agricultural or fishery worker 7. Craft or trades worker 8. Plant/machine operator or assembler) and elementary (elementary workers)

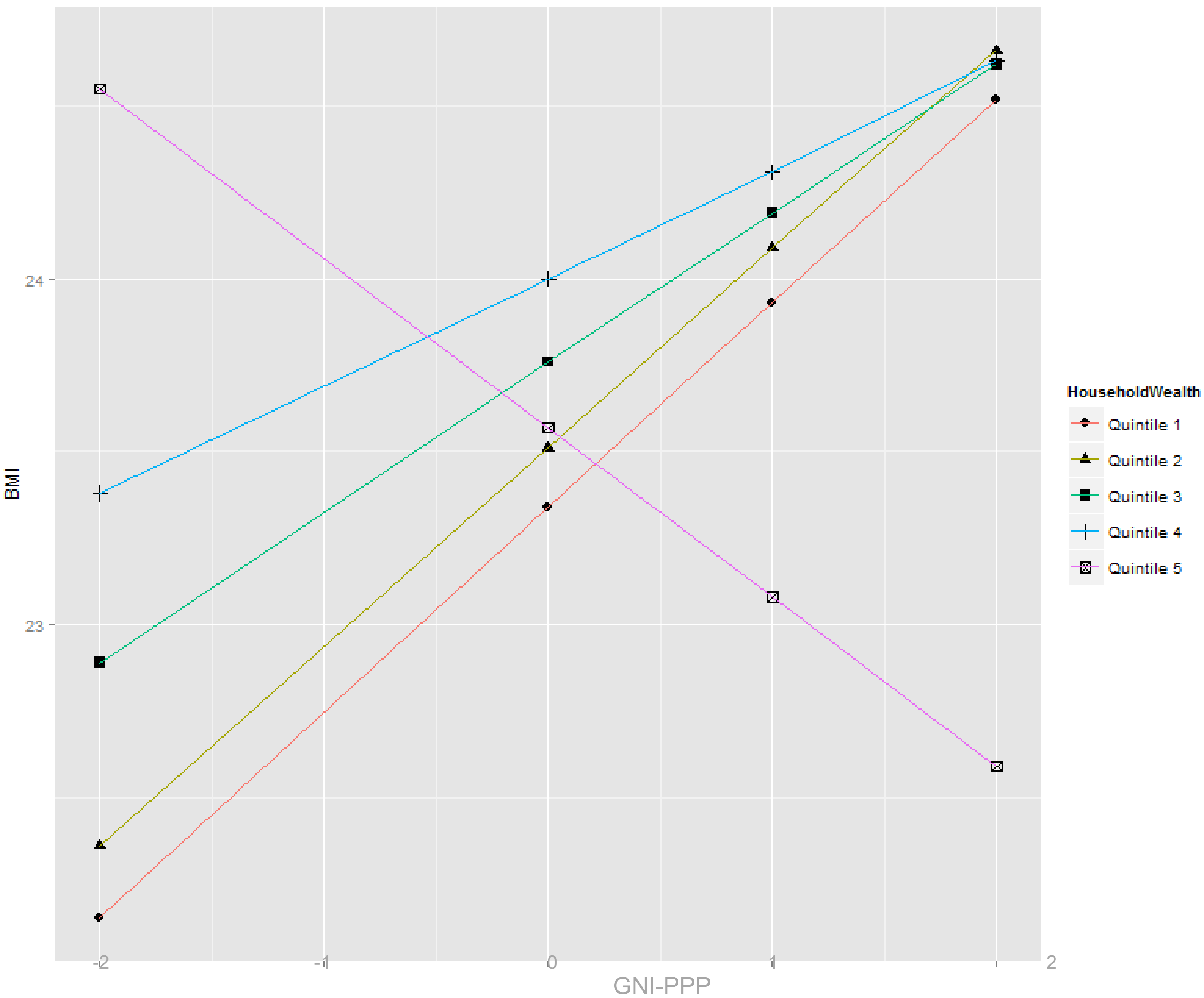

Figure 4.16: Plot showing the cross level interaction effect of individual level wealth quintiles and national income.

4.3 Cultural dimensions and BMI

A sample of 156,192 people from 53 countries was included in this analysis as the data for cultural dimensions was missing for 17 countries. The list of included and excluded countries, sample size and response rates for each country are presented in Table 3.1 in the methods section. Table 4.5 shows weighted and unweighted descriptive analysis of the data. The design based (weighted) mean BMI (SE) in these 53 countries was 23.95(0.08) and the design based (weighted) mean age (SE) of the sample from these 53 countries was 41.27(0.19). Nearly equal percentage (weighted) of male and females were present in this sample. For education level, this sample of 53 countries was similar to that from 70 countries. Nearly 40% of the sample had intermediate education, 45.6% had primary education and only 14.2% had completed higher education (college/university) and above education. More than half (59.7)% of the people were married (currently married/cohabitant), 20.3% of people were never married and 15.9% of people were previously married (divorced/widowed/separated). Household wealth quintile had nearly 19% of the people in each quintile and 6% of the data was missing in household wealth variable. In occupation variables, 46.2% data was missing, nearly quarter of the people were from low occupation (agriculture/fishery/ Craft or trades worker/ plant/machine operator or assembler occupation), 13.8% were from medium occupation (Technician/ Associate Professional/ Clerk/ Service/ sales worker), 7.3% were from high occupation (Legislator/Senior Official/ Manager/ professionals/ armed forces workers) and 5.1% were elementary workers. Nearly half of the participants were from urban and half from rural setting.

Table 4.5: Model based and design based descriptive analysis of outcome variable (BMI) and individual level explanatory variables in the 53 WHS countries.

	53 countries for cultural analysis	
	Model Based	Design Based
	n=156192	N=770151380
	Mean ± SD	Mean ± SE
Outcome variable		
BMI	24.05(4.92)	23.95(0.08)
Explanatory Variables		
Age	42.33(16.71)	41.27(0.19)
	n(%)	N(%)
Gender		
Female	71876(53.9)	3861707(50.2)
Male	61389(46.06)	3839769(49.8)
Missing values	5(0.003)	3802(0.0)
Marital Status†		
Never Married	24270(18.21)	156329916(20.3)
Married	74971(56.25)	459772891(59.7)
Previously married	25499(19.13)	122482578(15.9)
Missing values	8530(6.4)	31565995(4.1)
Education		
Primary	53122(39.86)	351559014(45.6)
Intermediate	64018(48.08)	304854666(39.6)
Higher	15041(11.28)	109509803(14.2)
Missing values	1026(0.76)	4227898(0.5)
Household Income		
1st Quintile (Poorest)	26030(19.53)	155540304(20.2)
2nd Quintile	26196(19.65)	151537449(19.7)
3rd Quintile	24542(18.41)	137002987(17.8)
4th Quintile	24592(18.45)	140199329(18.2)
5th Quintile (Wealthiest)	24267(18.20)	12525755316.3)
Missing values	7643(5.73)	60613759(7.9)

Occupation‡		
High	10090(7.57)	56431105(7.3)
Medium	18797(14.10)	106090097(13.8)
Low	31012(23.27)	212328723(27.6)
Elementary	6658(4.99)	39368661(5.1)
Missing values	66713(50.05)	355932795(46.2)
Setting¥		
Urban	75102(56.35)	355475737(46.2)
Rural	52265(39.21)	386726171(50.2)
Missing values	5903(4.42)	27949472(3.6)

†All data in this variable was missing for Turkey; ‡All data in this variable was missing for Turkey and Norway; ¥ All data in this variable was missing for Australia, Netherlands, Norway and Slovenia;

ΨOccupation categories: High (1. Legislator, Senior Official, or Manager 2. Professional and 10.armed forces), medium (3.Technician or Associate Professional 4. Clerk 5. Service or sales worker), low (6. Agricultural or fishery worker 7. Craft or trades worker 8. Plant/machine operator or assembler) and elementary (elementary workers)

As this analysis is a subset of 53 countries from the 70 countries, the distribution of sex, education level, marital status, household wealth quintile, occupation and setting for these 53 was same as that presented in the descriptive analysis for 70 countries (presented in figure 4.1 to 4.8). Pattern of mean BMI in these 53 countries was similar to that for 70 countries, as presented in figure 4.9. Most of the low-income countries such as Vietnam, India, Nepal and Myanmar were at the lower end of the BMI values and high or middle-income countries such as Australia, Hungary, UAE were at the higher end of the BMI values. Swaziland was an exception as a low-income country with a high BMI. Some of the high-income countries, such as Norway, Sweden, Austria, Netherlands, Israel, and Ireland fall in the middle of the spectrum. The distribution of BMI by individual level variables for these 53 countries was also same as hat presented in the descriptive analysis for the 70 countries presented in figures 4.9 to 4.14. These figures can be referred to get and compare the descriptive analysis of all included the 53 countries included in this analysis.

The correlations matrix was analysed for the economic and cultural country level variables (national income, national income inequality, uncertainty avoidance, individualism, power distance, masculinity) and outcome variables (BMI). The correlations matrix shows that across these 53 countries, a larger power distance is moderately correlated with lower levels of individualism (r=-0.65), and with lower GNI-PPP (r=-0.42). Lower individualism was also moderately correlated with higher GNI-PPP (r=0.51) and with lower Gini index (r=-0.50). Individualism in a country was positively associated with national income and negatively associated with income inequality. The more individualistic a country is, the smaller the power distance would be. Masculinity and uncertainty avoidance showed a weak correlation with the other Hofstede dimensions, namely GNI-PPP and Gini index. BMI shows a weak correlation with all the country level predictors. Table 3.3 and table 3.4 shows values for national income, income inequality and Hofstede dimensions for each country.

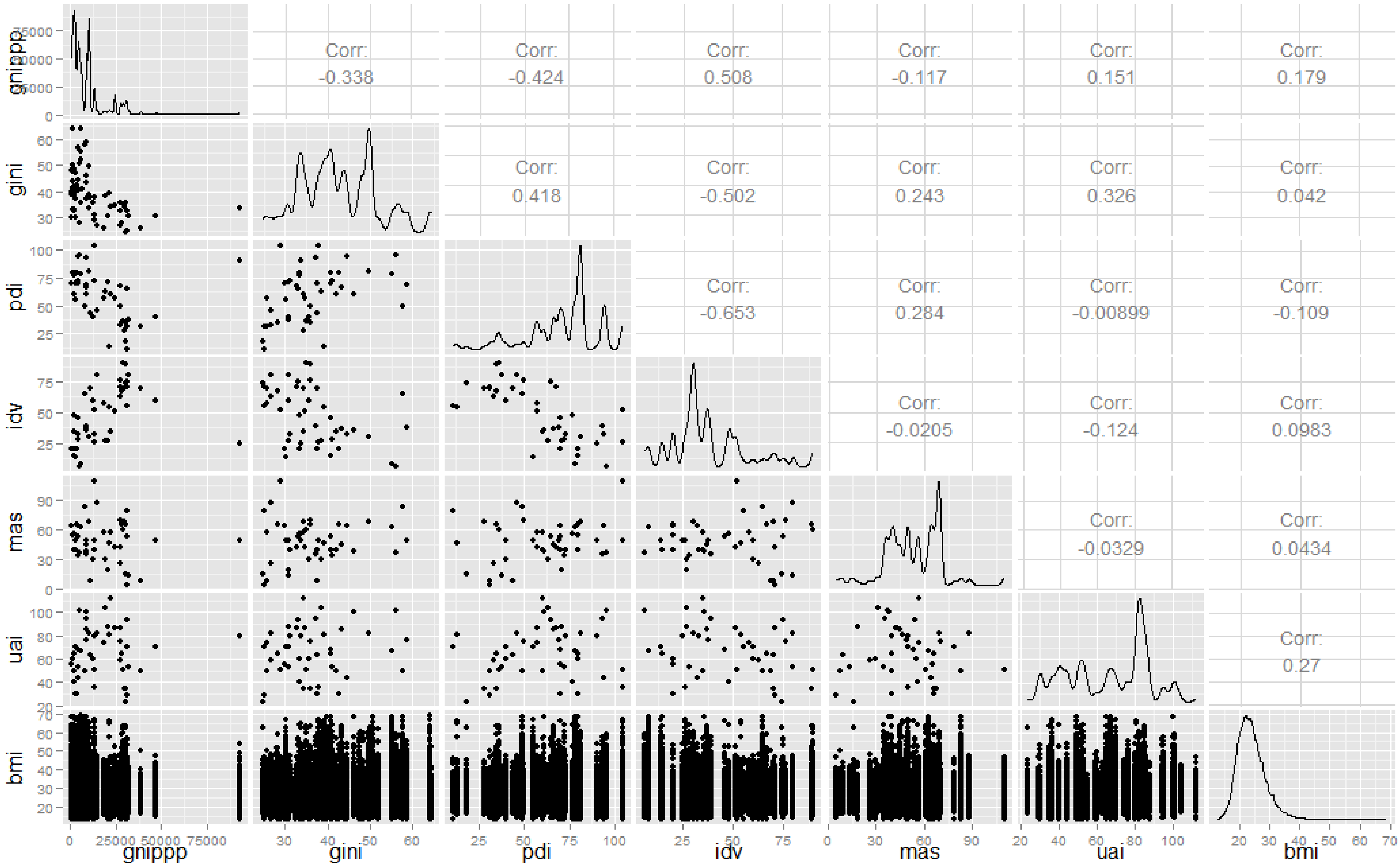

Figure 4.17: Correlation matrix and correlation coefficients for BMI, Gini, GNIPPP, power distance, uncertainty avoidance, individualism and masculinity.

Results of the bivariate multilevel models for BMI and country level and individual level variables are presented in Table 4.6 for 53 countries. First, I ran the null model (model 0a) or the variance component model for 53 countries. The fixed part is represented by the coefficient for the constant, which is 24.60 with a standard error of 0.25. That is to say, the estimated overall population mean for BMI is 24.60 for 53 countries. The random part is given under the heading “Random effect” for variance of level 1 residuals and “variance and covariance of random effects” for variance of the random intercept. Accordingly, the estimate of the between-subject variance is 2.82 and the estimate of within-subject variance is 20.41. Using equation 4.3, the intra-class correlation for BMI in these 53 countries was 0.12. ICC suggests that the proportion of the total variance that occurs between countries is 0.12. That is to say, about 12.0% of the variance of BMI can be explained by the variations in the characteristics of countries.

In order to assess the bivariate effect of country level variables on BMI, country level variables including Hofstede Cultural dimensions, national income and income inequality were modeled without any individual level covariates (table 4.6). I started with bivariate multilevel analysis for each country level explanatory variable. In model 14, a bivariate analysis for GNI-PPP and BMI was done. This model shows that GNI-PPP had significant positive relationship with BMI (β=-0.47, $P<0.01$). It also explained the highest amount of variation (20.9%) in BMI at a country level. Gini index was added in the next model (model 15); it was not significantly associated with BMI and explained only 0.4% of the country level variation in BMI. This model was not significantly better than the null model. Individualism and uncertainty avoidance had a very similar relationship with BMI (model 16 and model 17). Both Individualism (β=0.032, $P<0.01$) and uncertainty avoidance (β=0.032, $P<0.01$) were positively associated with BMI. These relationships of individualism and uncertainty avoidance with BMI were highly significant. That is to say, for every 1 point increase in the individualism or uncertainty avoidance score of a country, a 0.032 point increase in the BMI score can be expected. It appears to be a small change in BMI but remember that these dimensions are measured on a scale of 0-100, meaning that if two countries have a individualism or uncertainty avoidance difference of 80, then their mean BMI would differ by 2.56 units. These models were significantly better fitted then null model, both individualism and uncertainty avoidance explained substantially high country level variance in BMI. Effect of power distance on BMI was analyzed in model 18; it was negatively related to BMI (β=-0.030, $p<0.01$). It explained 1.6% of the total variance and 13.5% of the country level variance in BMI. This model was significantly better fitted then the null model. Masculinity was not significantly associated with BMI and did not explain any variation in BMI (model 19). These findings suggest that cultural dimensions of a country have significant effects on an individual's BMI. However, these relationships need to be analyzed after controlling other confounding factors.

I also analyzed the effect of individual level variables on BMI using the bivariate analysis in models 20 to 26 (Table 4.5). All these relationships for individual level variables and BMI were similar to those mentioned in the analysis of 70 countries. In the 53 countries analysis, BMI was not significantly different for male and females. People with higher age and living in urban areas were associated with a higher BMI. Having higher income or higher education level was associated with a significantly lower BMI. Married people had a significantly higher mean BMI than never married people. People with medium occupation (Technician/ Associate Professional/ Clerk/ Service/ sales worker) had BMIs similar to people with high occupation (Legislator/Senior Official/ Manager/ professionals/ armed forces workers). People with low occupation (agriculture/fishery/ Craft or trades worker/ plant/machine operator or assembler occupation) had significantly lower BMIs compared with people with high occupation. People with elementary occupation were significantly fatter than the people with high occupation.

Table 4.6: Multilevel linear regression models showing bivariate relationship of BMI and individual level and country level explanatory variables in the 53 WHS countries.

Model		Fixed Effect		Random effect		Fit Indices				Model Comparison^	R^2		
		Intercept	Estimates	Country	Residual	AIC	BIC	Log Likelihood	Deviance	Chisq(df)	Ind	Cou	Total
		β(SE)	β(SE)	σ(SD)	σ(SD)								
Model0a	Null Model	24.6(0.25)***	-	2.82(1.68)	20.41(4.52)	780437.4	780466.8	-390215.7	780431.4	-	-	-	-
	Country Level												
Model14	GNI-PPP/10000	24.2(0.25)***	0.47(0.14)***	2.23(1.49)	20.41(4.52)	780428.8	780468.0	-390210.4	780420.8	10.5(1)***	-	0.209	0.025
Model15	Gini Index	24.6(0.29)***	-0.02(0.02)	2.81(1.67)	20.41(4.52)	780439.3	780478.5	-390215.6	780431.3	0.5(1)	-	0.004	0.000
Model16	Uncertainty Avoidance	24.6(0.23)***	0.032(0.01)**	2.32(1.52)	20.41(4.52)	780430.5	780469.7	-390211.2	780422.5	8.8(1)**	-	0.177	0.022
Model17	Individualism	24.6(0.22)***	0.032(0.01)**	2.29(1.51)	20.41(4.52)	780430.0	780469.2	-390211.0	780422.0	9.4(1)**	-	0.188	0.023
Model18	Power Distance	24.6(0.23)***	-0.03(0.01)*	2.44(1.56)	20.41(4.52)	780432.9	780472.1	-390212.4	780424.9	6.4(1)*	-	0.135	0.016
Model19	Masculinity	24.6(0.25)***	-0.002(0.01)	2.81(1.67)	20.41(4.52)	780439.3	780478.5	-390215.7	780431.3	0.03(1)	-	0.004	0.000
	Individual Level												
Model20	Age	24.5(0.23)***	0.04(0.007)***	2.40(1.55)	19.84(4.45)	776619.2	776658.4	-388305.6	776611.2	3820(1)***	0.028	0.149	0.043
Model21	Gender	24.6(0.25)***		2.81(1.68)	20.41(4.52)	780426.5	780465.7	-390209.2	780418.5	12.8(1)***	0.000	0.004	0.000
	Female		Reference category										
	Male		0.09(0.03)***										
Model23	Marital Status	23.3(0.26)***		2.80(1.70)	20.01(4.47)	777795.4	777854.2	-388891.7	777783.4	2648(3)***	0.020	0.007	0.018
	Never Married		Reference category										
	Married		1.71(0.03)***										
	Previously married		1.50(0.04)***										
	Missing Values		2.0(1.7)										
Model22	Education	24.8(0.25)***		2.81(1.70)	20.39(4.51)	780345.4	780394.4	-390167.7	780335.4	96.0(2)***	0.001	0.004	0.001
	Primary		Reference category										
	Intermediate		-0.23(0.03)***										
	Higher		-0.40(0.05)***										
Model24	Household wealth	24.3(0.25)***		2.85(1.69)	20.37(4.51)	780205.5	780274.1	-390095.8	780191.5	239.8(4)***	0.002	0.007	0.003
	1st Quintile(Poorest)		Reference category										
	2nd Quintile		0.24(0.04)***										
	3rd Quintile		0.36(0.04)***										
	4th Quintile		0.45(0.04)***										
	5th Quintile(wealthiest)		0.57(0.04)***										

Model25	Occupation$^{\Psi}$	24.7(0.25)***		2.75(1.66)	20.40(4.52)	780370.4	780439.0	-390178.2	780356.4	74.9(4)***	0.000	0.025	0.003
	High		Reference category										
	Middle		-0.11(0.06)										
	Low		-0.20(0.05)***										
	Elementary		-0.21(0.07)**										
	Missing Values		-0.03(0.05)										
Model26	Setting	24.7(0.25)***		2.61(1.62)	20.39(4.52)	780270	780319	-390130	780260	171(2)***	0.001	0.074	0.010
	Urban		Reference category										
	Rural		-0.37(0.03)***										
	Missing Values		0.65(0.85)										

*pvalue≤0.05; **pvalue≤0.01; ***pvalue≤0.001; SE: Standard Error.

β- regression coefficient; SE- Standard Error; σ- Variance; SD: Standard Deviation; AIC- Akaike information criterion; BIC- Bayesian information criterion; Chisq- Chi Square test; df- Degree of freedom; ind- individual level, cou- country level

$^{\Psi}$Occupation categories: High (1. Legislator, Senior Official, or Manager 2. Professional and 10.armed forces), medium (3.Technician or Associate Professional 4. Clerk 5. Service or sales worker), low (6. Agricultural or fishery worker 7. Craft or trades worker 8. Plant/machine operator or assembler) and elementary (elementary workers)

^ All the models were compared with model 0

I used multivariate analysis to analyze the effect of cultural dimensions on BMI after controlling the effect of individual level variables and national income and national income inequality (Table 4.7). I first showed the results of multivariate model for all the control factors (individual level factors, national income and income inequality) and later added four cultural dimensions one by one. In the final model (table 4.8), I added all the 3 significant dimensions together in the multivariate analysis to see the effect of all the cultural dimensions together.

Model 27 shows multivariate multilevel analysis with control variables only (individual level variables and national income and income inequality). Among the individual variables, gender was not associated with BMI when holding all other variables constant. Education level was negatively associated with BMI in bivariate analysis. However, this relationship in multivariate analysis became positive for intermediate education but stayed negative for higher education. The relationship between age and BMI was positive and significant ($\beta=0.04$, $p<0.001$). That is to say, for every ten-year increase in age, a 0.4 units increase in the BMI can be expected when holding all the other variables constant. Married people ($\beta=1.16$, $p<0.001$) and never married ($\beta=0.74$, $p<0.001$) people had a significantly higher mean BMI than never married people. Household income was also significantly related to BMI. All higher household wealth quintiles had higher scores in mean BMI compared to lower quintiles when holding all the other variables constant. People from urban setting had significantly higher mean BMI than people from rural setting. People with low occupation (agriculture/fishery/ Craft or trades worker/ plant/machine operator or assembler occupation) had significantly lower BMI compared with people with high occupation. People with elementary occupation had significantly higher BMI than people with high occupation. National income ($\beta=0.51$, $p<0.001$) was positively related but Gini index didn't show any relationship with BMI. All these control variables together in this multivariate model (model 27) explained 4.0% of the individual level, 36.2% of the country level and 7.9% of the total variance in BMI.

Further analysis in this section measured the effect of power distance, individualism, uncertainty avoidance and masculinity in multivariate multilevel linear regression analysis after controlling other individual level variables, national income and national income inequality. In bivariate analysis, uncertainty avoidance was highly significant compared with the other dimensions. Hence, the effect of uncertainty avoidance on BMI was analyzed first by adding uncertainty avoidance in model 27. Addition of uncertainty avoidance improves the model fit statistics, demonstrating that uncertainty avoidance is an important factor (model 28). Uncertainty avoidance ($\beta=0.03$, $p<0.001$) was significantly associated with BMI. So, 1 unit increase in uncertainty avoidance score was associated with an increase of 0.03 unit in BMI, irrespective of national income, income inequality and individual level variables. The relationship of national income, income inequality and all the individual level variables was similar as in model 27. This model explained 46.8% of the country level and 9.2% of the total variance in BMI.

Similarly, model 29 tested the effect of individualism on BMI. In this model, individualism ($\beta=0.03$, $p<0.001$) was found to be significantly associated with BMI after controlling all the individual level variables and national income and income inequality, demonstrating that people have a higher mean BMI in more individualistic countries compared with less individualistic (collectivist) ones. GNI-PPP was also significant; with every 10,000 $ increase in GNI-PPP, BMI increased by 0.41. In this model, regression coefficient for Gini index becomes significant ($\beta=0.07$, $p<0.05$). This interesting finding indicates that individualism changes the effect of income inequality on BMI. This model explained 45.2% of the country level and 9.0% of the total variance in BMI.

Next, I tested the relationship of power distance with BMI in model 30. The effect of power distance on BMI got reduced after controlling individual level variables, national income and income inequality. However, it was significant. This model shows that each unit increase in power distance was associated with 0.02 unit decrease in BMI. This model explained 42.6% of the country level and 8.7% of the total variance in BMI. Relationship of national income and individual level variables was similar to that in model 29. Similar to the individualism model, the regression coefficient for Gini index was significant in this model signifying that the effect of power distance on the relationship of income inequality and BMI. In the next model, the effect of masculinity on BMI was tested (model 30). Similar to bivariate analysis, masculinity was not significantly related with BMI. This model was not a better fit compared with the control model. Therefore masculinity was not considered for further analysis.

Table 4.7: Multilevel multivariate linear regression analysis with individual and country level explanatory variables in the 53 WHS countries

	Model 27		Model 28		Model 29		Model 30		Model 31	
Fixed Effect	**β**	**SE**	**β**	**SE**	**β**	**SE**	**β**	**SE**	**β**	**SE**
Intercept	23.3	0.26***	23.3	0.24***	23.5	0.26***	23.5	0.26***	23.2	0.26***
Country Level										
GNI-PPP/10000	0.51	0.14***	0.44	0.13**	0.41	0.13**	0.45	0.13**	0.51	0.13**
Gini	0.05	0.03	0.03	0.02	0.07	0.02**	0.06	0.02*	0.05	0.02
Uncertainty avoidance			0.03	0.009**						
Individualism					0.03	0.009*				
Power Distance							- 0.02	0.009*		
Masculinity									0.005	0.009
Individual Level										
Age	0.04	0.001***	0.04	0.001***	0.04	0.001***	0.04	0.001***	0.04	0.001***
Gender										
Female	Reference category									
Male	0.012	0.03	0.012	0.03	0.012	0.03	0.012	0.03	0.012	0.03
Marital Status										
Never Married	Reference category									
Married	1.16	0.04***	1.16	0.04***	1.16	0.04***	1.16	0.04***	1.16	0.04***
Previously married	0.74	0.04***	0.74	0.05***	0.74	0.05***	0.74	0.05***	0.74	0.05***
Missing values	1.93	1.54	1.48	1.26	1.48	1.26	1.87	1.26	1.96	1.37

Education										
Primary	Reference category									
Intermediate	0.19	0.03***	0.19	0.03***	0.19	0.03***	0.19	0.03***	0.19	0.03***
Higher	-0.11	0.05*	-0.11	0.05*	-0.11	0.05*	-0.11	0.05*	-0.11	0.05*
Household Income										
1st Quintile (Poorest)	Reference category									
2nd Quintile	0.18	0.039***	0.18	0.039***	0.18	0.039***	0.18	0.039***	0.18	0.039***
3rd Quintile	0.30	0.039***	0.30	0.039***	0.30	0.039***	0.30	0.039***	0.30	0.039***
4th Quintile	0.38	0.039***	0.38	0.039***	0.38	0.039***	0.38	0.039***	0.38	0.039***
5th Quintile (Wealthiest)	0.50	0.039***	0.50	0.039***	0.50	0.039***	0.50	0.039***	0.50	0.039***
Occupation$^{\Psi}$										
High	Reference category									
Middle	-0.043	0.057	-0.043	0.057	-0.043	0.057	-0.043	0.057	-0.043	0.057
Low	-0.25	0.057***	-0.25	0.057***	-0.25	0.057***	-0.25	0.057***	-0.25	0.057***
Elementary	0.16	0.074*	0.16	0.074*	0.16	0.074*	0.16	0.074*	0.16	0.074*
Missing values	-0.16	0.053**	-0.16	0.053**	-0.16	0.053**	-0.16	0.053**	-0.16	0.053**
Setting										
Urban	Reference category									
Rural	-0.36	0.03***	-0.36	0.03***	-0.36	0.03***	-0.36	0.03***	-0.36	0.03***
Missing values	0.31	0.14	0.43	0.66	0.43	0.66	0.15	0.66	0.15	0.66
Random effect										
Country	1.8	1.34	1.5	1.23	1.54	1.23	1.62	1.27	1.77	1.33
Residual	19.60	4.41	19.60	4.43	19.60	4.43	19.60	4.43	19.60	4.43

Fit Indices					
AIC	775010.0	775004.2	775005.4	775007.5	775011.7
BIC	775225.6	775229.6	775230.8	775232.9	775237.1
Log Likelihood	-387483.0	-387479.1	-387479.7	-387480.8	-387482.9
Deviance	774966.0	774958.2	774959.4	774961.5	774965.7
Model Comparison	With model 0	With model 10	With model 12		
Chi-square (df)	5465.3(19)***	10.28(1)**	6.6(1)*	4.5(1)*	0.30(1)
R^2					
Country Level R^2	0.362	0.468	0.454	0.426	0.372
Individual level R^2	0.040	0.040	0.040	0.040	0.040
Total R	0.079	0.092	0.090	0.087	0.080

*pvalue≤0.05; **pvalue≤0.01; ***pvalue≤0.001; SE: Standard Error.

β- regression coefficient; SE- Standard Error; σ- Variance; SD: Standard Deviation; AIC- Akaike information criterion; BIC- Bayesian information criterion; Chisq- Chi Square test; df- Degree of freedom; ind- individual level, cou- country level

$^{\Psi}$Occupation categories: High (1. Legislator, Senior Official, or Manager 2. Professional and 10.armed forces), medium (3.Technician or Associate Professional 4. Clerk 5. Service or sales worker), low (6. Agricultural or fishery worker 7. Craft or trades worker 8. Plant/machine operator or assembler) and elementary (elementary workers)

The final model included all the individual level variables, national income, income inequality, uncertainty avoidance, individualism and power distance (model 31). Table 4.8 shows the results of this model. In this model, I added all the Hofstede dimensions one by one. I started with the model that had all the control variables. Uncertainty avoidance was added first in the model because it had the largest regression coefficient in the bivariate analysis. The other variables were also added in a different order but the same results were obtained. Uncertainty avoidance and individualism had the same results as mentioned in the previous models with significant positive effect on BMI. This model showed that on average one unit increase in Uncertainty avoidance could result in a 0.03 unit increase in BMI. Individualism was found to be significantly associated with BMI. Each unit increase in individualism was associated with a 0.03 unit increase in BMI. But the effect of power distance on BMI disappeared in this model; the regression coefficient for power distance was not significant in this model. It means that the power distance in a country doesn't have any effect on an individual's BMI after considering s uncertainty avoidance and individualism for the country. National income has a relationship as observed in the previous model. Each $10000 increase in GNI-PPP can increase the BMI by 0.30 units. The relationship of Gini index (β=0.06, $p<0.01$) with BMI got stronger in this model after considering all the cultural dimensions together. Each one unit increase in Gini index resulted in a 0.06 unit increase in BMI. It might be concluded that on income inequality scale, between a perfectly income unequal country (Gini index=100) and a perfectly income equal country (Gini index =0), the BMI difference can be 6.0 units. Adding these country level variables in the model did not change in the individual level regression coefficients much and it did not affect the level of significance of the individual variables. This final model explained 61.7% of the country level and 11.0% the total variance in BMI.

Table 4.8: Multilevel multivariate linear regression analysis with individual and country level explanatory variables in the 53 WHS countries

	Model 32	
Fixed Effect	β	SE
Intercept	23.6	0.23***
Country Level		
GNI-PPP/10000	0.30	0.14*
Gini	0.06	0.02**
Uncertainty avoidance	0.03	0.008***
Individualism	0.03	0.01*
Power Distance	-0.01	0.009
Individual Level		
Age	0.04	0.001***
Gender		
Female	Reference category	
Male	0.012	0.03
Marital Status		
Never Married	Reference category	
Married	1.16	0.04***
Previously married	0.74	0.04***
Missing value	1.36	1.54
Education		
Primary	Reference category	
Intermediate	0.19	0.03***
Higher	-0.11	0.05*
Household Income		
1st Quintile (Poorest)	Reference category	
2nd Quintile	0.18	0.039***
3rd Quintile	0.30	0.039***
4th Quintile	0.38	0.039***
5th Quintile (Wealthiest)	0.50	0.039***

Occupation		
High	Reference category	
Middle	-0.044	0.057
Low	-0.25	0.057***
Elementary	0.16	0.074*
Missing value	-0.16	0.053**
Setting		
Urban	Reference category	
Rural	-0.36	0.03***
Missing Value	0.31	0.14
Random effect		
Country	1.08	1.04
Residual	19.60	4.41
Fit Indices		
AIC	774995.3	
BIC	775250.1	
Log Likelihood	-387471.7	
Deviance	774943.3	
Model Comparison	With model 0	
Chi-square (df)	22.6(4)***	
R^2	With model 0	
Country Level R^2	0.617	
Individual level R^2	0.040	
Total R	0.11	

*pvalue≤0.05; **pvalue≤0.01; ***pvalue≤0.001; SE: Standard Error.

β- regression coefficient; SE- Standard Error; σ- Variance; SD: Standard Deviation; AIC- Akaike information criterion; BIC- Bayesian information criterion; Chisq- Chi Square test; df- Degree of freedom; ind- individual level, cou- country level

[Ψ]Occupation categories: High (1. Legislator, Senior Official, or Manager 2. Professional and 10.armed forces), medium (3.Technician or Associate Professional 4. Clerk 5. Service or sales worker), low (6. Agricultural or fishery worker 7. Craft or trades worker 8. Plant/machine operator or assembler) and elementary (elementary workers)

CHAPTER 5: Discussion

The overall goal of this thesis was to examine the relationship of BMI with the country-level cultural macro-environment, which was measured by national cultural dimensions, and economic macro-environment, which was measured by national income and national income inequality. The relationship of BMI and economic macro environment was studied across 70 low, middle and high-income countries after controlling individual level risk factors. The relationship of BMI and cultural macro environment was studied across 56 low, middle and high-income countries after controlling individual level risk factors. Researchers continue to explore the determinants of excess body weight in order to curb the increasing prevalence of obesity [Ball and Crawford, 2005; Crawford and Ball, 2002; Dean, 2012]. This exploration mainly involves genetic, behaviour, social and microenvironment determinants of obesity. However, far less effort has been made to explore the effect of macro-environmental determinants of obesity. The largest operationalized unit for macro environment is a country (e.g. taxation on food products such as sugar is a national policy), but very few studies have been done on the effect of country level macro environment on obesity. Most of the research on macro-environment explored the role of physical, policy and economic environment in various settings but not at a country level [Swinburn et al., 1999a]. An increased acknowledgement of the importance of the country level macro environment determinants of health (including obesity) is found in a range of disciplinary literatures, including social epidemiology and health geography [Davison and Birch, 2001; Egger and Swinburn, 1997; Swinburn et al., 1999a]. To our knowledge, the country level (national income, national income inequality and national culture) determinants have not yet been investigated in such detail with inclusion of low middle and high-income countries. Therefore, this thesis examined the role of country level factors in determining the BMI in 70 countries. The two focal points in this dissertation are: (1) the national income and income inequality as predictors of obesity and (2) cultural dimensions, in relationship to obesity. Therefore in this chapter, these two points are discussed separately and also their combined effect.

The first part of this chapter is devoted to a brief discussion of significant individual level factors before focusing on the country level effects. Then I provide a discussion on the association of national income and its interection effect on , national income inequality and cultural dimensions with BMI. As part of this section, I discuss the extent to which the results of this study are consistent or inconsistent with previous research. I also highlight the theoretical, methodological and substantive contribution of this work; and describe the implications and applications of this work for interventions and policies. The chapter concludes with the directions for future research.

5.1 Key Findings

The findings of this thesis revealed the importance of country level economic (measured with national income and income inequality) and cultural (measured with Hofstede cultural dimensions) macro-environment in shaping global obesity after controlling individual level factors. Individual level demographic factors and socioeconomic characteristics such as age, gender, marital status, educational attainment, occupation, household wealth, living in rural/urban setting were found to be significantly associated with obesity. The relationship of these individual level factors with obesity should be interpreted considering that the effect of these individual level factors was controlled for country level factors, especially national income. Therefore the association of individual level factors with obesity is present in all countries at any level of economic development. Results show that the BMI of people in a country increases with the increase in national income of the country. Association of BMI with income inequality was more complex as in the effect income inequality on BMI was only significant when controlled for national cultural dimensions. Results on cultural dimensions show that people from high individualism and low uncertainty avoidance countries have a higher BMI compared with low individualism and high uncertainty avoidance ones. Other cultural dimensions i.e. power distance and masculinity have no association with BMI. Understanding these country level macro-environment factors associated with BMI is crucial to modify intervention programs according to the specific characteristics of the country.

5.2 Individual level factors and obesity

5.2.1 Gender

Overweight or Obesity results by gender are usually a mixture of negative, positive, and no associations [Summerbell et al., 2009]. Studies found gender disparities in obesity according to the economic development of the country, in low and middle income countries it was observed that women had a higher prevalence of overweight and obesity whereas in high income countries, the reverse was true; men being more overweight than women [Bolton et al., 2014]. In this study, the descriptive analysis of BMI by gender showed a similar pattern where women had a higher BMI than men in low and middle-income countries and men had a higher BMI than women in high-income countries. However, multivariate multilevel regression analysis did not show any obesity-gender relationship after controlling for the other individual level variables. The possible reason for this null effect of gender on BMI in 70 countries is the opposite relationship of gender and BMI in low and middle countries when compared to high-income countries. Inclusion of low, middle and high-income countries in this study might nullify the effect of gender in combined analysis. To address this problem, I performed stratified analysis separately for low, middle and high-income countries (Appendix H). Results of these stratified analyses show a significant relationship of gender and BMI. BMI was significantly higher in women in low and middle-income countries and significantly higher in males in high-income countries.

A more plausible explanation of this gender difference in BMI in stratified analysis is based on sociocultural factors rather than on biological factors [Chamieh, 2013]. The underlying causes of the gender gap in obesity are related to discriminatory social and cultural practices that are embedded in the social, cultural, economic and policy structures. Gender norms that set men's and women's roles and status in the society, and perceived ideal body image, may underpin known social, cultural and behavioural causes of obesity [Garawi et al., 2014; Wells et al., 2012]. For example, social and cultural factors that emphasize a thin body image among women may be part of the reason why there are substantially more overweight men than women in developed countries. These contexts in which gender inequality is produced needs to be taken into account while developing obesity related policies for a specific country. Ultimately, understanding how gender might shape obesity in a particular country has the potential to contribute to improved policies and the development of effective interventions to reduce the female excess in obesity in low and middle-income countries and male excess in high-income countries [Garawi et al., 2014; Wells et al., 2012].

5.2.2 Age

Increase in weight with age has been observed among most of the population in all low, middle and high-income countries [Musaiger et al., 2011]. The results of this study are in agreement with this previous evidence showing a significant increase in BMI with age. Several researchers have found that the relationship of obesity and age is different for different age groups, especially elderly age groups[40]. However, these observations which were obtained from cross-

[40] I tested this categorical age relationship with BMI in a separate analysis (Appendix L), I didn't find any difference in the BMI for different age group.

sectional studies can be affected by survival bias, because obese persons have higher mortality rates at younger ages [Villareal et al., 2005a]. In fact, data from longitudinal cohort studies suggests that body weight and BMI do not change, or decrease only slightly, in older adults.

These findings should be interpreted with caution due to several factors; height measurement difficulties in the elderly related to spine curvature or an inability to stand in full; another is the change in body composition that occurs with age. Whereas BMI appears to have excellent validity as a measure of absolute fat mass adjusted for height in young and middle aged adults [Willett, 1998], it may underestimate body fat in persons who have lost muscle mass, such as the older population. Nevertheless, there is evidence that when the data was analysed excluding elderly (subject greater or equal to 75 years of age), the results were no different from studies conducted on the whole study population [Chamieh, 2013; Wilson, 2012].

5.2.3 Marital Status

Marriage was a significant predictor of obesity in WHS data from 70 low middle and high income countries. Descriptive analysis of the data showed that the marriage and obesity relationship was consistent across all the countries; married people had a higher BMI than unmarried and widowed/divorced. The relationship remained significant in multivariate multilevel regression analysis after controlling for other individual level variables including age and gender. The positive association of marriage and obesity was also reported in various cross sectional studies carried out in various countries [Doblhammer et al., 2009; Janghorbani et al., 2008; Musaiger et al., 2004; Sarlio-Lahteenkorva et al., 2006; Sobal et al., 2009; Tzotzas et al., 2010]. Some longitudinal studies have also suggested that when people enter into marriage, they are more likely to become overweight or obese [Averett et al., 2008]. Results of this study do not show how higher BMI was associated with marriage, but only showed that married people have a higher average BMI compared to single and never married people. The exact mechanism linking marital status and obesity is not fully understood [Tzotzas et al., 2010], and a number of hypothesis have been proposed. Some researchers have used intra-couple correlations to argue that a shared marital environment that may in turn influence partners' food choices and eating habits contributes to BMI [Wilson, 2012]. Other researchers have argued that social obligations may play an important role, particularly with respect to how eating patterns change after marriage, promoting increased food intake and energy consumption [Ogden et al., 2006] and a decline in the desire to maintain weight for the purpose of attracting a partner [Wilson, 2012].

Furthermore, entry into marriage had been associated with decreased physical activity, paralleled with increased social obligations [Bell and Lee, 2005]. Lee et al. (2005) show that divorce leads to a decrease in BMI, which is consistent with observed increases in physical activity and increase in smoking [Lee et al., 2005].

5.2.4 Education Level

Socioeconomic status, estimated in this study by educational attainment, occupation and household wealth (using material possession), showed associations with obesity. It is generally agreed that educational attainment has a negative association with obesity in high-income countries and an inverse relationship has been observed in low and middle-income countries [Aitsi-Selmi et al., 2014; Doblhammer et al., 2009; Muller, 2002]. This study found a relationship for education and BMI across low, middle and high-income countries; the attainment of secondary education was associated with significantly higher risk of obesity. On the other hand, people with a high level of educational attainment, such as college or university education, had levels of BMI which were similar to those of people with primary education. This group had a significant lower risk of obesity compared with people with secondary education across low, middle and low-income countries.

As my study involves all low, middle and high-income countries, these results show a mixed effect of education. These important findings shows that after controlling national income and national income inequality, mediocre education was a promoting factor for obesity and high education level was a protecting factor from obesity. The findings in this study corroborate the existence of a changing education-obesity association dependent on a country's level of economic development [Aitsi-Selmi et al., 2014]. Our findings concur with others emphasising that obesity is a growing problem among those with only secondary education, whereas low education and high education are protecting factors for obesity.

Stratified analysis was done for low middle and high-income countries to check the relationship of education and BMI for different economic development levels of countries. People with higher education show significant positive association with BMI in low-income countries, mixed relationship was observed in middle-income countries and a significant negative association was observed in high-income countries. These relationships were in agreement with previous studies on education and BMI in low, middle and high-income countries [Aitsi-Selmi et al., 2014;

Doblhammer et al., 2009; Filmer and Pritchett, 2001; Hajian-Tilaki and Heidari, 2010; Muller, 2002].

There are a number of possible pathways for the role of education [Aitsi-Selmi et al., 2014; Cutler and Lleras-Muney, 2010]. An obvious difference between poorer and well educated people is resources and knowledge. In low-income countries, people with low education have lower status jobs and fewer resources to buy, resulting in a lower BMI. People with higher education have higher status jobs with low physical work and have enough money to increase their energy intake beyond their energy expenditure [Aitsi-Selmi et al., 2014]. On the other hand, in high-income countries, people with more education have resources and knowledge to buy healthy food and maintain a healthy life style with more physical activities [Cutler and Lleras-Muney, 2010].

In general, higher education and higher income groups have been found to have healthier diets than those who are less educated or illiterate [Drewnowski, 2007]. Educated people have a higher awareness regarding the consequences of obesity, and thus more readily shift to a healthier physical activity pattern and a healthier diet characterized by greater consumption of fruits, vegetables and decreased intake of fats [McLaren, 2007]. The interpretation of this observation may be that people with higher educational attainment have more resources for a healthy lifestyle, which prevents them from being obese. It is consistent with a previous study which found education could influence obesity through its association with health literacy which translates into healthy behaviours [Sobal and Stunkard, 1989]. We suggest that the education-obesity association should be interpreted more carefully taking the understanding into greater consideration.

5.2.5 Household Wealth

The results of this study showed a strong positive association between individual income/wealth and obesity: BMI increases with increase in income/wealth, after adjusting for national income and national income inequality. This global association is similar to the obesity-income/wealth relationship in low and middle-income countries. In low and middle-income countries, people with higher income/wealth have a higher prevalence of obesity. The majority of the studies, which used income or wealth as an SES indicator showed that the richer people were more likely to be obese in low and middle-income countries [Dinsa et al., 2012]. An important reason for this trend in 70 WHS countries was that most of the WHS countries were low and middle-income countries[1]. As most of the countries were low and middle income, the overall analysis showed a pattern similar to low and middle-income countries.

Stratified analysis for low, middle and high-income countries showed that wealth/income has different associations with BMI for low, middle and high-income countries. In low and middle-income countries, a positive association between BMI and wealth/income was observed. This relationship was in agreement with previous studies from low and middle-income countries. In high-income countries, there was no significant relationship between wealth/income and BMI. These results were in contrast with most of the previous studies that showed an inverse income-obesity relationship in high-income countries: obesity prevalence has been reported to fall steadily as household income/wealth rises [Chang and Lauderdale, 2005; Robert and Reither, 2004].

There are various reasons for this positive association of BMI and wealth in low and middle-income countries. Household wealth/income enhances the household assets, including owning a car and washing machines, that significantly increased the risk of obesity. Additionally, It has been established that a better economic standing primarily affects obesity in terms of the resources available to buy more food. Therefore as the income increases, households and individuals increase their consumption of food and reduce their energy expenditure, and consequently the BMI increases [Chamieh, 2013; Zhang, 2012].

A shift in income from low to high is usually associated with the nutrition transition characterized by a shift towards an unhealthy diet of higher fat and calories and decreased physical activity at work or leisure [Du et al., 2002]. In the transition, peoples' daily diets rely more on animal food sources, and their lifestyles are increasingly sedentary, with less physical activity. Moreover, it could also be linked to excessive consumption of higher calories and fat condensed food (such as animal foods and processed food [Du et al., 2002]. In addition, high income people were at and increased risk of snacking and shifting away from traditional healthy cooking patterns to less healthy cooking patterns and less healthy food [Wang and Beydoun, 2007]. Hence, people with higher income and more wealth may increase their risk of obesity.

The mixed results for the effects of income and education on obesity seem to be surprising considering that the income/wealth and education are highly related measures of socio-economic status. However, in the context of global obesity, educational attainment and income/wealth do not necessarily show the same relationship with BMI or obesity. One may be rich but without high education, and another may be well-educated but only with a moderate level of income, especially in developing countries [Zhang, 2012].

5.2.6 Occupation

This study found a significant association between obesity and occupation. People in professional occupation had the highest average BMI and manual workers had the lowest BMI. People with professional, technical and elementary occupation had a similar level of BMI. Manual labor (Agricultural or fishery worker, Craft or trades worker, Plant/machine operator or assembler) was a protective factor against obesity.

The occupation-obesity link is consistent with Ng et al's occupation-related physical activity argument of obesity [Ng et al., 2009]. The nature of manual work is related to intensive physical activity, compared with that of professional and service workers. Hence, the underlying global obesity story is not a simple SES-obesity association but a combination of income, wealth, education and occupation. While the professionals and service workers do not differ significantly in their risk of obesity, manual workers have more intense levels of physical activity that prevents them from being obese.

This global association is similar to the obesity-occupation relationship in low and middle-income countries, an important reason for this trend being that most of the WHS countries are low and middle-income countries[41]. The stratified analysis (Appendix H) shows different pattern of BMI-occupation relationship in low, middle and high-income countries. In low income countries, a clear positive gradient for BMI was observed with increasing occupation status, indicating that people in professional and technical occupations a had higher BMI compared with people in manual and elementary occupations and people in manual occupations had a higher BMI compared with people in elementary occupations. In middle-income countries, there was no significant association of obesity and BMI. In high-income countries, people with elementary job had a significantly higher BMI compared with other occupation categories. These results are consistent with previous literature from low, middle and high-income countries [Dinsa et al., 2012; McLaren, 2007].

[41] This classification divides 70 countries into 30 high, 19 middle and 21 low-income countries.

5.2.7 Household Setting Rural/Urban

Evidence on association of urban rural setting and obesity is quite consistent. In low-income and middle-income countries, people living in urban areas tend to have a high obesity prevalence, but the burden of obesity shifts to people living in rural areas as a country's gross domestic product (GDP) increases [Fezeu et al., 2006; Neal, 1993; Wang et al., 2010; Yang and Kanavos, 2012]. In this study, I found that people living in rural areas have a lower mean BMI compared with people living in urban areas after controlling other individual and country level factors. In low and middle-income countries, it is highly related with more westernized diet in urban areas and less physical activities. "Western diet" is defined by high intake of refined carbohydrates, added sugars, fats, and animal-source foods. Diets rich in legumes, other vegetables, and coarse grains accounts for a small percentage of food sources for urban people. Likewise, in urban areas job functions have transformed dramatically reducing the occupation-related physical activity [Ng et al., 2009]. This study has found global patterns suggesting incremental income and wealth gradients for a higher BMI, a clear gradient for occupation-BMI but a mixed association for education–BMI at the individual-level. At the country-level, the low and middle-income countries have a similar positive association with obesity.

5.3 Country Level Economic Macro-environment and BMI

5.3.1 National Income

This study shows a clear gradient for national income and obesity relationship, where people in poor countries have a lower BMI than people in high-income countries. After keeping all other things equal, low and middle income countries on an average have a lower BMI compared with high-income countries. Every 10,000 USD increase in GNI-PPP is associated with a 0.3 unit increase in BMI. These results are in agreement with previous literature on positive association between obesity and national income in some cross-national studies [Egger et al., 2012; Ezzati et al., 2005; Pickett et al., 2005; Subramanian and Kawachi, 2004; Wells et al., 2012]. A positive correlation between national income and BMI exists, with the prevalence of obesity being greater in developed countries compared with less developed countries, and obesity rates increasing as the per capita incomes increases [Swinburn and Egger, 2004; Swinburn et al., 2004]. However, some previous studies showed no association of BMI and national income; a majority of these studies are based only on high-income countries [Su et al., 2012]. These results are also in agreement with the literature related to the association of national income and other diseases and health related issues such as cardiovascular disease and HIV prevalence [Kim and Johnston, 2011; Kim et al., 2008; Nikolopoulos et al., 2015].

The positive associations between high national income and a higher BMI or obesity are attributed to differences in lifestyle behaviours that accompany economic development and urbanization (e.g., alterations in the quantity and sources of caloric intake, and changes in physical activity). While its main proximate cause has been identified as a surge in extra-meal snacking and secondary eating consumption (including eating more, and buying more entertainment and energy saving devices), a decline in physically demanding labour [Philipson and Posner, 1999], changes in food production technologies and prices have all been found to contribute to obesity development [Chou et al., 2004; Cutler et al., 2003; Volland, 2012]. The links between national income and obesity, through an overconsumption of food energy [Hall et al., 2009; Swinburn et al., 2009], and links to climate change through overconsumption of fossil fuel energy [Egger, 2008; Egger and Swinburn, 2010] appear obvious, but have barely been explored [Egger et al., 2012].

However, there are some interesting characteristics of the WHS data and the relationship of national income, income inequality and BMI. Japan and Korea are both high income / low GINI / low BMI countries. All Pacific Island nations are low income / high BMI countries. The US has very high income and high GINI and high BMI. The Middle East countries have a range of national incomes but high BMIs. These countries were not included in the WHS data sets, but if they were, they may have influenced the results. Also, having more high-income countries, like all the countries from the Organization of Economic cooperation and Development (OECD), may have changed the linear relationship of income with BMI into a non-linear one. Future studies that included these countries would further enlighten the relationship of national income, income inequality and BMI.

5.3.2 Income Inequality

A major observation from this study is that when individual income and national income were included in multilevel regression after controlling for individual level factors, income inequality was not significantly related to BMI. The null results in this study for the income inequality and BMI relationship suggest that the relative income is less relevant in the mechanism paths than the absolute income. It is quite possible that the effects of income inequality are already explained by the income/wealth at the individual-level and national income at the country-level [Zhang, 2012]. It is also possible that the country level income inequality is genuinely not a determinant of BMI or obesity. It is perhaps the absolute income of a person and the absolute income of a country that makes the amount and unhealthy/health food accessible or unhealthy/health lifestyle accessible for a person in a country.

These results are in contrast with the majority of the earlier literature on income inequality and health [Su et al., 2012; Volland, 2012]. The positive correlation between income inequality and obesity prevalence was observed in most developed countries including the U.S. [Robert and Reither, 2004], Europe [Pickett et al., 2005], and OECD countries [Su et al., 2012]. Many studies by Wilkinson and colleagues reported the detrimental effect of income inequality on health (mortality, morbidity and self-reported health status) in the OECD countries [Wilkinson and Marmot, 1998, 2003]. As this evidence is from high income countries, it is possible that the positive association between income inequality and poor health reported by Wilkinson and colleagues only work for the high income countries where the Gini index is low, but not for the low and middle income countries. However, the inverse Gini effect on obesity has also been observed for some developing countries such as China and India [Subramanian et al., 2007]. On the other hand, there are studies that found no significant relationship between income inequality and health [Islam et al., 2010; Lynch et al., 1998; Mellor and Milyo, 2003; Shibuya et al., 2002; Subramanian and Kawachi, 2004].

However, a number of more recent contributions have suggested caution when interpreting these null- findings [Subramanian and Kawachi, 2004; Wilkinson and Pickett, 2006; Zheng, 2012]. For instance, Lorgelly and Lindley (2008) hold that the generally estimated static models relating current income inequality to current health outcomes, are not unlikely to report null-findings if the underlying process is inherently dynamic [Lorgelly and Lindley, 2008]. In this case, static models may show such effects only partially. Yet, medical research indicates that it may take several years of exposure to risk factors before chronic diseases, such as obesity, fully manifest. Consequently, a substantial number of lags, or some sort of stock variable, would have to be considered in the analysis of the inequality and health in order to obtain plausible results [Subramanian and Kawachi, 2004; Zheng, 2012]. Recently some researchers have implemented systems dynamics modelling with stock and flow approach to determine the obesity prevalence and to evaluate preventive strategies related to obesity prevention [Fallah-Fini et al., 2014; Frerichs et al., 2013; Ip et al., 2013]. Because such data is hardly ever available, and a correlation among the lags would present a considerable challenge for identification, an alternative is to analyze health outcomes (such as obesity), which are more likely to be sensitive to current fluctuations in income inequality [Volland, 2012; Zheng, 2012].

It has been suggested that this null relationship might be due to the non-inclusion of some other important factors including some social and cultural factors [Subramanian and Kawachi, 2004; Wilkinson and Pickett, 2009; Zheng, 2012]. After controlling for country level cultural factors, the relationship of income inequality with BMI became significant and positive associated. This implies that a higher Gini coefficient is associated with increased BMI in different cultures. Power distance and individualism (See chapter 1) in particular were the two cultural dimensions which modified the income inequality-BMI relationship. We observed the same phenomenon for the world described by Wilkinson et al. (2006, 2007, 2009) [Wilkinson and Pickett, 2009; Wilkinson and Pickett, 2006, 2007] that “more unequal is associated with poor health” in the study of Gini coefficient in relation to obesity, and specifically, “wider income gaps, wider waistbands" in Europe [Pickett et al., 2005] and OECD countries [Su et al., 2012], but only when we control for the culture of the countries.

This finding adds to major debates over the income inequality hypothesis on obesity in particular in view of the cultural dimensions of the country. So it indeed is worthy of attention and needs further investigation as to that how the culture of a country modifies the income inequality-BMI association. It is also important to understand the mechanisms that could potentially link income inequality to BMI in view of the country level cultural dimensions. A review of the literature by Subramanian & Kawachi (2004) on income inequality and health suggests ‘status anxiety’, ‘social cohesion’ or ‘social capital’, ‘policy’ and ‘structural’ pathway by which income inequality and obesity can be associated with each other [Su et al., 2012; Subramanian and Kawachi, 2004]. However, the most plausible pathways for income inequality’s apparent effect on obesity in view of the cultural dimensions are ‘status anxiety’, ‘policy’ and ‘social cohesion’ or ‘social capital’ pathways [Su et al., 2012].

The income inequality and higher power distance (cultural dimension) is harmful because it places people in a hierarchy that increases the status competition and causes stress. This, in turn, leads to poor health and other negative outcomes, including obesity [Pickett et al., 2005]. For example, researchers interpreted that an increased prevalence of obesity in developed countries might be a consequence of the psychosocial impact of living in a more hierarchical society [Pickett et al., 2005]. Some studies identified an association between chronic stress and obesity. According to 'social cohesion' or 'social capital' pathway, when societies become more unequal and individualistic (cultural dimension), mistrust and lack of reciprocity becomes more commonplace, leading to disinvestment in social capital, which in turn can contribute to a series of negative health outcomes [Kawachi et al., 1997]. This, in turn, will create more psychological stress at the individual level, which can contribute to an increase in behaviours that are detrimental to health e.g. smoking, alcohol abuse and the use of illicit drugs and perhaps over consumption of energy and under expenditure of energy. Possibly, an individual who has experienced emotional or psychological stress will become less attentive to issues related to diet, exercise and weight gain [Su et al., 2012]. This literature on the effect of income ineauality and culture on BMI and their possible pathways agrees with the complex relationship of income inequality, culture and BMI found in the results of this study.

The adverse influence of income inequality or power distance or individualism on obesity may operate through "policy pathways", the formulation and implementation of general social policies as well as through health related policies. Usually, the more polarized a society is (in terms of income inequality or power distance or individualism), the more difficult it will be to implement policy initiatives that can effectively address health or health care challenges faced by the segment of the population that is economically disadvantaged [Su et al., 2012].

In summary, both individual-level and country-level socioeconomic factors make an independent contribution to the BMI of the people. Also, different dimensions of culture, income inequality and national income have independent, albeit unequal effects on obesity. The pattern is consistent, regardless of the individual level factors. Meanwhile, the association between income inequality and obesity risk warrants further investigation.

An important policy implication of the findings from this study is that income inequality and redistributive policies that would help alleviate income inequality should be adequately considered when it comes to coping with the ongoing obesity epidemic in the US and Mexico. After all, obesity is not simply caused by having a high-calorie diet, a sedentary lifestyle or a combination of both but they are final common pathways with a series of deeper determinants. Underlying these symptoms or behaviours is usually something more fundamental – whether it be anxieties, psychological distresses, limited health literacy or lack of self-esteem or efficacy – which is intrinsically linked to individual-level socioeconomic status. These fundamental issues are presumably more important for countries with a high level of income inequality such as Mexico and South Africa, which so far have made little progress in reducing obesity prevalence within their borders. These results also suggest that policies for reducing the income inequalities should be developed in context of the cultural characteristics of the country.

5.4 Country Level Cultural Macro-Environment and BMI

In chapter one, I presented evidence of individual behaviour affecting overweight and obesity where high energy intake and low physical activity were identified as important risk behaviours for overweight and obesity. Despite the efforts to identify behavioural factors of obesity in health literature, the limitations of behavioural approach alone in preventing obesity are apparent because these behavioural determinants of obesity are conditioned by environmental, social and cultural factors. There is also a large and growing body of literature on the effect of obesogenic environments on overweight and obesity that raise the risk of overweight and obesity in populations. An obesogenic environment is the sum of influences of the surroundings, opportunities, or conditions of life that promote an unhealthy lifestyle through high energy intake and low energy expenditure [Swinburn et al., 1999a].

An area that has been shown to have a strong effect on other areas of health behaviour is the social and cultural milieu. Gender, age, ethnicity, socio-economic status and social relations (especially marital status) are the factors most frequently studied as social factors influencing overweight and obesity [Gallagher et al., 1996]. These social determinants are either unmodifiable or hard to modify but they still provide important insights (as discussed in the previous section) into the distribution of obesity and may therefore offer ways to target weight management [Sobal et al., 2009; Tzotzas et al., 2010].

Culture plays an influential role in shaping people's attitudes and behaviours, which is a major determinant of how people understand, interpret, and respond to various experiences [Orji and Mandryk, 2014]. In different cultures, people behave differently and the norms are set according to what is acceptable in that particular culture. For example in African and Arab culture, it is a norm to consider overweight women beautiful and this norm and culture determines the obesogenic behaviour of women in these countries [Hammoud et al., 2005; Scott et al., 2013; Ziraba et al., 2009]. This is even more evident in obesity interventions because several individual weight management programs have failed to achieve long-term reduction in weight through various interventions targeted at the individual. The contexts that have established and nurtured obesity are systemic and structural, hence the need to turn to culture. Culture, in this context, refers to a most recent and accepted definition of culture given by Hofstede (1997), who conceived culture as “the collective programming of the mind which distinguishes the members of one group or category of people from another”. In a more general sense, culture informs a group's behaviour, values, norms, and practices [Hofstede, 2001a]. It also provides rules that govern behaviour. It is acquired and transmitted from one generation to another and is shared and practiced by a group of people [Hofstede, 2001a; Hofstede et al., 2010].

In this study, we take a social epidemiological approach, but the “social” data are the national, cultural dimensions defined by the shared norms and values of the society. The goal of this research is not an anthropological or cultural epidemiological goal to understand the meaning behind the cultural dimensions, and the meaning embodied in the measurement. The goal is a distinctly social epidemiological goal, to understand the relationship between the variations in culture and the national variation in obesity.

Cultural artefacts have traditionally been the focus of anthropological investigations that relied on qualitative investigations involving small samples of people [Masood et al., 2010; Masood et al., 2011]. While measuring culture, most researchers have followed through beliefs/value systems and approaches to operationalize culture e.g. people belief about body image and body size, weight-based stigmatization[Craig et al., 1996; McCabe et al., 2013; Renzaho et al., 2012; Rush et al., 2004; Swinburn et al., 1999b], etc. Recent attempts to investigate empirically the differences in cultures based on the value system shared by various groups identified four finite and crucial cultural dimensions [Hofstede, 2011], which include: collectivism versus individualism, femininity versus masculinity, power-distance, and uncertainty avoidance. There have been attempts to look at the effect of culture on other social outcomes, using large survey data, such as eating behaviour [Orji and Mandryk, 2014], depression [Arrindell et al., 2003], medical communication [Meeuwesen et al., 2009a], antibiotic usage and MRSA prevalence in European countries [Antoci et al., 2013]. Cultural differences could potentially explain some of these and other geographical differences in body weight between countries. Within the current study, there is clear evidence that between-country variation persists even after adjustment for economic factors (National income and income inequality). Cultural values, such as individualism, uncertainty avoidance, power distance and masculinity may explain this, directly or indirectly through obesogenic environment and behaviour [Levin et al., 2011]. Using these Hofstede cultural dimensions, I investigated the relationship between the culture operating in countries and overweight and obesity after controlling for individual factors and country level socio-economic factors. In the next section, I have discussed relationship of each Hofstede dimension with BMI.

5.4.1 Uncertainty Avoidance

Uncertainty avoidance had a significant positive association with BMI in 53 WHS countries. This association was consistent in bivariate and multivariate analyses after controlling for other cultural dimensions, national income, income inequality and individual level factors. The predictive model identified uncertainty avoidance as the strongest cultural dimension related to BMI and explained a quarter of the country level variance in BMI.

Uncertainty avoidance refers to the extent to which people are made nervous by the situations they consider to be unstructured, unclear, or unpredictable, and the extent to which they try to avoid such situations by adopting strict codes, rules of behaviour and beliefs [Stohl, 1993]. Human societies develop ways of eliminating or dealing with this uncertainty, usually through the development or adaptation of laws, technology and interpretation of religion. Because uncertainty-avoiding cultures shun ambiguous situations, the stronger a culture's tendency to avoid uncertainty, the greater its need for rules [Hofstede, 2001b]. Some of the common traits found in countries that score high on the uncertainty avoidance scale are: usually in countries or cultures with a long history (e.g. Greece); the population is not multicultural; risks are avoided in business; and new ideas and concepts are more difficult to introduce [Baker and Carson, 2011]. Some of the common traits found in countries that score low on the 'uncertainty avoidance scale' are: these are usually countries with a young history, (e.g. Singapore); the population is much more diverse due to waves of immigration; risk is embraced as part of business; and innovation and pushing boundaries is encouraged [De Bellis et al., 2015].

In high uncertainty avoidance cultures, it is expected that individuals engage in careful planning to reduce risks by attempting to control future events [Conduit, 2001; De Bellis et al., 2015]. In this scenario, it is expected that the people from high uncertainty avoidance countries should have planned for the uncertainty related to obesity and related health outcomes and should have more strict rules and regulations related to those issues to prevent or reduce it. This argument indicates a negative association between uncertainty avoidance and BMI but results in this study showed a reverse pattern. There are a few reasons for this reverse pattern of high BMI in high uncertainty avoidance, countries. Paradoxically, in countries with weak uncertainty avoidance where rules are less sacred they are often better followed. However, in countries with strong uncertainty avoidance, laws can fulfill a need for security, even when they are not followed [Brain, 2011]. Additionally, these high uncertainty avoidance countries usually plan for future ambiguous situations related to obesity, mainly by planning for curative treatment with more specialists and utilization of more medicine [Hofstede, 2001a; Nakata and Sivakumar, 1996].

In general, people from high uncertainty avoidance countries do not view obesity as something that is caused or can be prevented through simple preventive approaches such as healthy eating or more physical activities [Hofstede, 2001a; Orji and Mandryk, 2014]. African and Arabs (high uncertainty avoidance) are more likely to attribute illness to external sources such as destiny or God that are beyond their controls and to believe in the healing power of prayers [Klonoff and Landrine, 1996]. People from high uncertainty avoidance cultures feel relatively powerless toward external forces and do not feel responsible for their health problems, and therefore are less likely take initiative to prevent them [Hammoud et al., 2005]. These characteristics of high uncertainty avoidance countries have important policy implications. Policies in these countries should be modified according to the perception of preventive approaches, power of prayer and powerless towards the external forces.

Indeed, people in high uncertainty avoidance countries are reported to be very tolerant of familiar risks [Bailey and Kind, 2010; Hofstede, 2001a; Reimann et al., 2008]. People in these countries are therefore more likely to underestimate obesity or overweight problem which they encounter on a regular basis, and tolerate risk activities that predispose them to these problems. In uncertainty avoidance countries, it is more challenging to instil ownership of obesity prevention when the problem is regarded as a countrywide issue, rather than a country in which relatively less percentage of population has obesity. In such situations, there is a greater likelihood of non-compliance of key preventive strategies and interventions, such as physical activity, which require extra effort or time [Antoci et al., 2013].

In cultures with high uncertainty avoidance, people expect health professionals or the government to provide solutions for the problems and expect that the experts always have a solution [Havold, 2007; Hofstede, 2011; Hofstede, 2001a]. They feel confident when they have a disease or a problem with a clear cause that is known to be under control by professionals and government. This leads to more curative rather preventive attitude in people towards obesity [Veldhuis, 1994]. In high uncertainty avoidance nations, it is expected that people in are likely to find difficulty in accepting a recommendation to prevent or manage obesity simply through health diet management and more physical activities.

Individuals in high uncertainty avoidance countries also tend to exhibit more brand loyalty [Baker and Carson, 2011]. These individuals are suspicious of new products. They view new products less favourably and are less likely to purchase these products [Lee et al., 2007]. If there are problems with a service or product, those higher in uncertainty avoidance are less satisfied when their expectations are not met as compared to those lower in uncertainty avoidance [Reimann et al., 2008]. Once they adopt a behaviour, healthy or unhealthy, it will be difficult to use new policies to change this behaviour. For example, uncertainty over the truthfulness of organic food claims is a major factor hindering consumption across a wider section of potential consumers [Baker and Carson, 2011]. The characteristics of the Malaysian culture (high uncertainty avoidance) offer insight into their purchasing behaviour in relation to organic food products. Malaysians are likely to be more cautious and sceptical of the genuineness of organic food labels as well as their benefits. Malaysians are less likely to take risks in consuming organic food products if they are not assured of the benefits and genuineness of these products [Voona et al., 2011].

There are a few factors that make people from high uncertainty avoidance countries less physically active. High uncertainty avoidance countries have a higher perception for existence of corruption and crime, which is a significant environmental barrier for outdoor physical activity and reduced physical activity [Gomez et al., 2004; Hofstede, 2001a; Hofstede and Hofstede, 2005]. In higher uncertainty avoidance countries, citizens are less likely to organize themselves voluntarily (such as sport activities) for their benefit or the benefit of their society. Use of less physically demanding activities such as Internet, television watching, newspaper and books reading are also more prevalent in high uncertainty avoidance countries [Hofstede and Hofstede, 2005].

High uncertainty avoidance goes hand in hand with higher work stress, higher anxiety and higher depression level [Tesinsky and Vydrova, 1979]. A vast number of medical and clinical studies have explored the relationship between individual stress and health. Within this line of research, it has also been demonstrated that a majority of individuals change their eating behaviours and habits as a reaction to chronic and acute distress, with significant increases in calorie consumption occurring in about 40% of the studied population [Dallman, 2010].

Moreover, distress has been shown to be linked to a shift in preferences towards foods high in fat and carbohydrate content, such as sweet and salty foods [Volland, 2012]. These stress-induced changes have been demonstrated in laboratory settings in the absence of hunger or a homeostatic need for calories, and against deliberately taken decisions on dietary restrictions. As people tend to justify their increased consumption of these foods by hedonic motivations, such as wanting to feel researchers have come to label such food items “comfort foods” [Volland, 2012].

There is evidence available for the relationship between diet pattern and uncertainty avoidance. High uncertainty avoidance countries have a higher consumption of sugar, mineral water and fresh fruits and they are more frequent snackers [Hofstede, 2001b]. Low uncertainty avoidance countries consume more milk, cereals, and frozen fruits. An important feature to note here is that high uncertainty avoidance countries are associated with high sugar consumption. High sugar intake with high obesity prevalence or high BMI has been well established and can be the main determining factor for the uncertainty avoidance and BMI relationship [Ludwig et al., 2001].

The uncertainty avoidance dimension has some very important features which need to be included in country specific public health approaches to prevent or control obesity. People from high uncertainty avoidance countries have a strong need for clarity in the message or in the content [Hofstede, 2001b]. Communication that includes free verbal play with its inevitable risks of misunderstanding is something to be feared in high uncertainty avoidance societies. Without the armour of verbal specificity, individuals with strong uncertainty avoidance cannot feel secure in their beliefs. High uncertainty avoidance cultures have formal rules for interaction, their motivation to control communication to avoid threatening uncertainty often translating into behaviour attempting to endorse explicit predictable ritualistic practices [Deschepper et al., 2008; Lee et al., 2007; Reimann et al., 2008]. Clear communication and proper planning are required in these countries to develop public health policies.

In high uncertainty avoidance countries targets, rules and regulation are extremely effective [Wennekers, 2003]. Rapid changes can be achieved when a health related issue like obesity is projected as a genuinely important national goal. Research on MRSA has shown a reduction of MRSA incidences in Italy and Malta after implementing national quality indicators to benchmark hospital performance [Antoci et al., 2013]. It is extremely necessary to develop policies to reduce obesity in high uncertainty avoidance countries by projecting it as a national level agenda or goal.

To implement a public health policy or programme in a country with higher uncertainty avoidance scores, don't expect unfamiliar policies, ideas or methods to be readily embraced [Deschepper et al., 2008]. Enough time needs to be allowed to help people to develop an understanding of the initiative to help foster confidence in it; Involve the community in projects to allow them a sense of understanding, and then decrease the element of the unknown [Hofstede, 2001a; Hofstede and Hofstede, 2005]. People may not feel fully in control and are therefore possibly less willing to make decisions with some element of the unknown. Remember that due to a need to negate uncertainty, proposals will be examined in fine detail. Back up everything with facts and statistics. For example, in Germany there is a reasonably 'high uncertainty avoidance' compared to countries such as Singapore and neighbouring country Denmark. By planning everything carefully, they try to avoid uncertainty. In Germany, there is a society that relies on rules, laws and regulations. Germany wants to reduce its risks to the minimum and proceed with changes, step-by-step. Policy system and policies (including healthcare policies) cannot survive for long if they are not in harmony with the mental programming or culture of the citizens [Hofstede, 2001b].

5.4.2 Individualism

Results in this study showed a significant positive relationship between Individualism and BMI. All other things being equal, belonging to a high individualism/low collectivism country is associated with a higher average BMI. The BMI in collectivist countries, such as India and China is quite low, when compared with the high rates in individualist societies, such as United Kingdom. These results remained significant in multivariate analysis after controlling for national income, national income inequality and individual level variables. The relationship also remains significant after controlling other cultural dimensions, power distance, masculinity and uncertainty avoidance.

Research has shown that individualism and collectivism influence people's opinion regarding their ideal body image and belief, and the related behaviour and perception about obesity [Hofstede et al., 2010]. Therefore, members of collectivist and individualist cultures will respond and behave differently to various obesity determinants (diet and physical activity) and preventive public health strategies [Orji and Mandryk, 2014]. Here, I will discuss the characteristics of individualist and collectivist societies related to obesity and will use them in the implimenting in public health approaches. There are some peculiar characteristics of the collectivist countries, which are different from individualistic countries, that keeps them at the lower end of the BMI.

Collectivist societies believe that health is controlled by external sources beyond their control such as the family, society. Cheng et al. (2013) described in their meta-analysis that members of collectivist societies are likely to view decision making and group behaviour as strongly influenced by outside forces and are largely determined by the contexts such as society or family [Cheng et al., 2013]. In the collectivist societies, families tend to eat together, portion sizes are reduced, and snacking behaviour is less frequent [Triandis et al., 1990; Vijver et al., 2008]. In contrast, members of individualistic societies tend to consider the decision making and individual behaviour to be contingent upon their own actions, under personal control, and relatively independent of the contexts such as society or family. This personal control on the food is associated with higher intake of food and more frequent snacking [Bergmuller, 2013].

For example, in most individualist countries such as the UK and the USA, there has developed the concept of 'children's food'. In most other cultures, young children graduate from a diet of baby food to family food. In these individualist countries, there is a genre of food (fish fingers, baked beans, chicken nuggets) which is designed and marketed especially for children [No et al., 2014; Skalicky et al., 2006]. This supports the children in decision making for their food type and amount. This has had two consequences. The first is that because this is children's food, children have more control over what is the size of the serving. Children do not have to compromise with the food tastes of adults, and they can demand the food that they like. Secondly, children have become a market in their own right for manufacturers who push easily prepared foods of poor nutritional value [Martin, 2008]. Family meal patterns have also been found to have relevance for obesity levels [Videon and Manning, 2003].

Additionally, collectivist societies, in general, do not view obesity as something that is caused simply by unhealthy diet and low physical activity or can be prevented through preventive approaches such as healthy eating and more physical activities [Conduit, 2001; Townend, 2010]. These are the important points to consider while developing a country specific policy or public health programme for obesity aimed at a collectivistic country. Therefore, motivating healthy eating by manipulating potential risks might not be a likely motivator for the collectivists who attribute illness or possible cures to external sources.

In general, people in a collectivist society live in a family or a group, where they shares areas, resources, food and time with other companions who are members of the same in-group [Hofstede, 2001b]. Resources such as food are shared among in-groups, thereby reducing the available portion size for each individual in the family or the group [Vartanian et al., 2008]. However, in individualist societies, sharing of resources is not common. In the United Stated, food portions and food containers tend to be larger; the Americans tend to eat faster and include less conversation with meals. They tend to snack more, partly because there are more opportunities to snack [Rozin, 2005]. People in a collectivist society spent more time in activities which are dictated by role or context, such as tending animals, gardening, being outdoors, sleeping, cooking and eating. Most of the people, in individualistic societies live independently [Hofstede, 2001b]. For people in individualist societies, lack of motivation emerged as the most frequently identified barrier to healthy eating and physical activity. For example, people in an individualistic society such as the USA tend to spend a lot of money in making their lives easier and minimizing exercise or effort. Economist Tibor Scitovsky calls these expenditures as "comfort expenditures", mainly on microwaves, air conditioners, power windows, and driving to a store only a few blocks way [Rozin, 2005]. Additionally, in contrast to collectivist societies, people from individualist societies who spend most of their time in idle leisure activities e.g. watching TV, internet and reading papers [Hofstede, 2001b; Pooye, 2010].

Between cultures, there also exist different motivations for the activity of eating and physical activity [Hofstede, 2001b]. People in a collectivist society are usually triggered to eat based on physical and environmental motivations. Physical eating occurs in response to hunger cues, such as a growling stomach or the feeling of dizziness. Environmental eating is triggered by something in the surroundings, like the hearing of the lunch bell, the smell of food, or check-out stands. People in a collectivist society are less triggered to eat on basis of an emotional status [Hawks et al., 2003]. People in collectivist societies prefer to eat together with family or group of friends and they prefer to eat at the meal times rather frequent snacking [Pooye, 2010]. By eating in response to emotional status and environmental cues, people in an individualistic society eat without specific feelings of hunger or nutritional needs, which is called deliberate eating. People in an individualistic society get triggered to eat by watching TV or movies and out of boredom. This develops itself into deliberate eating, without specific feelings of hunger or nutritional needs [Hawks et al., 2003]. For example, Hawks et al. (2003) reported a significant difference in the motivation for eating between Japanese (collectivist country) and US (individualistic country) [Hawks et al., 2003]. Japanese are more likely to eat in response to physical and environmental cues and are less likely to eat in response to emotional states as compared with people in the US. Participants with a US background are prone to emotional eating. But at the same time, they feel that losing weight is important. These findings support the argument that individual differences in motivation for eating are influenced by unique cultural backgrounds [Tannahill, 2002]. However, these differences in motivation are underexplored and largely ignored by many public health intervention designers.

5.4.3 Power Distance

Initially, I hypothesized a significant relationship between power distance and BMI, which suggested that socially unequal or polarized countries are fatter than the countries which are more socially homogenous. In this study, I didn't find any relationship between power distance and BMI after controlling other cultural dimensions. Power distance was negatively associated with BMI in bivariate analysis but this relationship attenuated when the model was controlled for individualism. The null association of power distance and BMI in this study after controlling for individualism indicates that the effect of Power Distances on BMI is insignificant compared with individualism. This study only tested the relationship of power distance at the country level. However, this association needs to be tested at different levels such as neighbourhood or family level. In my analysis, individualism had a high negative correlation with power distance but the regression analyses are particularly important because they control for the multicollinearity among the multiple predictors. Additionally, the loss of influence of PDI when controlling for individualism means that, for this relationship with BMI, PDI and individualism are measuring the same characteristic as it plays out for BMI.

5.4.4 Masculinity

In results of this study, masculinity dimension was not significantly associated with BMI and this association remained insignificant after controlling for individual level variables (especially gender) and country level national income, income inequality and rest of the cultural dimensions. There are two possible reasons for this null association of masculinity and BMI. First, as the masculinity dimension has a strong association with gender, it is quite possible that the association of masculinity and BMI is different for males and females. To answer this issue, I checked this relationship by doing a stratified analysis separately for male and female participants[42]. In this stratified analysis, I did not find any association for male and female groups. I also tested this relationship for different economic levels of the countries as we have seen that the BMI-gender association was opposite in high income and low-income countries. Again, there was no relationship found for BMI-masculinity for any group of low, middle and high-income countries. These stratified analyses confirmed that this null relationship between BMI and masculinity is real for the 53 WHS countries.

When making statements regarding the many cross-national differences, one must also realise that there are large regional differences even within countries, especially for large countries such as India and China.

5.5 Strengths of This Study

This study has several methodological and substantive strengths. First, many of the explored relationships had not been previously tested, and prior research has not compared the relative strength of country level and individual-level factors for BMI. Additionally, the models developed in this thesis explained most of the variance at the country level. Second, In contrast to previous assessments that have focused exclusively on obesity or overweight, we chose BMI as our primary focus because it captures the entire nutritional spectrum in a population as opposed to an exclusive focus on the high-risk group [Subramanian et al., 2011]. Third, this study included comparable nationally representative data for 70 low, middle and high-income countries. No other study has included as many countries, over a mix of low, middle and high-income countries. Fourth, multilevel analysis was used to examine the country and individual level factors. The multilevel design is critical to understand the relationships between obesity and country level factors while simultaneously taking into account individual characteristics. Multilevel studies on the macro-micro effects on obesity are very limited. The country level factors are not often considered in obesity studies of developing societies, probably due to data limitations. In this study, the income-related hypotheses are evaluated at multiple levels (individual level household wealth and country level national income), and also investigated for potential cross-level interactions. Finally, in order to examine the impact of the country level factors on obesity, I used a model building procedure that modelled the difference in the main effect of country level factors on obesity by adding different sets of covariates. This approach gives us some useful information regarding the sources of disparities in obesity by observing the

[42] See Appendix H for stratified analysis for male and female and low, middle and high-income countries.

diffrences in the coefficients for variable of interest for understanding of the sources of obesity [Diez-Roux et al., 2000; Gelman and Hill, 2007; Hox, 2010; Kondo et al., 2012].

5.6 Limitations of this study

Notwithstanding the strengths, the findings of this study should be considered in light of its limitations. There are some arguments that highlight the limitations of Hofstede's cultural dimensions, First, some researchers have claimed that the these cultural dimensions are too old to be of any value in the current scenario, particularly with today's rapidly changing global environments, internationalisation and convergence [Jones, 2007]. Hofstede argued that the cross-cultural outcomes were based on centuries of indoctrination and recent replications have supported the fact that culture will not change overnight [Hofstede, 1998]. Studies correlating the old country scores with related variables available on a year-by-year basis in many cases find no weakening of the correlations. A good reason for this is that the country scores on the dimensions do not provide absolute country positions, but only their positions relative to the other countries in the set. Influences, such as globalization and new technologies tend to affect all the countries without necessarily changing their relative position or ranking; if their cultures change, they change together. Only, when based in a specific dimension one country leapfrogs over others, the validity of the original scores will be reduced. But this remains to be demonstrated in carefully designed research. Some authors predict that new technologies will make societies more and more similar. Technological modernization is an important force towards culture change and it leads to partly similar developments in different societies. However, there is not the slightest proof that it wipes out variety on other dimensions. It may even increase differences due to the fact that on the basis of pre-existing value systems, societies cope with technological modernization in different ways [Hofstede, 2011].

Second, these dimensions assume the country population as a homogenous whole. However most nations are groups of ethnic units [Redpath and Nielsen, 1997] e.g. It will be difficult to categorise all of India as an homogenous country because the culture in India varies largely among Hindus, Muslims and Sikhs. Analysis is therefore constrained by the character of the individual being assessed and therefore, the outcomes have a possibility of arbitrariness. Therefore, these dimensions ignore the importance of community and the variations of the community influences within a country. On the other hand, cultures are not necessarily bound by borders [Jones, 2007]. Hofstede points out that national identities are the only means we have of identifying and measuring cultural differences [Hofstede, 1998; Hofstede et al., 2010]. Recent research has found that culture is in fact fragmented across group and national lines [Jones, 2007].

Some critics suggest that the number of dimensions should be extended. Four or five dimensions do not give sufficient information about cultural differences. Triandis (2004) has defended this position, and the GLOBE project actually tried to extend the five Hofstede dimensions to 18 [Triandis, 2004]. But additional dimensions are only meaningful if they are both conceptually and statistically independent from those already available, and they should also be validated by significant correlations with conceptually related external measures [Hofstede, 2011]. There is an epistemological reason why the number of meaningful dimensions will always be small. Dimensions should not be reified. They do not 'exist' in a tangible sense. They are constructs: if they exist, it is in our minds [Robinson and Shaver, 1973]. They should help us in understanding and handling the complex reality of our social world. But human minds have a limited capacity for processing information, and therefore dimensional models that are too complex will not be experienced as useful. In a famous short article, Miller (1956) argued that useful classifications should not have more than seven categories, plus or minus two [Hofstede, 2011; Miller, 1994].

5.6.1 Cross-sectional Nature of the Study

Cross-sectional studies, especially national representative surveys such as WHS are usually conducted to estimate the prevalence of the outcome of interest for a given population and investigate its association with risk factors. This cross-sectional design does not provide convincing answers for causal, time lag effects and directionality, i.e. whether exposure occurred before or after the onset of obesity outcome [Santos Silva, 1999]. For instance, it cannot be assumed that inactivity precedes obesity when inactivity can, on the other hand, be a consequence of obesity [Chamieh, 2013; Santos Silva, 1999]. Therefore, cross sectional studies are of limited value to investigate causal relationships and therefore infer causality [Mann, 2003].

Although this thesis has observed effects of national income, income inequality and cultural dimensions on obesity, this single-year, cross-sectional design prevented it from evaluating any directionality of associations. For example, previous studies indicate that the direction of the association between the individual-level SES, inequality and obesity could also be bi-directional, as found in the U.S. [Wang and Beydoun, 2007]. Plausible answers will only be possible by analyzing quality country level longitudinal data through conceptually sound mechanisms

[Zhang, 2012]. Nevertheless, cross sectional studies indicate associations that may exist and are therefore be useful in public health planning, understanding disease aetiology, and for generating hypotheses for future research [Mann, 2003].

Cross sectional studies are however capable of revealing the presence or absence of a relationship between the study variables (cultural dimensions and obesity) and prevalent cases. This implies a need for caution, since prevalent cases may not be representative of all cases of the disease. Cases of short duration, corrected by intervention or ended by death, have a smaller chance of being detected in a one-time prevalence survey [Breslow and Day, 1980]. On the other hand, cases of long duration, such as an enduring obesity, may be over represented in a cross sectional study. The characteristics of these long-duration cases may, on an average, differ in a variety of ways from the characteristics of all cases of the disease being studied. Associations between outcomes and exposures of long duration are particularly difficult to establish using cross-sectional studies. In this study, over representation is not a problem as the cultural dimensions are relatively constant for each other. However the national income and income inequality might be changing with time; but the change in these dimensions is slow with time.

5.6.2 Non-response

Most of the countries included in this study had good response rates of more than 60%, except Bangladesh and Ethiopia. Achieving high response rates in national surveys is always challenging, especially for low and middle-income countries. Participants in any survey are likely to differ in some of their characteristics from those who do not respond [Santos Silva, 1999]. Lack of information on non-respondents and exclusion of these non-respondents for weight or height is a limitation of this study. However, the extent of the bias, if any, which could have been introduced into this study by the absence of non-responders, could not be assessed.

5.6.3 Data Collection

The data collection in WHS involved face-to-face interviews. In this type of data collections, interviewers are usually challenged with participants' compliance, mostly related to social and cultural factors (social desirability, misinterpretation of questions and errors in recalling information). There is a possibility that the study subjects provide socially desirable responses that affect the validity of the reported answers and contribute to the information bias [Chamieh, 2013]. In this study, we used self-reported data on height and weight of the individuals. People in surveys tend to perceive themselves towards ideal BMI and reports lower weight or taller height. Therefore, these self-reported measures of BMI in this study might have underestimated the BMI values for individuals [McAdams et al., 2007]. However, objective measures of BMI or obesity also have limitations, as measurement was more often refused than self-report of BMI, thereby introducing systematic non-response in the data [Chau et al., 2013]. Additionally, these objective measures of BMI are also relatively expensive for large-scale data collection such as national surveys. Thus, questionnaires and interviews are the standard methods for large-scale data collection, especially in nationally representative surveys for obesity research [McAdams et al., 2007]. The use of valid and reliable tools, such as the WHS questionnaires, helped ensure that the data collected was valid and reliable and constituted another strength of this study.

Data on household income was not collected in WHS but data on household assets was collected. A household wealth indicator based on asset ownership was developed and used in this study as a proxy indicator for income. This approach yields estimates of permanent income that are comparable with those of other methods in terms of rank correlation with reported income or expenditure, and offers the potential for substantially enhanced comparability across populations and greater precision and efficiency [WHO, 2000a].

In this study, data was not available for the indicators of obesogenic micro-environmental and behavioural factors of the people for theoretical development of the mechanism and pathways of country level cultural macro-environment's effect on obesity. Therefore, the effect of obesogenic micro-environmental and behavioural factors as mediators was not measured. Furthermore, I was unable to include some important explanatory covariates of obesity, such as individual level food consumption and physical activity, as the data on these two variables was not available for many WHS countries. In WHS survey data on smoking status was also not available for the high-income countries. Therefore, this could not be included in the analysis. The results of this study were not adjusted for the pregnant participants, as the data on current pregnancy was not collected in the WHS survey.

This study also carries some limitations of secondary data analysis. WHS questionnaires and the WHS project were not designed specifically for this study. Therefore, data was not available for some important variables of interest. For example, the data on food consumption and physical activity was not available for all the countries. However, the strength of using secondary data was in capitalizing on the opportunity to use existing data to advance the understanding of the association between the country level cultural macro-environment and obesity. Secondary data analysis enables to generate more knowledge using far less financial and human resources than were required for data collection. Also, the use of secondary data analysis allows this knowledge to be generated in a relatively short period of time. Moreover, the advantage of using WHS data, in particular, was that the design and large sample size enabled the use of MLM to examine country level factors while controlling for individual level factors.

5.6.4 Analysis

Limitations regarding data analysis include, first, weighted regression analysis was not possible to get the population regression estimates. Multilevel modelling incorporating survey design features is a matter of on-going debate [Cai, 2013; Carle, 2009] and not currently available in R. Therefore, results from multilevel modelling were not weighted. In addition, although this study used high quality data, there might be inherent errors in the survey, including sampling errors, coverage errors and measurement errors. However, these errors may be of minor importance [Popkin et al., 2010]. In summary, the results in this multilevel study need to be explained with caution based on the limitations and delimitations concerning data quality.

5.6.5 Future Research Directions

5.6.5.1 Determine Pathways

This study found important differences in the obesity in 70 countries that are partly explained by the country level determinants. However, this study was not able to see the underlying mechanism or pathways to how these country level determinants, especially culture dimensions really affect the individual level obesity. It can be hypothesized that the effect of these country level cultural macro-environment is mediated through obesogenic micro-environment and behaviour. Future studies are required to show how this cultural macro-environment modifies the microenvironment and behaviour related to obesity. To better specify these relationships, measures of mediators and cultural dimensions should be explored. For example, Individualism might link with increased BMI through the large portion size in individualistic countries. Exploring this relationship from a different direction would be useful to determine the “protective” factors associated with living in an individualistic country. Obviously, we cannot pinpoint the specific mechanism that leads to these observed differences, rather than highlighting that cultural differences exist in a systematic and predictable fashion. Future research is needed to examine the environmental and behavioural processes leading to higher and lower levels of BMI. Our results can be used for developing such studies. Structural Equation modelling with path analysis can be used to address these research questions. Different paths starting from macro-environment →microenvironment → food intake and physical activity behaviour → amount of energy intake and expenditure → BMI can be used to identify the relationship for these variables.

As discussed earlier the importance of Systems Dynamics modelling to address the underline complexity in the obesity development. To overcome the limitations of this study, the future Systems Dynamics models could be used to build on the results of this study and incorporate the other factors such as lag times, feedback loops, non-linear effects, interaction effects etc. System dynamics models represent systems as interconnections between stocks, flows, and feedback loops (bidirectional relationships). These interconnections are represented mathematically using regression models. Some studies have used system dynamics modelling to overcome the lag times and study the feedback loops in obesity research [Fallah-Fini et al., 2014; Frerichs et al., 2013; Ip et al., 2013].

5.6.5.2 Establish Causality

Due to cross sectional nature of this study, causality was not possible to be established. Future research is needed to understand the causal mechanisms that link national cultural dimensions, national income and national income inequality with individual BMI or obesity. To establish causal relationships, longitudinal data is needed. Longitudinal data from the countries that are in economic and cultural transition can be used to measure the effect of economic and cultural factors. A longitudinal study on immigrants from one country to another can also help in addressing this research question. From a policy perspective, longitudinal studies can help policy makers to determine the optimal interventions to overcome obesity for that particular country considering country's cultural characteristics. Future longitudinal research is therefore important in order to determine whether modifying these cultural dimensions is effective in reducing obesogenic environments, behaviour and ultimately obesity of the people [Dean, 2012; Diggle, 2002; Doblhammer et al., 2009; Heck et al., 2010; Jacka et al., 2011].

5.6.5.3 Measurement of Culture

It was clear from this study that the scale of culture measurement is also important to fully grasp the obesogenic cultural environment. Future research should examine with more specificity the types of cultural dimensions or factors that create obesogenic cultural environment and which are associated with BMI and obesity. In particular, the aspects of culture which directly impinge on obesity such as food culture or cuisine differences; use of food as a social exchange and social symbol; body size perception; cultural norms and practices around physical activities and sedentary behaviours (e.g. school work verses playing sport); and even parenting styles. In the current study, a more detailed analysis of cultural dimensions/factors was not conducted given that the variables to measure culture of the population were not available. Qualitative research studies are warranted to better understand the different cultural environments across countries with varying levels of economic, social and cultural factors, and the extent to which different social and cultural environments might affect individual-level obesity outcomes [Orji and Mandryk, 2014].

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Masood M., Reidpath D. Intraclass correlation and Design effect in BMI, physical activity and diet: A cross-sectional study of 56 countries. (Under Review). (Appendix I)

Appendices

Appendix A

WORLD HEALTH SURVEY

2002

B – Individual Questionnaire

Rotation - A

World Health Organization, Evidence and Information for Policy

WORLD HEALTH SURVEY

INDIVIDUAL QUESTIONNAIRE

CONTENTS

WORLD HEALTH SURVEY

0990. Individual Consent Form

Dear Participant,

You have been randomly selected to be part of this survey and we would, therefore, like to interview you. This survey is conducted by the World Health Organization and will be carried out by professional interviewers from (name of institution). This survey is currently taking place in several countries around the world.

The information you provide will only be used to understand the main things that affect peoples' health in different countries and how people view their own health and access to health services.

The interview will take approximately 60 minutes. I will ask you questions about:

- some personal details,
- your health including activities that you generally carry out,
- any health problems you have experienced and treatment you may have received,
- the health care centres you use and how well these have responded to your needs.

The information you provide is totally confidential and will not be disclosed to anyone. It will only be used for research purposes. Your name, address, and other personal information will be removed from the questionnaire, and only a code will be used to connect your name and your answers without identifying you. The Survey Team may contact you again only if it is necessary to complete the information on the survey.

Your participation is voluntary and you can withdraw from the survey after having agreed to participate. You are free to refuse to answer any question that is asked in the questionnaire. If you have any questions about this survey you may ask me or contact (name of institution and contact details) or (Principal Investigator at site).

Signing this consent indicates that you understand what will be expected of you and are willing to participate in this survey.

Q0990. Who was the Individual Consent Form read by?	1. Read by Respondent [ ]	2. Read by Interviewer [ ]	
Q0991. Was the Individual Consent Form Agreed to and Signed / but Not Signed or Refused?	1. Agreed and Signed [ ]	2. Agreed but Not Signed [ ]	7. Refused [ ]

Respondent: ____

Interviewer: ____ Date: ___ / ___ / ___

1000. Respondent's Socio Demographic Characteristics

Time Begin: __ __ : __ __

I would like to start by asking you some background questions before asking you questions on your health. This information is confidential and will only be used for research purposes.

Q1000	**What is your mother tongue?**							
Q1001	**Record sex as observed**	**1.** Female			**2.** Male			
Q1002	How old are you? (Years)	______________________			**888.** DK			If age is known: Go to Q1004
Q1003	If you don't know/don't want to tell me your age could you tell me the age range if I read the different options to you **(choose what is most appropriate)** ? (**READ THE OPTIONS TO THE RESPONDENT**)	**1.** 18-19 **2.** 20-29 **3.** 30-39 **4.** 40-49 **5.** 50-59 **6.** 60-69 **7.** 70+						
Q1004	Your weight in Kilos?	______________________						If weight is in kilos: Go to Q1006
Q1005	Your weight in Pounds?	______________________						
Q1006	Your height in Centimeters	______________________						If height is in centimeters: Go to Q1008
Q1007	Your height in Feet / Inches	______________________						
Q1008	What is your current marital status?	**1.** Never Married	**2.** Currently Married	**3.** Separated	**4.** Divorced	**5.** Widowed	**6.**Cohabiting	
Q1009	What is the highest level of education that you have completed?	**1.** No formal schooling **2.** Less than primary school **3.** Primary school completed **4.** Secondary school completed **5.** High school (or equivalent) completed **6.** College / pre-university / University completed **7.** Post graduate degree completed						
Q1010	How many years of school, including higher education have you completed?	______________________						

Q1011	What is your *[**ethnic group / racial group / cultural subgroup / others**]* background? ***Each country to substitute appropriate phrases or terms and list the relevant response options.***	________________					

Now, I would like to ask you a few questions about your work status.

Q1012	What is your current job?	**1.** Government employee	**2.** Non-government employee	**3.** Self-employed	**4.** Employer	**5.** Not working for pay	If not working for pay: Go to Q1014

Q1013	During the last 12 months, what has been your main occupation?	**1.** Legislator, Senior Official, or Manager	Go to Section 2000
		2. Professional (engineer, doctor, teacher, clergy, etc.)	
		3. Technician or Associate Professional (inspector, finance dealer, etc.)	
		4. Clerk (secretary, cashier, etc.)	
		5. Service or sales worker (cook, travel guide, shop salesperson, etc.)	
		6. Agricultural or fishery worker (vegetable grower, livestock producer, etc.)	
		7. Craft or trades worker (carpenter, painter, jewelry worker, butcher, etc.)	
		8. Plant/machine operator or assembler (equipment assembler, sewing-machine operator, driver, etc.)	
		9. Elementary worker (street food vendor, shoe cleaner, etc.)	
		10. Armed forces (government military)	

Q1014	What is the main reason you are not working for pay?	**1.** Homemaker / caring for family
		2. Looked but can't find a job
		3. Doing unpaid work / voluntary activities
		4. Studies / training
		5. Retired / too old to work
		6. Ill health
		7. Other

Time End: __ ___: __ __

Appendix B

WORLD HEALTH SURVEY

2002

A – Household Questionnaire

World Health Organization, Evidence and Information for Policy

WORLD HEALTH SURVEY

CONTENTS

World Health Survey

0000. COVERSHEET

Q0001	Research Centre Number	__ / __ / __
Q0002	Household ID	__ / __ / __ / __ / __
Q0003	Is this the initial or retest interview?	Initial 1 / Retest 2
	Q0003a If retest interview, indicate number of days between initial and retest	________________
Q0004	Rotation Code	__
Q0005	Interviewer ID	__ / __ / __
Q0006	Name of interviewer	
Q0007	Total number of calls:	
Q0008	Date of final results:	____ / ____ / ____ dd mm yy
Q0009	Final result code:	__________
	Signature of Supervisor:	

Q0010	Date of editing:	____ / ____ / ____ dd mm yy	
Q0011	Data entry Data entry information:	1st data entry ____ / ____ / ____ dd mm yy	2nd data entry ____ / ____ / ____ dd mm yy
	Signature of Supervisor:		

0100. Sampling Information (To be filled in by the supervisor)

	Sampling				
Q0100	Primary Sampling Unit (PSU) Name/Code				
Q0101	Secondary Sampling Unit (SSU) Name/Code				
Q0102	Tertiary Sampling Unit (TSU) Name/Code				
Q0103	Quarternary Sampling Unit (QSU) Name/Code				
	Additional Information				
Q0104	Setting	Urban 1	Peri-urban /Semi-urban 2	Rural 3	
		Other 4	Specify: _		

0200. Geocoding Information

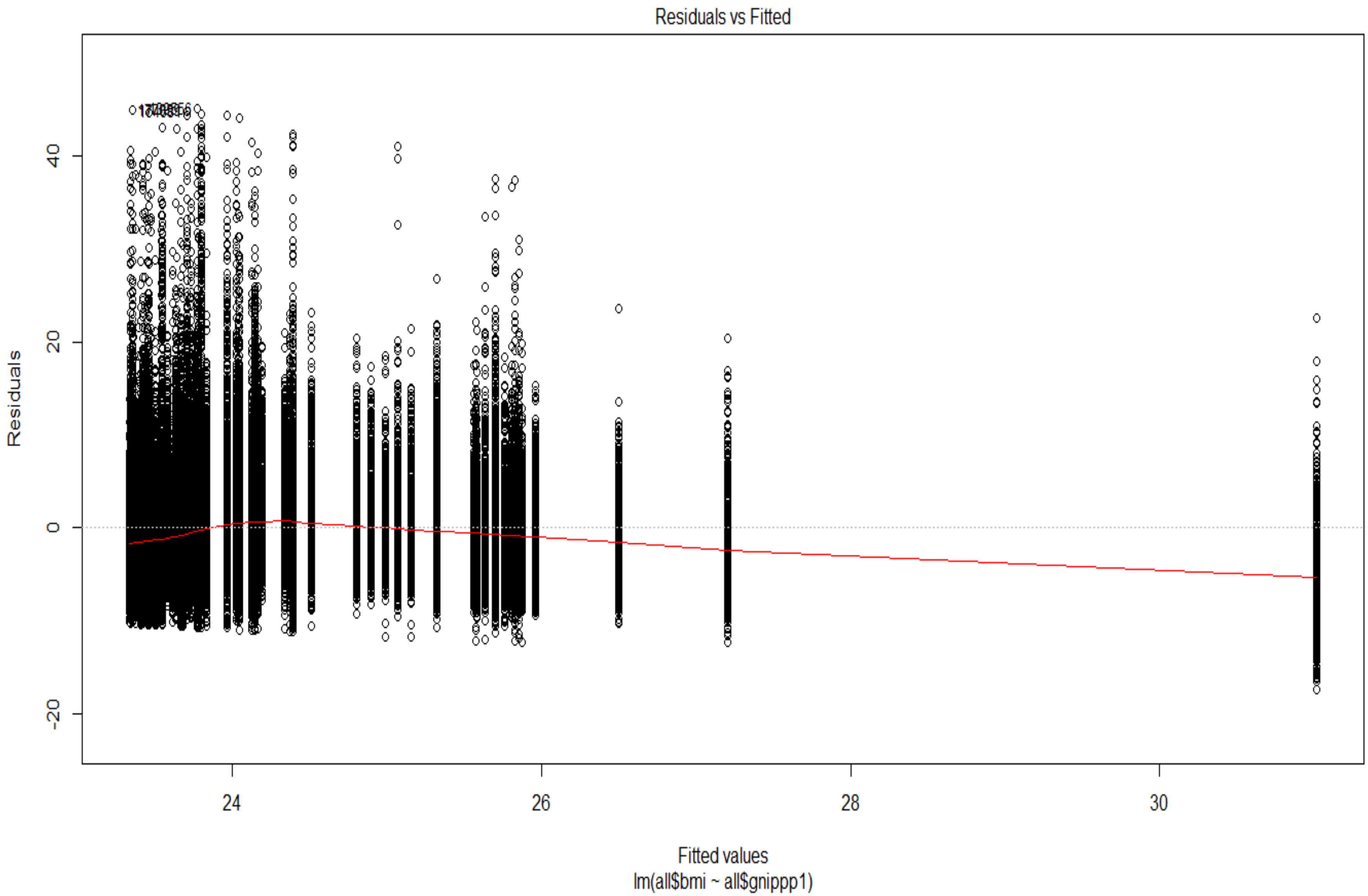
Q0200	**Latitude:**	N/S	Degrees ____ ____ .	Decimal Degrees ____ ____ ____ ____ ____
Q0201	**Longitude:**	E/W	Degrees ____ ____ ____ .	Decimal Degrees ____ ____ ____ ____ ____
Q0202	**Waypoint:**	Center of gravity of the cluster 1	In front of the household 2	Nearby location (park, parking lot, etc.) 3

0700. Permanent Income Indicators (Higher Income Countries)

I would like to quickly ask you a few questions about your home. Remember that any information you provide will be kept confidential.

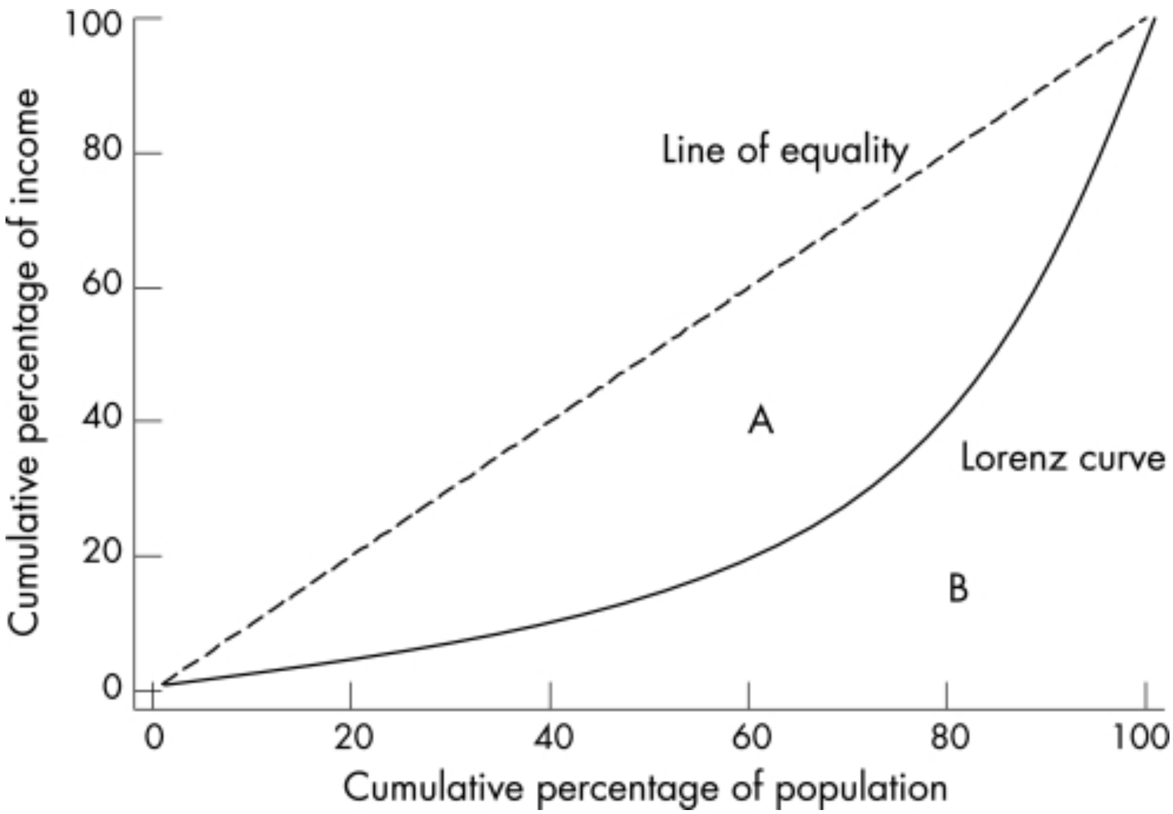
Q0700	Can you please tell me how many rooms there are in your home?	____________________	
Q0701	How many cars are there in your household? **(If none enter "0")**	____________________	
Q0702	How many televisions are there in your household? **(If none enter "0")**	____________________	
	Does anyone in your household have:		
Q0703	A bicycle?	**1.** Yes	**5.** No
Q0704	A video cassette recorder (VCR)?	**1.** Yes	**5.** No
Q0705	A stereo system?	**1.** Yes	**5.** No
Q0706	A DVD player?	**1.** Yes	**5.** No
Q0707	A video camera?	**1.** Yes	**5.** No
Q0708	A washing machine for clothes?	**1.** Yes	**5.** No
Q0709	A washing machine for dishes?	**1.** Yes	**5.** No
Q0710	A vacuum cleaner?	**1.** Yes	**5.** No
Q0711	A refrigerator?	**1.** Yes	**5.** No
Q0712	A fixed line telephone?	**1.** Yes	**5.** No
Q0713	A mobile / cellular telephone?	**1.** Yes	**5.** No
Q0714	A computer ?	**1.** Yes	**5.** No
Q0715	Access to the internet / World Wide Web from your home?	**1.** Yes	**5.** No
Q0716	Any subscriptions to magazines and/or newspapers?	**1.** Yes	**5.** No
Q0717	A security system in your home (alarm, reinforced doors, guards etc.)?	**1.** Yes	**5.** No
Q0718	Do you employ anybody in your house who is not a member of your family (gardener, cook, cleaning lady, driver etc.)?	**1.** Yes	**5.** No
Q0719	Do you have a second home?	**1.** Yes	**5.** No

Appendix c



Appendix c: Residual vs fitted plot to test the linearity assumption between national income and BMI

Appendix D



Appendix D The Lorenz curve framework (hypothetical data). (Presented with permission) [De Maio, 2007]

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Original article

Multi-country health surveys: are the analyses misleading?

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Abstract

Background:
The aim of this paper was to review the types of approaches currently utilized in the analysis of multi-country survey data, specifically focusing on design and modeling issues with a focus on analyses of significant multi-country surveys published in 2010.

Methods:
A systematic search strategy was used to identify the 10 multi-country surveys and the articles published from them in 2010. The surveys were selected to reflect diverse topics and foci; and provide an insight into analytic approaches across research themes. The search identified 159 articles appropriate for full text review and data extraction.

Results:
The analyses adopted in the multi-country surveys can be broadly classified as: univariate/bivariate analyses, and multivariate/multivariable analyses. Multivariate/multivariable analyses may be further divided into design- and model-based analyses. Of the 159 articles reviewed, 129 articles used model-based analysis, 30 articles used design-based analyses. Similar patterns could be seen in all the individual surveys.

Conclusion:
While there is general agreement among survey statisticians that complex surveys are most appropriately analyzed using design-based analyses, most researchers continued to use the more common model-based approaches. Recent developments in design-based multi-level analysis may be one approach to include all the survey design characteristics. This is a relatively new area, however, and there remains statistical, as well as applied analytic research required. An important limitation of this study relates to the selection of the surveys used and the choice of year for the analysis, i.e., year 2010 only. There is, however, no strong reason to believe that analytic strategies have changed radically in the past few years, and 2010 provides a credible snapshot of current practice.

Background

In the area of health and health services research, internationally comparable data are important[1]. They allow researchers and policy-makers to contrast the best outcomes and the worst outcomes internationally, look for 'lessons learned', establish benchmarks, and identify areas of unmet need. National governments can use these data to track their own progress relative to geographic neighbors, economic cousins, or a development reference group[2,3]. Furthermore, by looking across countries it becomes possible to 'step out' of a fixed national context, and begin to ask questions about the effect of the context itself on health. The World Health Survey (WHS) is one example of a multi-country survey providing internationally comparable data from 70 countries[4]. Other current examples of multi-country health surveys include the Demographic and Health Surveys (DHS)[5], the Global Youth Tobacco Survey (GYTS)[6], and World Mental Health surveys[7].

Beyond the simple descriptive analyses they typically produce (e.g., WHS Report of India[8], the DHS Measure country reports, and topic specific papers[9]), such multi-country data make it possible to explore explanatory models that may begin to answer such questions as: 'what factors could explain differences in behavior X across countries?', 'what are the possible effects of individual attribute Y on health?', or 'what are the ecological exposures between countries that may account for Z?' Research from disparate fields have sought to use internationally comparable data ranging from family planning[10] and disability screening studies[11], through to analyses of cause-specific mortality and health program development[12,13].

Multi-country surveys almost universally employ complex sampling procedures which include stratification, clustering, and unequal probability of selection. Complex sampling strategies are used because they often make the process of estimation more efficient; i.e., they reduce the cost of data collection for a given level of precision[14]. Cluster sampling is particularly useful in the case of a population that is geographically dispersed, where a simple random sample would entail traveling significant distances, and require greater time and effort for data collection. An example of a two-stage cluster design would be a national health survey clustered by village and household[15]. An example of a three-stage cluster survey would be a national survey of risk behavior among school students: counties as PSUs, schools as secondary sampling units (SSUs), and classes as tertiary sampling units (TSUs)[16].

A number of papers exist reviewing the appropriateness of the analytic approaches taken to survey data in general[17]. Additional complexity, however, is added, when inter-country comparisons or global estimates are being made, and this has attracted little or no attention from the research community; and this is in spite of the considerable cost associated with duplicating a survey internationally including translation and co-ordination. More and more researchers are encouraged to utilize existing data through secondary data analyses, but if the approach to the analysis of the data is flawed, then leaving the data to lie fallow may be a better alternative.

If one thinks about a typical regression analysis, the complex survey design of the data could lead to two possible approaches to analysis. The first approach is to analyze the data as if they were derived from a simple random sample of the population—a 'Model Based Analysis', e.g., Harling *et al.*[18]. In the analysis of predictors of a continuous outcome, this typically involves a straightforward application of ordinary least squares regression[19,20]. The second approach is to take account of the unequal probability of selection, stratification, and the clustering in the data—a

Table 1. Impact of survey design characteristics on study results if treating data as simple random sampling[35,36].

	Point estimate†	Standard error	Confidence interval	Hypothesis testing
Unequal probability	Biased	Underestimate	Narrow	Type I
Stratification	Biased	Overestimate	Wider	Type II
Clustering	Biased	Underestimate	Narrow	Type I

†Point estimate can be regression coefficient (β) from liner regression, or Odds Ratio (OR) or Relative Risk (RR) from logistic regression, or probabilities from probit model.

'design-based analysis' (DBA), e.g., Merikangas *et al.*[21]. The design-based estimators provide an unbiased estimate of the independent variables in the regression model[21].

In the survey literature, there is general agreement that the analysis of survey data without addressing the survey design characteristics can lead to biased point estimates of population parameters, incorrect standard errors and confidence intervals for population parameters, and misleading tests of significance (Table 1)[22]. Lemeshow *et al.* (1998)[23], and Wheeler (2008)[24], among others, have demonstrated important differences in the results when adopting an appropriate design-based analysis or an inappropriate model-based analysis with complex survey data identifying biased point estimates and inappropriate standard errors[25]; it should be remembered that a 'point estimate' in this context (Table 1) includes regression coefficients from linear regression, odds ratios and relative risk estimates from logistic regression models, or probabilities from probit models. Changing the analytic procedure without addressing the underlying sampling design does not avoid the issues.

Notwithstanding the face-value of multi-country surveys and the descriptive reports, there has been little evaluation of the broader scope and utilization of multi-country survey data. The lack of evaluation is particularly pertinent where the research relies on more complex sampling and/or modeling strategies. In particular, there has been no evaluation of the analytic approach taken to these data, and the validity of any inferences.

The importance of taking the sampling design into account when analyzing survey data is now well established, but it is less clear whether the research community has embraced design-based analyses, and the extent to which other analytic approaches have been adopted. The aim of this paper is to review the types of approaches currently utilized in the analysis of multi-country survey data, specifically focusing on design and modeling issues.

Methods

To address the aim of this study we systematically searched articles published from the data of the 10 most important

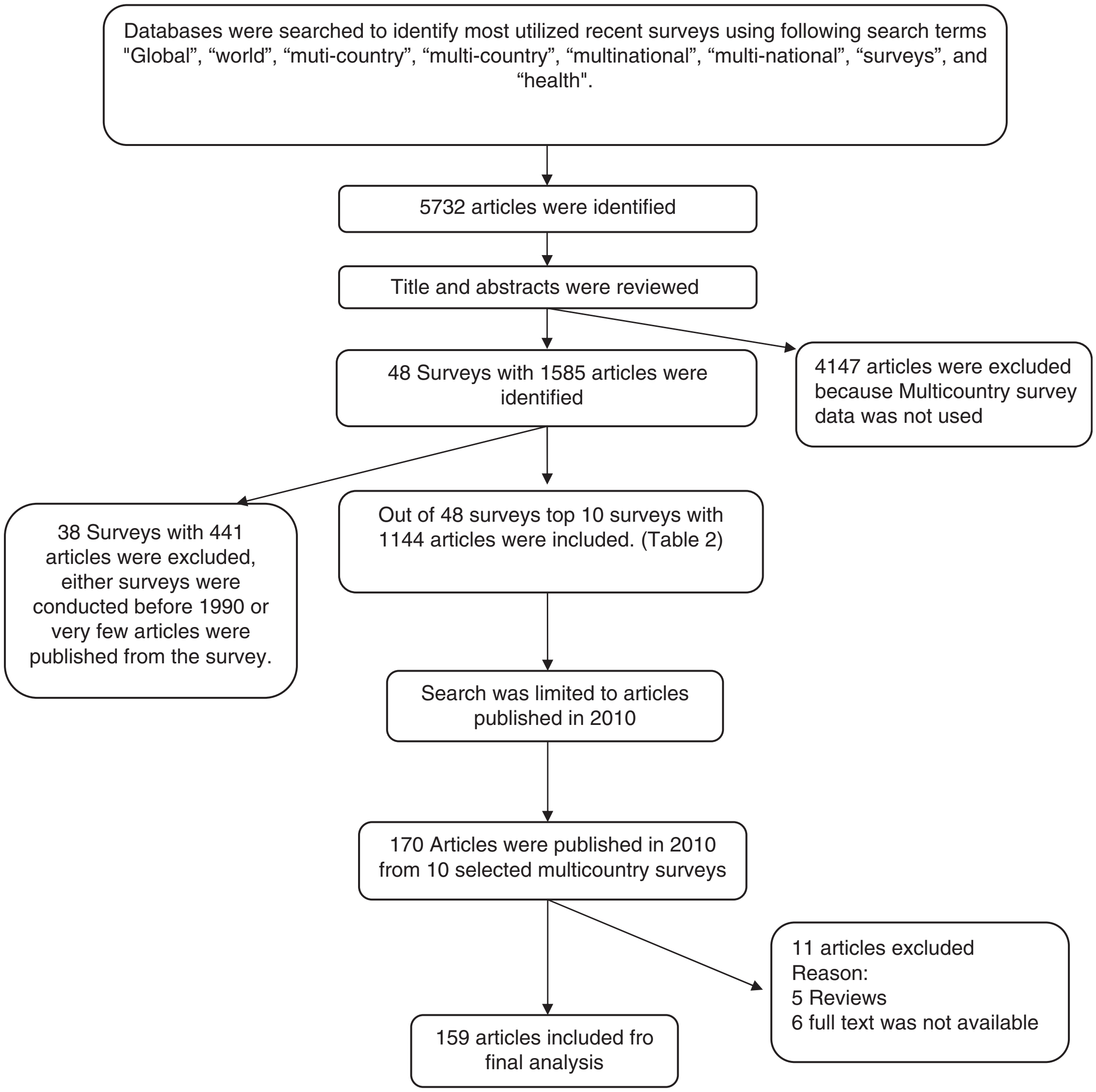

Figure 1. Multi-country health surveys and studies selection procedure.

multi-country surveys. The number was chosen because publications by survey appear to follow a typical power distribution, with rapidly diminishing returns for the inclusion of more surveys. The systematic search and the process to select multi-country surveys and studies selection process has been described in Figure 1.

PubMed and Ovid Medline were systematically searched with appropriate Boolean combinations using terms 'Global', 'world', 'multi-country', 'multinational', 'multi-national', 'surveys', and 'health' (Figure 1). A total of 5732 articles were identified. Title and abstracts were reviewed (1) to find the multi-country surveys from which the data was used in the articles, and (2) to categorize how many articles were published from each multi-country survey. Forty-eight multi-country health surveys with 1585 articles were identified; the remaining 4147 articles were excluded because they did not analyze the data from multi-country surveys.

For further analysis, we selected only the 10 multi-country surveys with the highest number of publications (Table 2) (Appendix 1); the excluded 38 surveys were either old, conducted before 1990, or produced few published papers. The World Fertility Survey, for instance, produced a large number of publications, but the survey was conducted over 30 years ago[26].

A total of 1144 articles were published from the 10 identified surveys. The search was limited to studies published in 2010 to limit the size of the review and to focus on current approaches. In 2010, 159 articles from multi-country health surveys were published, and these formed the data for the present review (Figure 1).

Table 2. List and number of published papers from 10 selected multi-country health surveys.

Survey	Papers published
1. Demographic and health surveys (DHS)	549
2. Global youth tobacco survey (GYTS)	198
3. European Community Respiratory Health Survey (ECRHS)	188
4. World mental health survey (WMHS)	96
5. World health survey (WHS)	49
6. Global School-based Student Health Survey	26
7. Global Health Professions Student Survey (GHPSS) Or Global Health Professionals Survey (GHPS)	14
8. WHO Global Survey on Maternal and Prenatal Health	10
9. WHO Multi-country Study on Women's Health and Domestic Violence against Women	8
10. Global Adult Tobacco Survey (GATS)	6

All 159 articles were read with a view to extracting the information about the statistical management of the sampling design (clustering, stratification, and the probability of selection) and whether the design was accounted for, or failure justified, in the text. The abstracts and the methods sections were the principal focus of the reading, but the full papers were all scanned. When reading the abstract and methods sections of the articles we looked for explicit indications that a design-based approach was used. Indicators of this included the use of specialist software for survey analysis (e.g., SUDAAN[27]), or the use of a general statistical environment combined with the use of specialist packages, such as the 'survey' package in the R statistical environment[25]. The incorporation of the PSU in the analysis (except as a dummy variable) or the inclusion of the intra-class correlation and a weighted analysis was also used as an indicator of a design-based analysis. In the absence of an explicit statement or indication of a design-based analysis, it was assumed that a model-based analysis was adopted.

Results

The majority of papers (28%) were associated with analyses of Demographic and Health Survey data, followed by the Global Youth Tobacco Survey (14%), the World Mental Health survey (13%), and the European Community Respiratory Health Survey (10%). The other surveys had correspondingly fewer associated research articles.

The approaches to the statistical analysis adopted in the multi-country surveys can be loosely classified according to two dimensions. The first dimension attempts to capture something of the intent and complexity of the analysis and is related to the number of variables involved: univariate/bivariate analyses and multivariate/multivariable analyses. The second dimension along which the survey analyses can be divided relates to the use (or non-use) of a design-based analysis.

The univariate and bivariate analyses were typically descriptive in nature, focusing on the production of two-way tables, and point estimation of (often stratified) population parameters. A good example of a univariate analysis was Page *et al.*'s[28] analysis of GSHS survey data to describe the prevalence of cigarette smoking and other tobacco use in the 110 different sites across 44 countries. Understanding complex (sometimes causal) relationship between multiple variables is beyond the scope of such analyses; nonetheless, while the modeling is less complex than mutivariable analysis, the uni-/bivariate analyses are not free from survey design issues. The multivariate/multivariable analyses rely on more complex modeling to estimate the inter-relationships between the variables typically relying on regression approaches[29]. A good example of such an analysis was Kyu *et al.*'s[30] analysis in which the authors used the DHS data to examine the relationship between child anemia and biofuel smoke across 29 countries.

It became clear while reviewing the papers that the strict division between design and model-based analyses was complicated by the more recent use of multi-level models, also known as mixed effects models or hierarchical linear models[31]. Table 3 breaks down the 159 research articles by the multi-country survey from which the data were drawn, and the type of analysis used. It can be seen in the table that 81% of the published papers fail to use a design-based analysis, opting for the procedurally simpler single level, model-based analysis. Only 19% of the papers used design-based analysis. Similar pattern can be seen in all the individual surveys. The greatest proportion of design-based analyses was observable in the Global school-based student health survey (33.3%) and World Health survey (25%) (Table 3).

Discussion

The striking result of this analysis is the preponderance of research articles that use a model-based approach to the analysis of complex, multi-country, survey data. This is particularly surprising given the extensive work showing problems with a failure to take account of the survey design in the analysis of the data. Mitigating this observation, to some degree, is the fact that relatively few of the papers (13%) were simple univariate, point estimation studies. These latter studies are particularly vulnerable to the criticisms of simplifying the analysis for convenience. There are some arguments, however, for not being overly concerned with model-based analyses of survey data when the interest is in the relationships between variables, a point that we pick up later[29].

Table 3. Relationship of survey design characteristics and various statistical data analysis approaches.

	Total papers published in 2010, *n*	Model-based approach, *n* (%)	Design-based approach, *n* (%)
Demographic and health surveys (DHS)	48	37 (77)	11 (23)
Global youth tobacco survey (GYTS)	23	20 (87)	3 (13)
European Community Respiratory Health Survey (ECRHS)	25	20 (80)	5 (20)
World mental health survey (WMHS)	26	23 (88.4)	3 (11.6)
World health survey (WHS)	16	12 (75)	4 (25)
Global School-based Student Health Survey	9	6 (66.7)	3 (33.3)
Global Health Professions Student Survey (GHPSS) Or Global Health Professionals Survey (GHPS)	3	3 (100)	–
WHO Global Survey on Maternal and Prenatal Health	4	3 (75)	1 (25)
WHO Multi-country Study on Women's Health and Domestic Violence against Women	1	1 (100)	–
Global Adult Tobacco Survey (GATS)	2	2 (100)	–
Global school personal survey (GSPS)	2	2 (100)	–
Total	159	129 (81)	30 (19)

An important limitation of this study relates to the selection of the surveys used and the choice of year for the analysis, i.e., year 2010 only. Therefore, no information on trends in the use of different statistical approaches can be derived from the present study. However, it is reasonable to ask, if different multi-country surveys or year 2011 or 2012 were chosen, would the results be substantially different. There is no strong reason for believing things have radically changed in the past few years. There was little variation amongst the chosen surveys with respect to the proportion of articles that used a design-based analysis. The figure was never greater than one third—the majority of articles across all the surveys were model-based analyses. Although this study reviewed articles from 2010, a quick re-examination of the multi-country survey literature suggests that this has not changed significantly in the past few years. Similarly, the inclusion of more surveys is unlikely to change the results, because the power distribution of published papers ensures that the strongest effect is accounted for by the surveys that we have reviewed.

The purpose of this paper was not to obtain a precise point estimate of analytic approaches; it was about examining the approaches currently being adopted for complex survey designs in multi-country surveys. The answer is pretty straightforward: most researchers are not taking account of the studies' design characteristics in their analyses.

Notwithstanding the apparently disappointing finding, there are a variety of reasons why researchers may have made this choice. First, historically, there has been a dearth of statistical software that permitted design-based analyses of sample survey data. This is no longer the case, and a variety of statistical software packages, such as R[25], SUDAAN[27], and Stata[32], support a design-based analysis of complex sample survey data with relative ease, and, in the case of R, without cost. Second, until recently, few standardized guidelines existed for incorporating survey design into statistical analysis[33], and, in our teaching and graduate experience in Australia, the UK, and Southeast Asia, most graduate programs in health sciences teach model-based analyses of data and make either no (or only passing) reference to design-based analyses unless the students specialize.

Some researchers have argued that adjusting for the sampling design is not important when estimating regression parameters for comparing risk groups[29]. However, Sarndal *et al.*[34] pointed out that there are distinct theoretical drawbacks to this approach. First, optimal properties of the statistics only hold if the model is correct. Second, obtaining standard errors of estimates that reflect the true variability from the sampling design is difficult, and using a sample-weighted estimator is best[29]. However, some researchers use traditional techniques that treat the clustered nature of complex survey data as a nuisance by adjusting the standard errors for the sampling design. This method delivers adjusted standard errors and properly accounts for non-independence, but the method fails to allow analysts to examine the amount of between-cluster variance unaccounted for by predictors included in the model[17,25].

An argument for not using sampling weights was put forward in an article by Harling *et al.*[18]. In their 10 country analysis of the relationship between women's experiences of Intimate Partner Violence and HIV sero-status, they used a model-based analysis. They argued against using sampling weights because their study included only the sub-group of individuals who responded to both sets of questions, and thus it was unclear which population weights were appropriate; i.e., for which population was the sample intended to be representative[18]. Wei *et al.*[35], however, recommend simply avoiding analyses that relied on a sub-set of the data unless the design information could be properly incorporated into the analysis.

In circumstances where large numbers of strata and/or sampling clusters have no valid data or, when limited data were linked to other surveys/databases, they concluded that design-based method themselves may be problematic; and in these cases the flexibility of model-based methods might provide an alternative means to obtain information for the objectives of some studies[36].

Conclusion

Multi-country health surveys are important for the estimates they provide for individual countries, and for the comparative analyses that they permit between countries. The surveys inevitably rely on complex design characteristics including stratification, clustering, and unequal selection probability. These all have implications for the analysis of the data. Notwithstanding this, the majority of recently published papers relying on multi-country survey data, analyzed here, have adopted model-based analyses of the data. This can lead to biased point estimates of population parameters, incorrect standard errors, confidence intervals, and tests of significance. Recent development of design-based, multi-level analysis of complex survey data may be an alternative option for including all the survey design characteristics. This is a relatively new area, however, and methods for incorporating sampling weights in analysis remain novel, and require additional statistical, as well as applied analytic research.

What is already known on this subject?

The surveys inevitably rely on complex design characteristics including stratification, clustering, unequal selection probability, and non-response, which requires design-based analysis of survey data.

What does this study add?

The majority of recently published papers relying on multi-country survey data have adopted model-based analyses of the data. This can lead to biased point estimates of population parameters, incorrect standard errors and confidence intervals for population parameters, and misleading tests of significance.

Transparency

Declaration of funding
No funding was provided for this project.

Declaration of financial/other relationships
None declared.

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Appendix

Search strategy and number of published papers from identified multi-country health surveys.

Survey	Search terms	Papers published
Demographic and health surveys (DHS)	'Demographic and health surveys', 'Demographic', 'health', 'surveys', 'DHS'	549
Global youth tobacco survey (GYTS)	'Global Adult Tobacco Survey', 'Global', 'Adult', 'Tobacco', 'Survey', 'GATS'	198
European Community Respiratory Health Survey (ECRHS)	'European Community Respiratory Health Survey', 'European', 'Community', 'Respiratory', 'Health', 'Survey', 'ECRHS'	188
World mental health survey (WMHS)	'World Mental Health Survey', 'World', 'Mental', 'Health', 'Survey', 'WMHS'	96
World health survey (WHS)	'World Health Survey', 'World', 'Health', 'Survey', 'WHS'	49
Global School-based Student Health Survey	'Global School-based Student Health Survey', 'Global', 'School', 'based', 'Student', 'GSHS', 'Health', 'Survey'	26
Global Health Professions Student Survey (GHPSS) Or Global Health Professionals Survey (GHPS)	'Global Health Professions Student Survey', 'Global Health Professionals Survey', 'Global', 'Health', 'Professions', 'Student', 'Survey', 'GHPSS', 'GHPS'	14
WHO Global Survey on Maternal and Prenatal Health	'Global Survey on Maternal and Perinatal Health', 'Global', 'Survey', 'Maternal', 'Perinatal', 'Health', 'GSMPH'	10
WHO Multi-country Study on Women's Health and Domestic Violence against Women	'Women's Health and Domestic Violence against Women', 'Women's', 'Health', 'Domestic', 'Violence', 'against', 'Women'	8
Global Adult Tobacco Survey (GATS)	'Global Adult Tobacco Survey', 'Global', 'Adult', 'Tobacco', 'Survey', 'GATS'	6

Appendix F

Comparison of model estimates from four analytic strategies for complex survey data: a case-study of World Health Survey data, Spain.

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Abstract

Background: The aim of this secondary data analysis was to investigate the effect of four different analytical strategies: Model Based Analysis (MBA), Design Based Analysis (DBA), Multilevel Model Based Analysis (MMBA), and Multilevel Design Based Analysis (MDBA), on the model estimates for complex survey data.

Methods: Using data from the World Health Survey-Spain explanatory models for the outcome Metabolic Equivalent of Task (METs) were calculated using MBA, DBA, MMBA, and MDBA. Regression coefficients, standard errors (SE) and the Akaike Information Criterion (AIC) from all the models were compared.

Results: DBA showed highest estimates for most of the variables, including consistently higher SE than all other model - 20% to 48% higher than estimates for MBA, 10% to 37% for MMBA and 23% to 35% for MDBA. The SE for MDBA were 2.5% to 13% higher than estimates derived from MMBA in level 1 predictors, but SE in MMBA was higher by 18% for level 2 predictors. Values of AIC suggested the model derived by MDBA was the best fit and DBA the poorest fit of the four models.

Conclusion: With minimum AIC, MDBA appeared to be the most appropriate approach to analyze complex survey data. To confirm the finding of present study a future work on a simulation data would be required.

Key Words: Design based, multilevel, complex survey

Introduction

Large surveys almost universally employ multistage complex sampling procedures for data collection, where clusters (or primary sampling units – PSUs) are sampled at the first stage, sub-clusters at the second stage, etc., until final units (typically an individual) are sampled at the final stage [1 2]. The World Health Survey is an example of multistage complex sampling where districts were selected as PSUs, enumerated area as secondary sampling units (SSUs) and households as tertiary sampling units (TSUs) [3]. Complex sampling strategies are used because they often make the process of estimation more efficient by reducing the cost of data collection for a given level of precision [4 5]. Complex sampling strategies are particularly useful in the case of a population that is geographically dispersed, where a simple random sample would entail traveling significant distances, and require greater time and effort for data collection. Complex sampling approaches almost inevitably result in unequal probabilities of individual selection, giving rise to the so called design features of complex survey data [1].

A complex sampling strategy, however, also imposes a multilevel or hierarchical structure on the data. For instance, in the World Health Survey described, above, the multilevel structure can be where individuals are embedded within a households, households embedded within a enumerated area and enumerated areas within a district. Data from such complex surveys are therefore the product of both an underlying multilevel structure and the design features. If a multilevel structure has been imposed on the data through the sampling strategy, then that multilevel structure can itself become the focus of research. In the example of the health survey, a multilevel analysis can provide a level of sophistication to the analytical strategy that is not found in a typical design-based analysis. It is possible for instance to explore school level effects (e.g., the availability of a primary health clinics in school) on individual health outcomes that are independent of the individual level effects (e.g., age, sex, and income). At a different level of structure, multi-level analysis was used in a study of health care expenditure in which the authors estimated the simultaneous effects of individual-level and cluster-level characteristics on maternal health care spending [6 7]. The rise of interest in multilevel analyses of hierarchically structured data introduces another dimension to consider in the analysis of complex survey data.
For a typical regression analysis, the design features and the multilevel nature of the data suggest four possible approaches to the analysis of data from complex survey design. The first approach is to analyse the data as if it was a simple random sample derived from the population ignoring both design features and multilevel structure of the data. This analysis can be termed a "model based analysis" (MBA) [8], for example the application of ordinary least squares regression (e.g., [9]. The second approach is to take account of the design features, and the clustering in the data, while still treating all predictors as if they are measured at the lowest level – a "design-based analysis" (DBA) (e.g., [10]. This would involve including the weighted sample to provide unbiased estimates of the independent variables in the regression model [11-13]. The third approach would be to ignore the design features but instead focus on the multilevel nature of the data, allowing interpretations of individual and area level effects on individual outcomes using multilevel analysis (e.g., [14]. Such an approach would explain variation in the dependent variable at one level as a function of variables defined at other levels, plus interactions within and between levels [11], this could be described as a "multilevel, model based analysis" (MMBA). Like its non-multilevel counterpart, the model-based analysis may lead to biased estimates when employed in samples that include design features in the data [15]. Finally, the fourth approach is an analysis in which both the design features and the multilevel

nature of the data are taken into account – a "multilevel, design-based analysis" (MDBA) (e.g., [16] and [17].

Previous research has studied the effect on model estimates of ignoring a design-based analysis of data from surveys employing complex sampling strategies [12 18 19]. Similarly, there has been work looking at the effect on model estimates of ignoring multilevel structure in multilevel data [11] . There has never, however, been a systematic comparison of the effect of the four different modeling strategies (MBA, DBA, MMBA, and MDBA) on the model estimates, when the data are collected using a complex survey design. Therefore, this study will investigate the effect of the MBA, DBA, MMBA, and MDBA analytic strategies on model estimates from Spanish, World Health Survey (WHS) data.

Methods

Secondary analysis of a publicly available data set. Model estimates derived from four analytical strategies were compared: MBA, DBA, MMBA, and MDBA.

Data source:

The World Health Survey (WHS) is a large cross-sectional survey, that was administered in 70 countries between 2002–2003 to assess healthcare expenditure, adult mortality, birth history, risk factors, chronic health conditions, and the coverage of health interventions [20]. In the WHS conducted in Spain, face-to-face interviews were conducted by lay people with at least a high school education. The WHS adopted extensive interviewer training, standardized measurement tools and techniques, an identical questionnaire, and instrument pretesting to ensure standardization and comparability across diverse sites and times. The WHS's sampling frame covered 100% of a Spain's eligible population, and no ethnic groups nor geographic areas were excluded from the sampling frame. The target population included any adult, male or female, aged 18 years living in private households, who were not out of the country during the survey period. The WHS used a multistage stratified design in most countries including Spain with probabilistic sampling with each elementary unit having a defined probability of selection [20]. WHS data is made freely available by the World Health Organization for secondary analysis by the research community.

Data from Spain was selected for this study based on the sample size (n=6364) and the number of PSUs (997). The Spanish WHS also had an extremely high response rate (95.5%) compared with other WHS countries. After excluding cases with missing data, the final analytic sample was 6079 individuals.

Variables:

The outcome variable used in this study was a measure of physical activity per week in units of Metabolic Equivalent of Task (METs). One MET is defined as the energy spent sitting quietly (equivalent to 4.184 kJ per hour per kilogram of body mass) [21]. In the WHS, to assess physical activity respondents were asked to report the number of days on which they engaged in and the duration of vigorous, moderate, and walking activities during the last week. Taking the different intensities and duration of the activities into account a measure of energy expenditure per individual was estimated [22]. METs were selected for this analysis specifically because of the high intra-class correlation for this variable (ICC=.23).

Explanatory variables:
Age, sex, education, occupation, fruit and vegetable intake, body mass index (BMI), household income and setting (urban/rural) were the key explanatory variables. They were selected on the basis of factors identified in previously published research looking at relationships with METs [23-25].

Age was measured in years of life. Education was measured in number of years of schooling. Occupation was a categorical variable distinguishing “employed”, “housewife”, “retired”, and “not working”. BMI, defined as mass in kilograms divided by height in meters squared, was based on self-reported height and weight. The WHS did not contain a comprehensive nutrition survey measuring whole diets, but rather sought measurement of fruit and vegetable intake only. Two questions employing a 24-hour dietary recall were used: “How many servings of fruit do you eat on a typical day?” and “How many servings of vegetables do you eat on a typical day?” [26]. Household wealth was defined in terms of ownership of material possessions, with each individual assigned a wealth score on the basis of a ownership of a range of household goods. Factor analytic procedures were used to provide a wealth score for each household, and households were then divided into quintiles of wealth. The urban-rural nature of the PSU was provided in the WHS dataset based on local definitions. These urban/rural PSUs were used as area level or level 2 predictors for multilevel analysis. Table 1 describes information for all explanatory variables used in all four models.

(Table 1 about here)

Analytical strategies:
Four analytical strategies were developed. The first model was a model based analysis (MBA) which assumed the data were drawn as a simple random sample from the population. All predictors were treated as individual level attributes, and no account was taken of the design features or the clustering of the data. The second model was a design based analysis (DBA) which took account of design features of the data, whereas, all the predictors were treated as individual level attributes. The estimation was based on inverse probability weighting and design based standard errors. The third model was a multilevel, model based analysis (MMBA). In this third model all the predictors were treated as level 1 predictors except the urban-rural predictor which was treated as a level 2 (i.e., PSU) predictor. Design features were not applied to the data, however, the multilevel nature of the data was considered where individuals were clustered within PSU. The fourth model was a multilevel, design based analysis (MDBA). The analysis took account of clustering, as well as the design features.

All analyses conducted using the M-Plus statistical package [27]. M-PLUS is one of the available software which can run multilevel analysis for complex survey design. DBA was performed using command "Analysis Type = COMPLEX" with input of "CLUSTERING", "STRATIFICATION" and "WEIGHTS" variables. MMBA was performed using command "Analysis Type = TWOLEVEL" with input of "CLUSTERING" variable. MDBA was performed using command "Analysis Type = COMPLEX TWOLEVEL" with input of "CLUSTERING" "STRATIFICATION" and "WEIGHTS" variables and urban and rural setting at level2. Regression estimates and standard error for all four models were compared, additionally, the AIC (Akaike information criterion) was also calculated for all the four models to measure the relative goodness of fit and to compare the best fitted model among the four models.

Results

The descriptive statistics (weighted and unweighted) for the outcome variable (METs) and each of the explanatory variables are shown in Table 2.

(Table 2 about here)

The four models of METs using the 8 predictors are shown in Table 3. The parameter estimates, standard errors and level of significance for each model is shown as well as the AIC.

The average age of the population assuming a model based design is about 2 years older than the design based sample; the model based population also generated about 8% fewer METs. There was little difference in the estimated BMI. Differences may similarly be observed in years of school, the percentage in occupation, and the percentage in each wealth quintile. The highest difference of nearly 6% was seen in urban or rural settings, average BMI, and level of fruit and vegetable intake.

(Table 3 about here)

There were important consistencies and variations in the results of the analyses across the four models. At a superficial level, predictors that were identified as statistically significant in one model were, with few exceptions, identified as statistically significant in the other models. Gender, for instance was a significant effect across the four models, and urban-rural setting was not a significant effect in any model. Education level was an exception – statistically significant in all models except the MBA.

The regression estimates did not show a consistent pattern across the models. DBA gave the highest estimates among the four models for most of the variables but it showed lowest estimates for gender. That is, the effect of being male was about 32% less in the DBA than it was for the MMBA or MDBA. The estimates for the effect of BMI were lower for the MMBA and MDBA models and higher for the MBA and DBA models. The lowest variation between the models (15%) was seen in age. The urban-rural variable was not significant, and showed extreme variation in the estimates.

For the significant effects of gender, occupation, and fruit-vegetable intake, the estimates from the two multilevel models (MMBA and MDBA) were more consistent with each other than they were with the single level models (MBA and DBA). For the age and years of education estimates, however, the two design based analyses were more consistent with each other than they were with the model based analyses. For the estimate of gender, the model based and design based (non-multilevel) were reasonably consistent.

Some interesting patterns were observed in standard error values while comparing the results from four models. As one would expect, DBA estimates showed consistently higher standard errors than the other models. They showed higher standard errors compared with the MBA by 20% to 48%, with the MMBA by 10% to 37% and with the MDBA by 23% to 35%. On the other hand, MDBA had consistently higher standard errors by 2.5% to 13% in comparison to the MMBA model in level 1 predictors, but the standard error in the MMBA model was higher by 18% for the level 2 predictor. The MDBA also had a higher standard error when compared to the MBA model but the variation was comparatively smaller (from 3.7% to 12.5%). In comparison it had a lower standard error by 6.8% in occupation housewife category. The AIC value was lowest for the MDBA model and highest for DBA.

Discussion

Four possible methods (MBA, DBA, MMBA, MDBA) of data analysis for complex survey data were compared On the basis of the fit of the models (AIC) the best fit in this case is achieved, in order, by the MDBA, MMBA, MBA, followed by the DBA.

Data collected using multi-stage sampling and design features are common for large surveys. In the past it was relatively difficult to take account of the complex survey design in the data analysis, but recent advances in statistical software have made design based analysis accessible. Notwithstanding the availability of the improved software, judgments still need to be made about the best approach to take with the data, in the absence of actual knowledge about the underlying data generating model. The Results of this analysis raise important questions about how researchers should approach data from complex sampling designs. Although, the model-based methods have gained popularity over the design-based methods as these methods can be readily implemented using standard commercial software there is a consensus among statisticians that a straightforward MBA is inappropriate, because it fails to take account of the design. The common observation is that the approach underestimates the uncertainty of the estimate. The analysis here, however suggests that the estimates themselves can vary substantially in magnitude although not in sign. The standard errors are, unsurprisingly, higher for the design-based approach in all the explanatory variables. This generally did not affect the statistical significance of the results, except in one case. Surprisingly, in that case it was the MBA estimate that was non-significant.

In general the multilevel models tended to show greater agreement with each other than with the other models. Most of the estimates for MDBM were closer to MMBA as compared to other models, moreover, the AIC of the MDBA was closest to that of the MDBA model. MMBA explicitly model the clustered nature of the data which should narrow the standard errors and eventually increase inferential accuracy. However incorporation of design features in MMBA increases standard error again. Combining both design features and multilevel modeling leads to a standard error estimate that falls in between DBA and MMBA. Regarding the reliability of the estimates, the standard errors are lower with the MMBA for all of the variables. Therefore, the design-based analysis estimates are overall more precise than those from the model-based analysis.

A complicating factor is that one needs to have a view about the generating process underlying the data. It is not enough to know how the data were sampled (i.e., design-based versus model-based), one needs to know how the data were sampled, and the process underlying the data. Traditionally the sampling design and characteristics were not available with the data set but the recent advancement in technology, the availability and access to the information on sampling is relatively easier.

To confirm the finding of present study future work could be performed on simulation data where hypothetical population data fitting the multilevel model could be made available. A sample could then be drawn from this hypothetical population using complex survey sampling designs to compare deviation of regression parameters from actual parameters in each MBA, DBA, MMBA, MDBA.

Conclusion

The four analytic strategies to analyze complex survey data provide substantially different model estimates, standard errors and AIC. The lowest AIC was derived from the Multilevel Design Based analysis, which appears therefore to be the most appropriate approach to analyze complex survey data.

What is already known on this subject?

- Previous research has studied separately the effect of complex survey design and hierarchical data structures on model estimates.

What does this study add?

- There has never, however, been a systematic comparison of the combined effect of including consideration of the complex survey design and hierarchical structure of the data on the model estimates, when the data are collected using a complex survey design.
- One limitation of this study that to confirm the finding of present study a future work on a simulation data would be required. Simulation can be done by generating a hypothetical population fitting the multilevel model.

Competing Interests

The authors declare that they have no competing interests.

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Authors' contributions

All the authors contributed in the manuscript and approved the final draft of the manuscript. MM contributed to conceptual framework, data analysis and manuscript writing; DR contributed to the conceptual framework and write up and TN contributed in write up.

Ethical Approval

The analysis described in this study utilized a public data set containing anonymous data collected with informed consent, made freely available for secondary data analysis by the World Health Organization. Therefore institutional ethics committee clearance was neither required nor sought for this analysis.

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Table 1: Statistical methods and variables used in analysis

	Model based (MBA)	Design based (DBA)	Model based multilevel (MMBA)	Design based multilevel (MDBA)
Outcome variable	METs	METs	METs	METs
Dependent variables (Level1)	Age, Sex, Education, Occupation, Household income, Fruits and Vegetables intake, BMI, Setting (Urban, Rural).	Age, Sex, Education, Occupation, Household income, Fruits and Vegetables intake, BMI, Setting (Urban, Rural).	Age, Sex, Education, Occupation, Household income, Fruits and Vegetables intake, BMI.	Age, Sex, Education, Occupation, Household income, Fruits and Vegetables intake, BMI.
Survey Design	-	Survey Design: PSU, Strata, individual weights.	-	Survey Design: Individual Weights, weights at other levels
Level 2	-	-	Level 2: PSU, Setting (Urban, Rural).	Level 2: PSU, Setting (Urban, Rural).

Table 2: Unweighted and weighted descriptive statistics of outcome and explanatory variables.

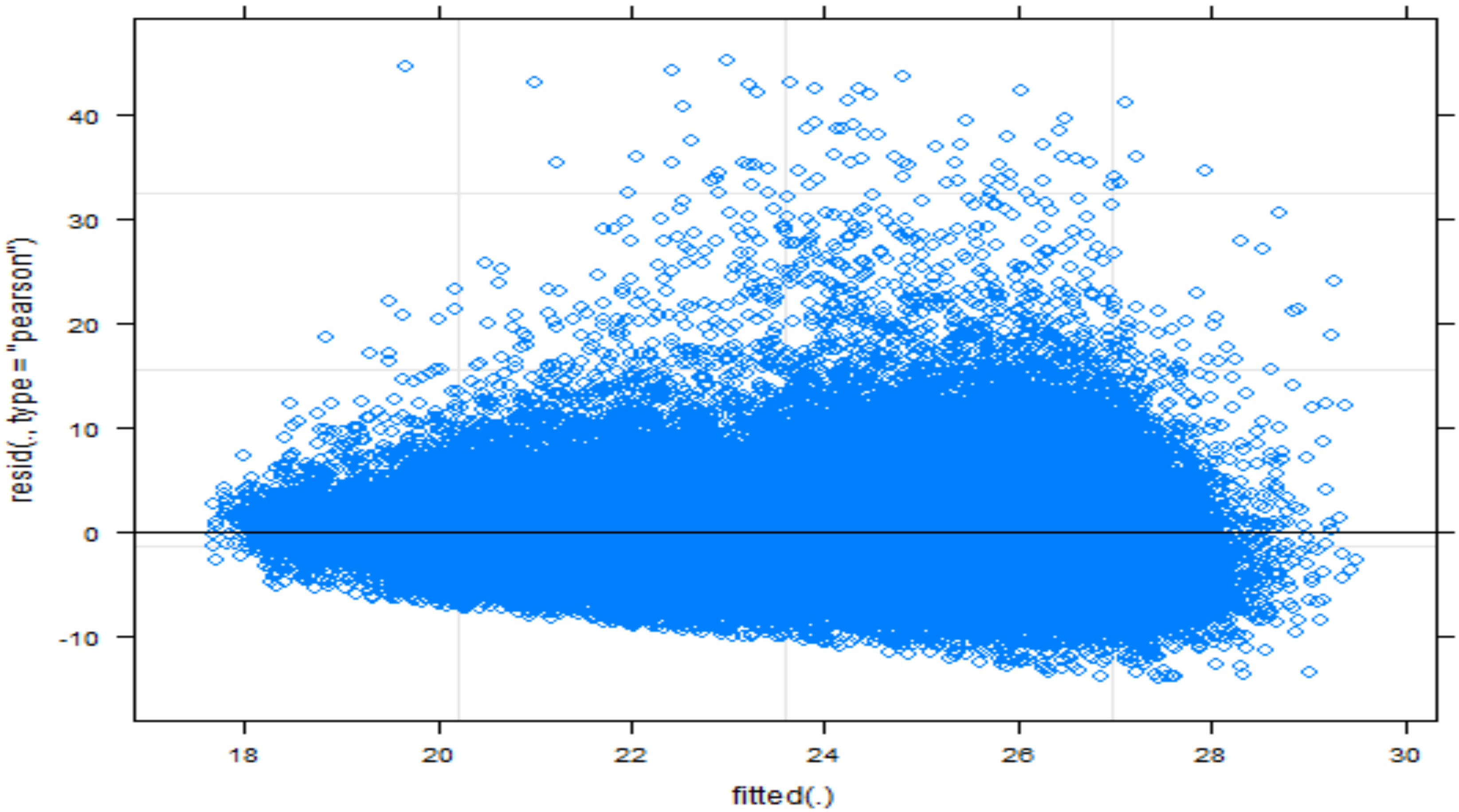
	Unweighted		Weighted	
Continuous Variables				
	Mean	**SD**	**Mean**	**SD**
MET	3068.7	60.05	3322.9	103.7
Age	52.7	0.23	50.3	0.33
Education (School years)	8.98	0.068	9.40	0.11
Fruits and Vegetable intake	3.44	0.022	3.01	0.032
BMI	26.04	0.054	25.93	0.081
Categorical Variables				
	n	**%**	**N**	**%**
Gender				
Female	3677	58.6	18434123	58.0
Male	2598	41.4	13337321	42.0
Occupation				
Employed	2462	39.2	13280952	41.8
Housewife	1703	27.1	8428540	26.6
Retired	1673	26.7	7337952	23.1
Others	437	7.0	2713999	8.5
Household Income				
Lowest quintile	1330	21.5	5216859	16.7
2nd quintile	1172	18.9	5741298	18.3
3rd quintile	1257	20.3	6137899	19.6
4th quintile	1241	20.0	6988845	22.2
Highest quintile	1196	19.3	7290751	23.2
Setting				
rural	1780	28.3	7150839	22.5
Urban	4495	71.6	24620605	77.5

Table 3: Multivariate linear regression analysis showing MET association with various micro and macro level explanatory independent variables, with and without consideration of sampling design.

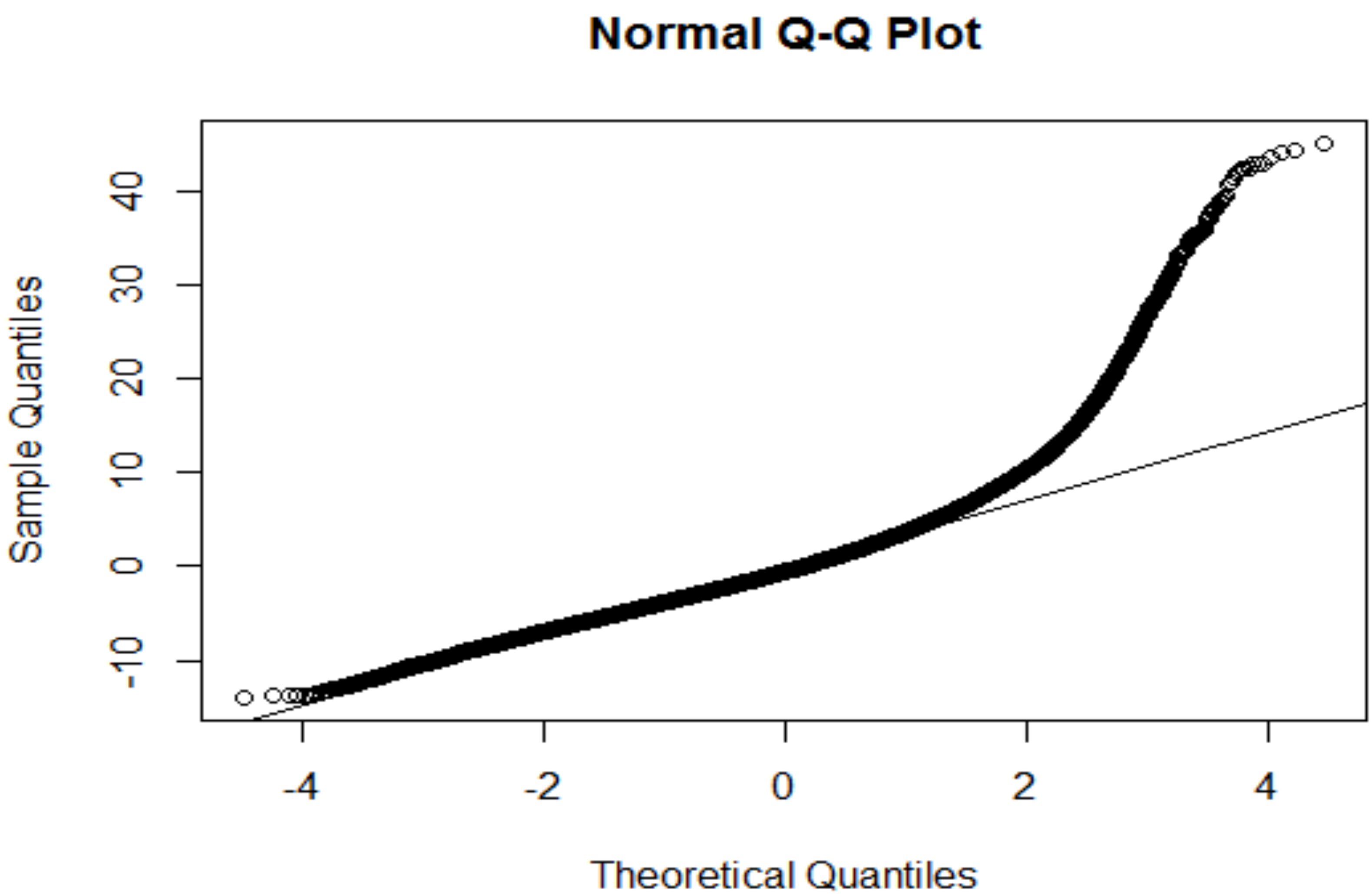
	Model Based (MBA)		**Design Based (DBA)**		**Multilevel Model Based (MMBA)**		**Multilevel Design Based (MDBA)**	
	Estimate	**SE**	**Estimates**	**SE**	**Estimates**	**SE**	**Estimates**	**SE**
Intercept	5180.9	600.9*	5828.9	879.7*	3336.3	632.4*	4512.0	619.0*
Age	-32.0	5.1*	-38.1	7.3*	-33.1	4.7*	-37.0	5.3*
Gender								
Female	Reference Group							
Male	1146.2	144.6*	1084.2	215.5*	1504.4	143.9*	1499.1	153.6*
Education (School years)	-21.6	14.0	-58.8	21.8*	-47.6	15.1*	-57.5	16.0*
Occupation								
Employed	Reference Group							
Housewife	-1192.7	189.2*	-1197.5	241.6*	-839.8	169.6*	-785.0	176.5*
Retired	-1348.0	208.6*	-1200.4	283.0*	-1619.0	193.9*	-1519.1	200.5*
Others	-1220.0	249.6*	-1453.8	313.5*	-1062.1	234.8*	-1078.6	240.9*
Household Income								
Lowest quintile	Reference Group							
2nd quintile	-227.1	193.0	-101.2	266.8	33.6	178.5	-57.8	204.6
3rd quintile	70.4	189.6	176.0	310.7	236.4	188.4	198.1	209.6
4th quintile	61.8	190.1	152.7	289.0	164.4	205.1	28.1	219.4
Highest quintile	-112.1	193.7	415.3	312.8	55.6	212.4	17.8	227.4
Fruits and Vegetable intake	181.1	35.4*	251.8	59.9*	117.4	37.2*	94.0	38.9*
BMI	-45.6	15.3*	-61.2	21.6*	-20.7	13.9	-27.4	14.9*
Setting								
Rural	Reference Group							
Urban	-247.8	138.5	-128.2	267.3	-290.1	241.2	-47.6	196.6
	AIC= 116323.8		AIC=116635		AIC= 116068		AIC=115911	

* p-value $\leq$0.05

Appendix G



Appendix G: Residual verses fitted plot showing the distribution of the residuals.



Appendix G: Normal Q-Q plot showing the distribution of residuals

Appendix H

Appendix H: Stratified multilevel linear regression analysis for low middle and high income countries with BMI as outcome variable.

	Low income countries	Middle income countries	High income countries
	β(SE)	β(SE)	β(SE)
	20.7(1.20)***	22.6(1.9)***	23.9(1.1)***
Age	0.01(0.006)***	0.04(0.009)***	0.05(0.005)***
Gender			
Female			
Male	-0.20(0.01)***	-0.29(0.03)***	0.76(0.01)***
Education Level			
Primary education			
Secondary education	0.21(0.02)***	0.24(0.04)***	-0.41(0.02)***
College and above	0.34(0.03)***	0.06(0.04)	-0.98(0.03)***
Marital Status			
Unmarried			
Married	0.98(0.05)***	1.18(0.07)***	1.32(0.04)***
Divorced	0.62(0.03)***	0.81(0.04)***	0.78(0.03)***
Missing Value	1.1(1.5)	1.8(1.5)	2.1(2.3)
Household Wealth			
Poorest			
2^{nd} Quintile	0.20(0.03)***	0.25(0.03)***	0.05(0.04)
3^{rd} Quintile	0.36(0.04)***	0.39(0.05)***	0.03(0.04)
4^{th} quintile	0.54(0.04)***	0.39(0.05)***	0.01(0.01)
Wealthiest	0.89(0.04)***	0.47(0.05)***	-0.01(0.01)
Professionals			
	-0.09(0.08)	0.07(0.08)	-0.17(0.09)
	-0.49(0.05)***	-0.11(0.06)	0.01(0.04)
	-0.26(0.05)**	0.12(0.07)	0.39(0.04)*
	-0.59(0.04)***	-0.33(0.03)***	-0.17(0.12)
Missing values	-0.31(0.01)	-0.4(0.01)	0.02(0.01)
Setting			
Urban			
Rural	-0.79(0.03)***	-0.38(0.04)***	0.19(0.02)***
Missing values	0.53(0.50)	1.1(1.2)	1.3(1.8)

Appendix I

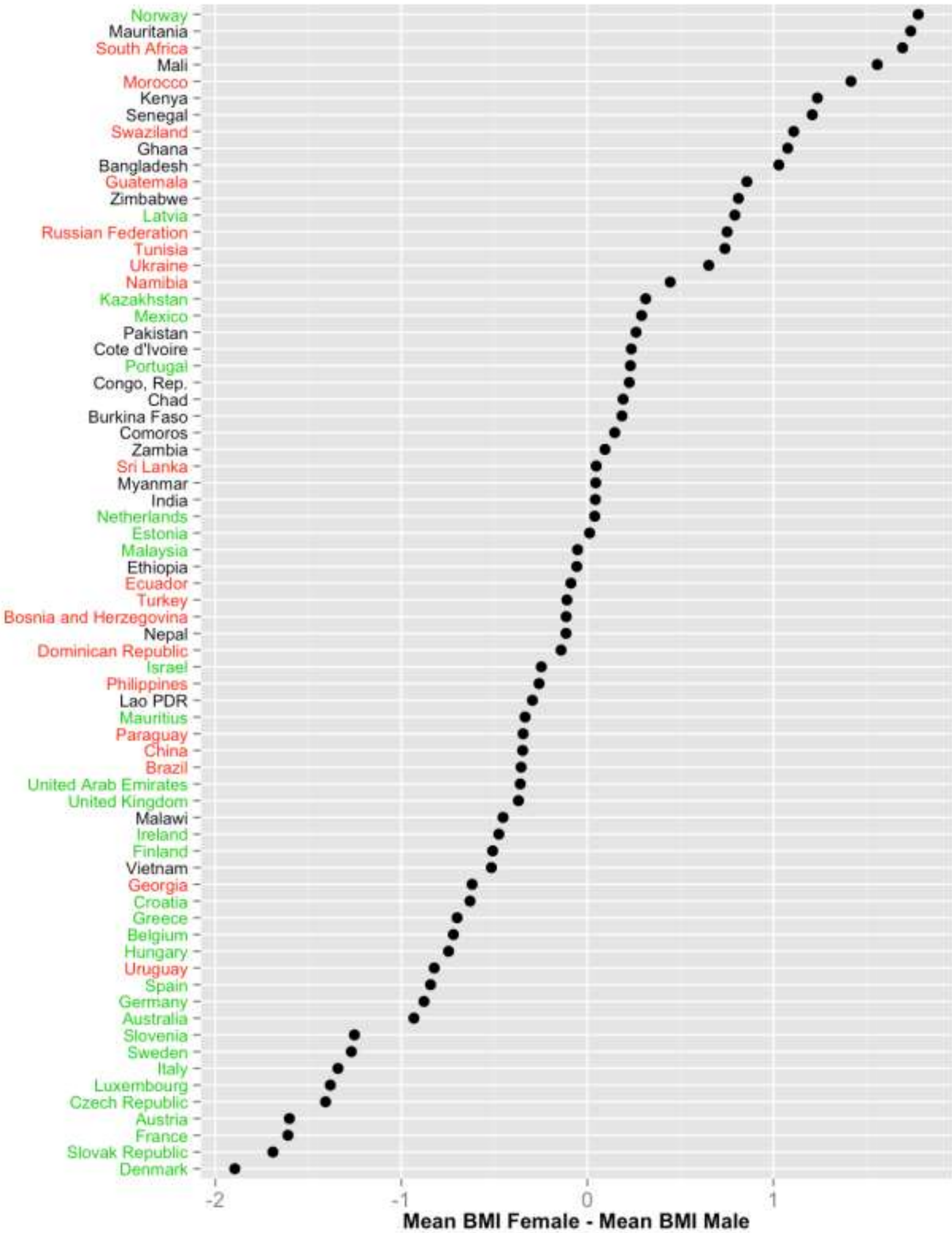


Figure 1 Appendix H: Design based Mean BMI difference by gender in 70 countries.

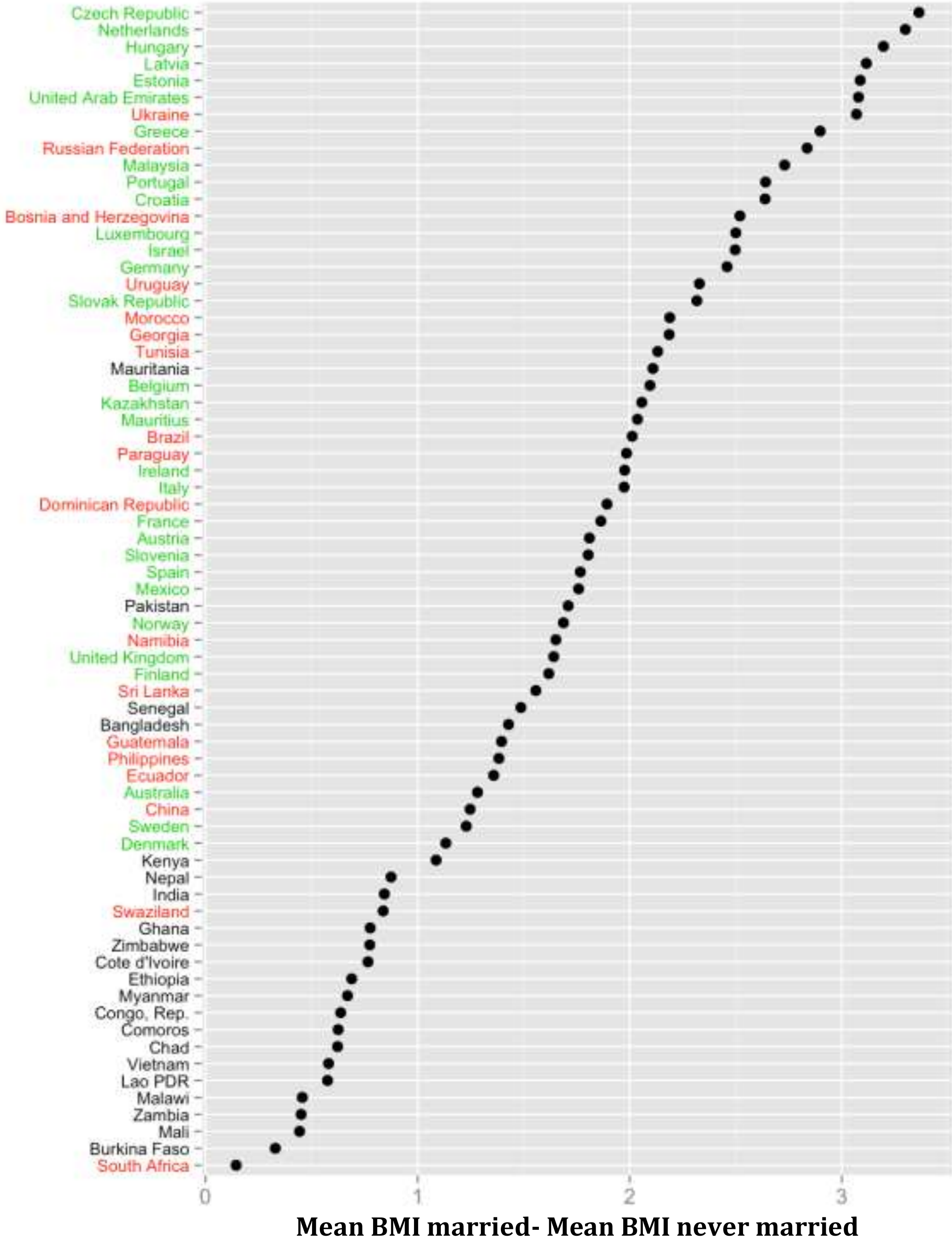


Figure 2 Appendix H: Design based Mean BMI difference by Marital Status in 70 countries.

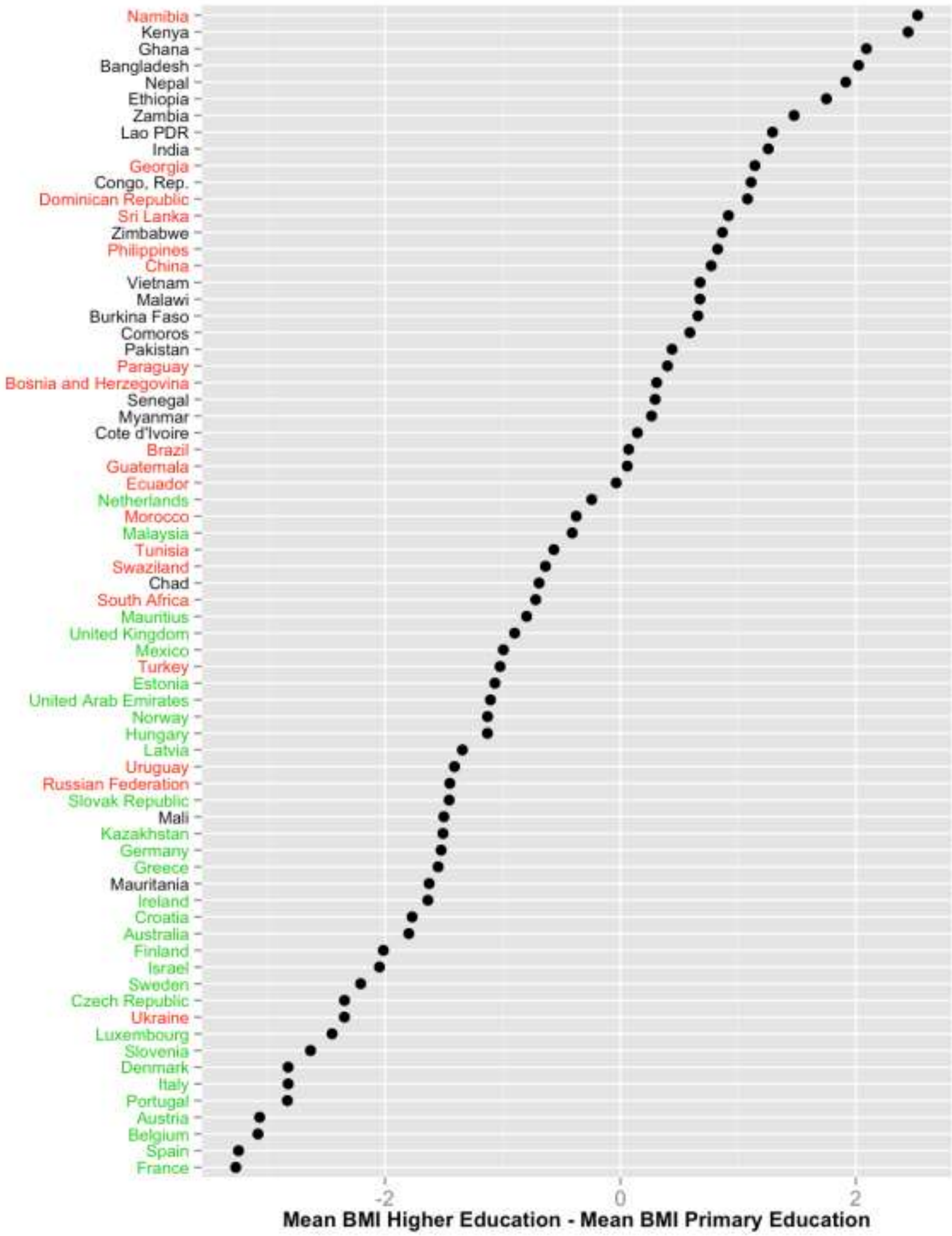


Figure 3 Appendix H: Design based Mean BMI difference by education level in 70 countries.

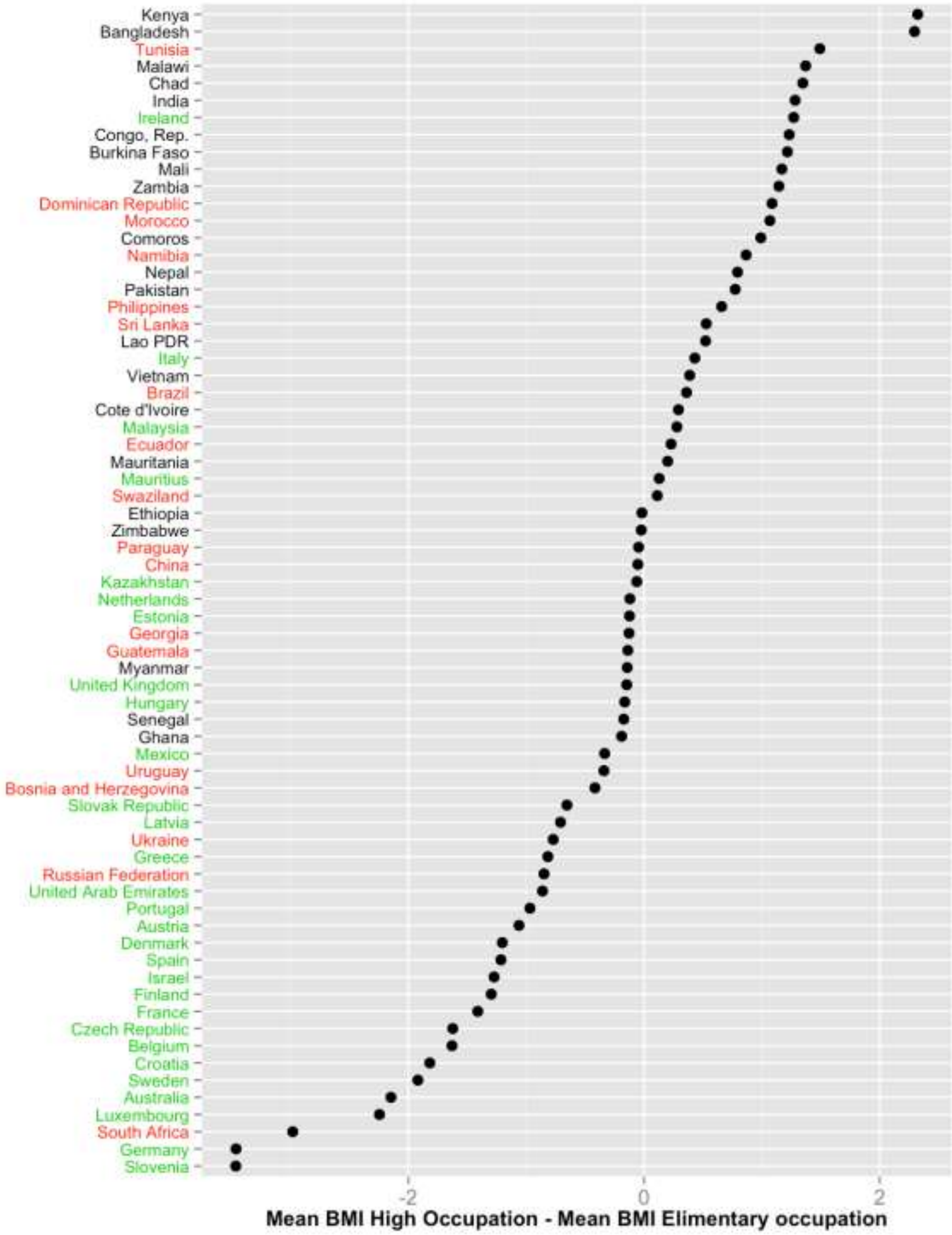


Figure 4 Appendix H: Design based Mean BMI difference by occupation in 70 countries.

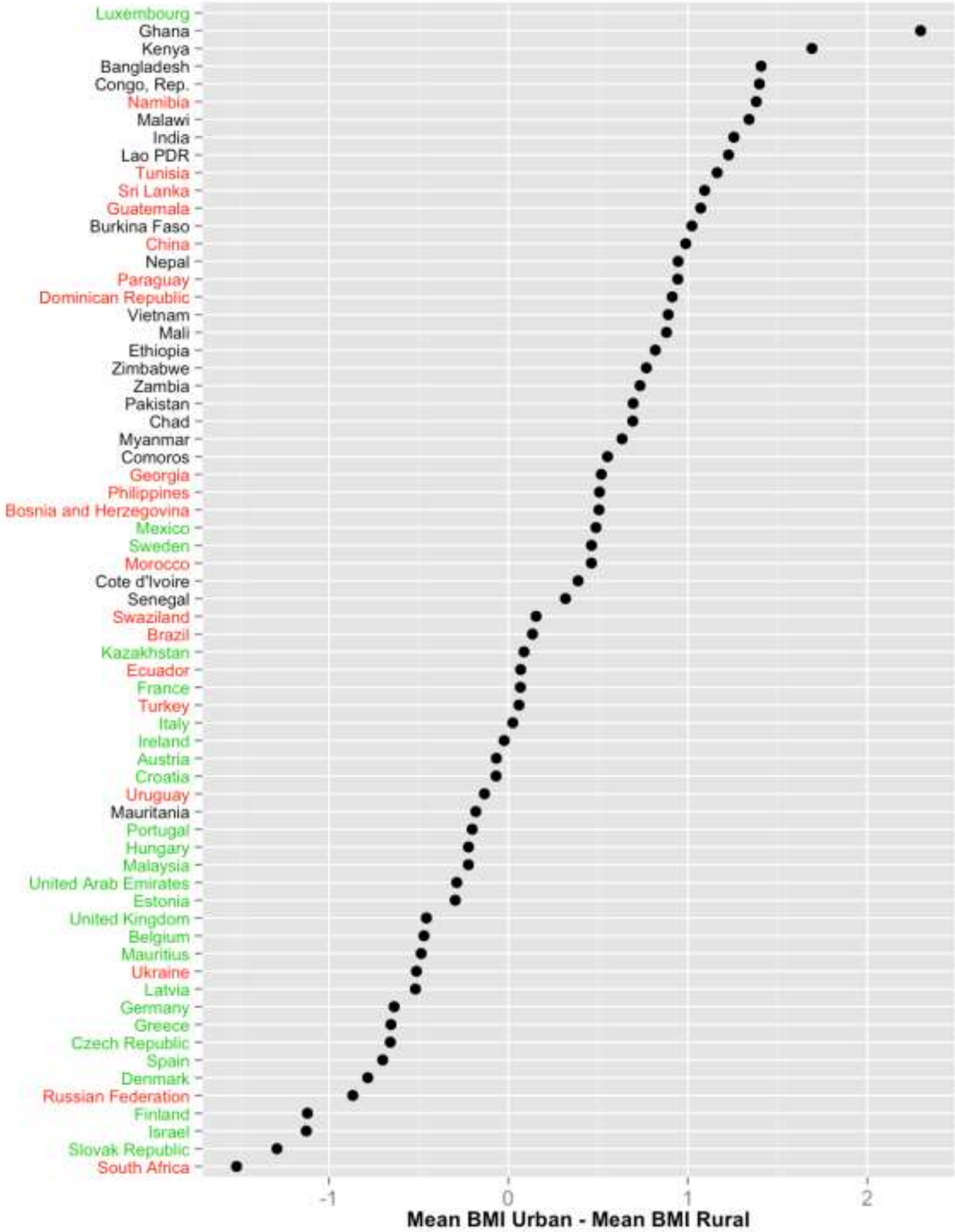


Figure 5 Appendix H: Design based Mean BMI difference by setting in 70 countries.

Appendix J

Intraclass correlation and Design effect in BMI, physical activity and diet in 56 countries.

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Abstract

Purpose: to quantify the level of clustering and design effect in BMI, physical activity and diet in 56 low, middle and high-income countries.

Methods: The World Health Survey, 2003, data was used to examine clustering in BMI, physical-activity in Metabolic Equivalent of Task(METs) and diet in fruits and vegetables intake(FVI) from low, middle and high-income countries. WHS used geographical clusters as primary sampling units(PSU), these PSUs were used as clustering variable. Multilevel intercept only regression models were used to calculate ICC and DE for each country.

Results: Median ICC(0.039) and DE(1.82) for BMI was low, however FVI had higher median ICC(0.189) and median DE(4.16). For METs Median ICC was0.141 and median DE was4.59. In some countries, however, the ICC and DE for BMI were large. For instance, South Africa has the highest ICC(0.39) and DE(11.9) for BMI. Whereas, Uruguay had highest ICC(0.434) for METs and Ethiopia had highest ICC(0.471) for FVI.

Conclusion: Across a wide range of countries, there was low area level clustering for BMI. Whereas, MET and FVI showed high area level clustering. These results suggested that country level clustering effect should be considered in developing preventive approaches for BMI, improving physical-activity and healthy diets for specific country.

Keywords

- Intraclass correlation coefficient (ICC)
- Body Mass Index (BMI)
- Physical activity

Introduction

Public health interventions to control obesity for a population can be broadly divided into two(1). Firstly, whole population approaches that target everyone in the population. When everyone in the population is not at risk, however, this can be expensive, spreading resources thinly. In contrast, narrowly targeted (or high risk) approaches can deliver substantial resources to some of those at risk, but may fail to reach everyone at risk(2, 3). The challenge of where to target interventions may be exacerbated by uniform policies that are developed at national or supranational levels,(e.g., WHO provides recommendations for member countries, on the promotion of healthy diets and regular physical activity for the prevention obesity and overweight)(4) without giving due consideration to the practicalities of implementation within countries' at state or district levels.

In this paper, we specifically identify 'state' and 'district' as a consideration because one of the factors that may affect the practicalities of intervention is the manner in which a health outcome or risk factor is geographically distributed in a population(5). For example, limited access to parks and recreational facilities, may hinders physical activity and increased the risk of overweight and obesity. Analogous issues may arise with respect to access to food(6).

If a health outcome or risk factor is distributed(geographically) uniformly in a population, then policies that target resources narrowly (targeted population approach) may miss many of those in need(1). Conversely, if a health outcome or risk factor is geographically clustered, then a policy that distributes resources uniformly will see some resources delivered to areas at the greatest risk, but will see as many resources distributed to areas at the smallest risk(5, 7).

Achieving the most cost-effective distribution of resources is a perennial problem for government that requires an understanding of how risk factors and health outcomes are actually clustered. One of the few studies to have looked at the geographical clustering of a health outcome across countries, considered stunting and wasting in 46 low income countries covered by the Demographic and Health Survey(3). That study found that stunting and wasting was(on average) not highly clustered, and geographically targeted interventions were likely to lead to a substantial under-coverage. Another multi-country study motivated to look at the clustering of diarrhoea in country surveys from Malawi, Zambia, Indonesia, and Nepal(8) and showed substantial public health implications of clustering in outcome and risk factors(9).

The kind of analysis described in the study of stunting, however, has not been extended to other health outcomes and risk factors, nor has it been extended to higher income countries. Indeed, surprisingly little is actually known about the geographical concentration of important health outcomes e.g. obesity and associated risk factors such as physical activity and healthy food consumption across countries. This is unfortunate, because if health outcomes and risk factors are geographically clustered two consequences arise. First, as already discussed, opportunities are created for targeted interventions; or if they are not concentrated it provides opportunities to remove unwarranted targeted interventions. Second, it invites investigations into the cause of geographical clustering(10, 11). One explanation for clustering is one of composition: birds of a feather flock together. That is, the geographical concentration of a health outcome or risk factor arises because people with a particular health outcome or risk factor aggregate together. The second explanation is a contextual one. That is, there is something about those communities that gives rise to exposures that cause the health outcomes or risk factors of concern. These two different explanations for geographical clustering create opportunities for different kinds of interventions; but one need not consider this line of inquiry if geographical clustering is not an issue(5).

BMI, physical-activity in Metabolic Equivalent of Task(METs) and diet in Fruits and Vegetable intake(FVI) were selected for this study of geographical clustering. It is important to look at the area level clustering effect on these selected variable in different countries for the number of reasons 1) Knowing amount of area level clustering in different countries may help understanding the underlying factors are fundamental to public health. 2) It may also help to modify the public health interventions for BMI, physical activity and diet according geographic targeting of interventions in different countries. 3) Estimate of the design effect is critical for calculating the most efficient sample size for cluster surveys. Therefore, the aim of this study was to quantify the level of clustering and design effect in BMI, physical-activity and diet in 56 low, middle and high-income countries.

Methods

Study population

The data from the World Health Survey, 2003, (analysed in 2013) provide an important opportunity to examine clustering in BMI and associated factors physical activity and diet from high, middle and low income countries. The WHS was conducted in 70 countries across five continents(Europe, Australia, South America, Asia and Africa) to provide valid, reliable, representative and comparable population data on the health status of adults, aged 18years and older. All samples were probabilistically selected with every individual being assigned a known non-zero probability of being selected. The samples were nationally representative except in China, Comoros, Congo, Côte d'Ivoire, India, and the Russian Federation, where the WHS was carried out in geographically limited regions. To adjust for the population distribution represented by the UN Statistical Division(12) and also non-response, post-stratification corrections were made to sampling weights(13, 14).

Sampling in WHS relies on a staged process in which primary sampling units(PSUs) are selected at random districts and then within selected PSUs further stages of sampling occur at households before the final selection of individuals. In 10 countries, a single-stage random sample was drawn, therefore PSU information was unavailable for Austria, Belgium, Denmark, Germany, Greece, Guatemala, Italy, Netherlands, Slovenia and the United Kingdom and these countries were excluded. The sampling procedure in the remaining 60 countries was based on multi-stage stratified procedures. Three countries, Israel, Luxemburg and Norway provided information about PSUs but all PSUs had only one individual, which make them inappropriate for the analysis of the clustering effect. Although Zambia used multi-stage sampling but information about PSUs was unavailable. Therefore, these four countries were excluded from analysis leaving a total of 56 countries for BMI variable. More detailed information on the sampling approach can be found elsewhere(15). A further 8 countries were excluded from the METs and FVI variables (see below), leaving 48 countries for these two variables.

Variables

Self-reported height and weight responses from the WHS were used to estimate individual BMI. BMI, calculated as weight in kilograms divided by height squared in meters, was used to assess obesity status. Physical activity was measured as METs. METs is defined as the energy spent sitting quietly(equivalent to [4.184 kJ] · kg_1 · h_1)(16). In WHS, to assess physical activity respondents were asked to report the number of days and the duration of the vigorous, moderate, and walking activities they undertook during the last week. Taking the different intensities of the activity components into account, reported weekly minutes spent were multiplied by 8 METs for vigorous activities, by 4 METs for moderate activities, and by 3.3 METs for walking. Energy expenditure per individual was obtained by adding the MET-minutes of the three activity components(2). Diet was measured as FVI in numbers of servings in a typical day, using the 24-hour dietary recall data as the gold standard(17). Data on METs, FVI was missing for Australia, Finland, France, Ireland, Portugal and Sweden. MET data was missing for Latvia and FVI data was missing for Mexico.

Grouping or Clustering variable

Multistage sampling in WHS used as primary sampling units(PSU). These PSUs were geographical clusters of the population. These PSUs were used as clustering or grouping variable in this analysis.

Data Analysis

The standard measure of the extent to which observations are correlated by cluster(area or sampling unit) is the intraclass correlation coefficient(ICC):

$$ICC = \frac{\sigma_b^2}{\sigma_x^2} \qquad (1)$$

Where σ_b^2 is the between-cluster variance of outcome variable X, and(for continuous variable outcomes) $\sigma_x^2 = \sigma_b^2 + \sigma_w^2$, where σ_x^2 is the within-cluster variance.

Multilevel regression models were used to produce an estimate of the ICC(3, 18). The model used for this proposes is a model that contains no explanatory variable at all, the so called Intercept only model. It only decomposes the variance of *Y* into two independent components: σ_b^2, which is the variance of the lowest level errors e_{ij}, and σ_w^2 , which is the variance of the highest-level errors u_{0j}. Using this model, the ICC was calculated using equation 1. Design effect for each country was also calculated using the formula mentions in introduction section in equation 2.

A better-known measure related to the ICC is the 'design effect' due to clustering, defined as 'the loss of effectiveness [resulting from] use of cluster sampling, instead of simple random sampling'. The relationship between design effect, cluster size and ICC is represented in the following equation:

$$DE = 1 + (m-1).ICC \qquad (2)$$

Where, DE is the design effect and b is the average number of respondents per cluster, or average cluster size(3, 18). The ICC is a portable parameter that can be compared across the countries since it does not depend on the cluster size or on the numbers of clusters(although it may be imprecisely estimated due to sampling variability). The design effect, on the other hand, is affected by the sample design, and is strongly dependent on cluster size(8). The statistical package R-project version was used to create the dendrogram using Euclidean distance as the similarity measure and complete linkage as the amalgamation rule.

Results

A total of 56 countries for BMI and 48 countries for METs and FVI variable were used in this analysis, descriptive statistics for the countries can be found in Table 1. The total sample size was smallest for Latvia(n=856) and greatest for Mexico(n=38,746). There was a wide variation in the within PSU sample size, ranging from n=1 to n=375 across the countries. The median within PSU sample size varied across the countries from 1 to 133. Interestingly, 21(42%) of the countries had a minimum PSU sample size of 1, but according to the WHS sampling guidelines all PSUs should have a sample size between 20 and 30.

Table 2 shows descriptive analysis of ICC and DE for BMI, METs, and F&V consumption across all 48 countries. BMI had the smallest median ICC and DE whereas FVI showed the largest median ICC and DE. The median DE for BMI was less than 2. In some countries, however, the ICC and DE for BMI were large In South Africa for instance, the BMI ICC was 0.39 and the DE was 11.9. For BMI, METs and F&V the minimum ICC was very small and minimum DE was 1.0. Results for ICC and DE for each country are given in Table 1. Appendix A shows correlation among Intraclass Correlation Coefficient (ICC) for BMI, ICC for Metabolic Equivalent of Task (METs) and ICC for Fruits and vegetable intake (FVI) in all 48 countries.

Figure 1 and Figure 2 shows the kernel-smoothed distribution of ICC and DE for BMI, METs, and FVI. The distribution of DE is somewhat similar for the three variables showing a unimodal peak with a DE considerably less than 10. The picture for the distribution of ICC is somewhat different. The kernel-smoothed distribution of the ICC for BMI median below 0.05, Both METs and F&V showed great clustering with medians around 3 times and 5 times greater, respectively.

The radically different distribution of ICC, in particular, invited speculation about the possibly shared ICC profile of countries on the three variables. This was explored using hierarchical cluster analysis. Initially a screeplot of agglomeration distances was generated, which suggested a two-cluster and four-cluster solutions. Appendix B shows the dendogram associated with the HCA.

Discussion

This study explored the area level variation(ICC) in BMI, MET and FVI for 56 countries from WHS data. This study shows that across a wide range of countries, there was low area level clustering for BMI. Whereas, MET and FVI showed high area level clustering. These results suggested that virtually in most of the countries variance in BMI determined at the other levels then area level may be at the household, or even the individual level, rather than being the result of shared unfavourable environmental conditions due to area level effect(19). These results indicate that to combat obesity whole population approaches e.g. legislation to reduce sugar consumption might be more appropriate as compared to targeted population approach(1).

However, ICC for BMI for individual countries varied highly from minimum 0.001 in Croatia and UAE and maximum 0.399 for South Africa. These results indicate that universal strategies to control obesity might not show consistently effective results in all the countries(19). Where, some strategies might be effective in Dominican(ICC=0.014) and Finland(ICC=0.001) might not be equally effective in SriLanka(ICC=0.172) and Zimbabwe(ICC=0.232). Therefore, each nation should modify WHO or other international strategies according to country's need in terms of clustering in areas (ICC). Countries with low ICC (countries towards left side of the graph in figure 1) should give more emphasis on whole population approach such as Denmark, Austria, Iceland and Switzerland have banned the use of trans-fatty acids in food processing completely (20). And countries with high ICC (countries towards the right side of the graph in figure 1) should add targeted population approach together with whole population approach for example

Mexico's *Oportunidades* programme nameed 'Progresa' aims to assist households on low incomes, which are identified as eligible through strict targeting. Around 6.5 million households are enrolled in the programme, most of them in rural and semi-urban areas(21).

On the other hand, ICC for MET and FVI was high with more than 81% countries with ICC more than 0.10. Therefore results suggested implementing public health interventions targeting the clusters with low METs to improve METs in those areas(5, 22). Similarly, to improve the FVI targeted population approach should be implemented for example controls on advertising, meals and the marketing of fast foods in or close to schools and hospitals. Most European countries have controls on advertising directed at children, as does the province of Quebec in Canada. Some other examples are Supplemental Nutrition Assistance Programme(SNAP) to encourage healthy diets in the US(23).
ICC for MET's are moderately correlated with the ICC for FVI, this suggests that the countries which implements targeted population approach to improve MET's for highly cluttered areas should implement an approach for improvement in FVI for same clusters(5).

On the face of it, this finding may seem incompatible with what is widely known about the marked differences in the prevalence of obesity(BMI), for example, differences in the BMI in two different countries (south Africa and Vietnam)(24). However, it is quite possible to have a rather large average difference in BMI status between two countries and still show a low ICC if the within-area variance of BMI status is sufficiently large. This is precisely the situation revealed by this study, repeated in country after country. It underlines the importance of the issue of within-area heterogeneity of obesity.

Although some of the countries have low ICC and DE but the general conclusions which can be drawn from these reports are that ICC and design effects are often appreciable and cannot be ignored. The possible reason for that is for some of the countries this ICC and design effect can go very high e.g. Maximum Design effect in MET was 45.7. ICC Design effects may vary substantially among different types of variables and different countries(25). The ICC is generally considered to be more generalizable than the design effect, because the latter is dependent on the cluster size. However, an inverse relation between cluster size and the degree of between-cluster variation has been well described(26). Our data, which included a wide range of variables, confirm that ICCs tend to be larger for smaller clusters. However, the design effect will be influenced by the number sampled per cluster, and substantial design effects will result when the number per cluster is large, even if the ICC is small.

An exogenous explanation for the observed clusters in either the 2-group or 4-group solutions was sought, focusing on country level economic predictors such as national income and income inequality, or an endogenous based on sampling design, focusing on PSU size and PSU numbers. Neither approach generated satisfactory explanations for the clustering.

Conclusion

This study shows that across a wide range of countries, there was low area level clustering for BMI. Whereas, MET and FVI showed high area level clustering. These results suggested that country level clustering effect should be considered in developing preventive approaches for BMI, improving physical-activity and healthy diets for specific country.

Highlights

Obesity is a global public health problem emerging almost in all countries, but the geographical distribution of obesity in different countries is not well established. Investigation of obesity distribution using clustering is important to develop effective public health policies adapted to particular country according to clustering effect within the country. For example, countries with high ICC should give emphasis on "targeted population approach" together with whole population approach.

Acknowledgement

None

Conflicting interest

The authors have declared that no competing interests exist.

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Table 1: Descriptive analysis of sample size, PSU characteristics and Intra-cluster Correlation (ICC) and Design Effect (DE) for BMI, Metabolic Equivalent of Task (METs) and Fruits and Vegetable Intake (FVI).

Country	Sample size	Number of PSUs	Minimum PSU Size	Maximum PSU Size	Mean PSU Size	BMI		METs		Fruits and Vegetable intake	
						ICC	DE	ICC	DE	ICC	DE
Australia	1845	125	4	22	15	0.001	1.001	NA	NA	NA	NA
Bangladesh	5552	186	18	35	30	0.001	1.001	0.082	3.378	0.211	7.127
Bosnia	1028	112	1	11	10	0.056	1.501	0.263	3.365	0.333	4.000
Brazil	5000	250	20	20	20	0.023	1.432	0.119	3.253	0.128	3.425
Burkina	4822	148	5	35	34	0.072	3.390	0.131	5.321	0.258	9.503
Chad	4652	103	28	50	47	0.134	7.186	0.386	18.767	0.338	16.562
China	3993	30	121	145	133	0.083	11.911	0.339	45.772	0.329	44.432
Comoros	1752	49	13	52	37	0.037	2.341	0.102	4.673	0.085	4.076
Congo	2490	109	1	128	15	0.065	1.914	0.082	2.148	0.292	5.085
CotedIvoire	3178	172	6	22	19	0.017	1.308	0.219	4.939	0.200	4.596
Croatia	990	184	1	8	6	0.000	1.000	0.171	1.853	0.190	1.948
Czech	935	192	1	92	4	0.037	1.111	0.112	1.335	0.103	1.310
Dominican	4534	256	4	24	18	0.014	1.234	0.034	1.585	0.117	2.990
Ecuador	4627	220	1	70	20	0.032	1.613	0.121	3.303	0.091	2.727
Estonia	1012	49	4	225	11	0.001	1.000	0.087	1.867	0.097	1.968
Ethiopia	4938	99	3	207	46	0.038	2.721	0.218	10.832	0.471	22.176
Finland	1013	169	5	7	6	0.001	1.001	NA	NA	NA	NA
France	1008	116	1	25	10	0.073	1.658	NA	NA	NA	NA
Georgia	2752	68	8	119	32	0.028	1.876	0.237	8.351	0.356	12.021
Ghana	3932	290	1	21	14	0.132	2.719	0.141	2.836	0.093	2.215
Hungary	1419	194	1	23	7	0.032	1.193	0.126	1.758	0.016	1.093
India	9985	379	13	38	26	0.076	2.906	0.121	4.036	0.470	12.739
Ireland	1014	100	5	20	10	0.092	1.830	NA	NA	NA	NA
Kazakhstan	4496	66	16	199	55	0.033	2.799	0.238	13.854	0.252	14.605
Kenya	4416	275	1	21	17	0.102	2.628	0.124	2.988	0.177	3.827
Lao	4889	250	15	20	20	0.081	2.542	0.257	5.892	0.135	3.568
Latvia	856	134	1	20	6	0.001	1.000	NA	NA	0.286	2.429
Malawi	5300	71	26	200	60	0.039	3.273	0.171	11.064	0.274	17.186
Malaysia	6040	399	4	24	16	0.021	1.308	0.122	2.824	0.090	2.353
Mali	4271	284	1	31	16	0.384	6.766	0.172	3.580	0.231	4.471
Mauritania	3776	158	2	50	24	0.128	3.939	0.267	7.139	0.170	4.911
Mauritius	3888	100	23	56	40	0.061	3.391	0.131	6.090	0.237	10.237
Mexico	38746	797	15	100	49	0.033	2.585	0.075	4.622	NA	NA
Morocco	4716	250	14	20	19	0.026	1.475	0.063	2.137	0.176	4.163
Myanmar	5886	110	47	55	54	0.076	5.016	0.283	16.015	0.463	25.542
Namibia	4248	229	5	31	18	0.093	2.573	0.098	2.672	0.171	3.914
Nepal	8688	292	8	31	30	0.068	2.977	0.155	5.503	0.055	2.608
Pakistan	6379	355	1	20	19	0.124	3.238	0.216	4.896	0.156	3.802
Paraguay	5143	498	1	22	10	0.054	1.490	0.109	1.984	0.097	1.870
Philippines	10078	240	7	89	39	0.030	2.126	0.134	6.077	0.176	7.674
Portugal	1020	100	2	66	9	0.067	1.537	NA	NA	NA	NA
Russia	4421	123	1	306	25	0.034	1.820	0.200	5.809	0.217	6.211
Senegal	3219	259	1	44	13	0.088	2.059	0.067	1.809	0.050	1.605
Slovakia	2514	312	1	375	1	0.062	1.000	0.291	1.000	0.090	1.000
SouthAfrica	2324	183	1	20	14	0.399	6.191	0.324	5.212	0.341	5.435

Spain	6364	997	1	12	7	0.041	1.244	0.234	2.403	0.079	1.476
SriLanka	6732	145	15	102	47	0.172	8.901	0.200	10.188	0.309	15.191
Swaziland	3070	96	1	100	29	0.018	1.506	0.128	4.590	0.212	6.938
Sweden	1000	53	1	89	13	0.016	1.187	NA	NA	NA	NA
Tunisia	5065	265	8	20	20	0.041	1.784	0.213	5.054	0.255	5.845
Turkey	11218	472	1	51	23	0.022	1.487	0.053	2.162	0.091	3.000
UAE	1180	60	13	23	20	0.000	1.004	0.054	2.030	0.201	4.821
Ukraine	2802	113	1	50	25	0.033	1.793	0.336	9.053	0.298	8.162
Uruguay	2978	61	1	123	24	0.035	1.801	0.434	10.986	0.112	3.578
VietNam	3492	137	2	32	30	0.108	4.126	0.351	11.182	0.444	13.889
Zimbabwe	4072	130	2	122	25	0.232	6.564	0.070	2.669	0.128	4.067

Table 2: Descriptive analysis of Intraclass Correlation Coefficient (ICC) and Design Effect (DE) of BMI, Metabolic Equivalent of Task (METs) and Fruit and Vegetable intake (FVI) in 56 Countries

	BMI		METs		Fruits and Vegetable intake	
	ICC	DE	ICC	DE	ICC	DE
Minimum	.001	1.0	0.034	1.0	0.015	1.0
Maximum	0.39	11.9	0.43	45.7	0.47	44.4
Median	0.039	1.82	0.141	4.59	0.189	4.16
IQR	0.056	1.61	0.127	4.16	0.182	5.43

Figure 1. Distribution of the values of the intra-cluster correlation coefficient (ICC) for BMI, Metabolic Equivalent of Task (METs) and Fruits and Vegetable intake (FVI) in 48 countries.

Figure 2. Distribution of the values of the Design Effect (DE) for BMI, Metabolic Equivalent of Task (METs) and Fruits and Vegetable intake (FVI) in 56 countries.

Appendix A: Correlation among Intraclass Correlation Coefficient (ICC) for BMI, ICC for Metabolic Equivalent of Task (METs) and ICC for Fruits and vegetable intake (FVI) in all 48.

Appendix B. Denderogram showing clustering of 48 countries.

Appendix K

Table 1 Appendix J: Multilevel multivariate linear regression analysis with individual and country level explanatory variables with inter-level interaction between Gender and national income (GNI-PPP)

	Model J1	
Fixed Effect	β	SE
Intercept	22.19	0.82***
Country Level		
GNI-PPP/10000	0.36	0.13*
Individual Level		
Gender		
Female	Reference category	
Male	-0.03	0.03
Gender:GNIPPP		
Female:GNIPPP	Reference category	
Male:GNIPPP	0.25	0.02***
Random effect	σ	SD
Country	1.92	1.38
Residual	19.36	4.40
Fit Indices		
AIC	1197005	
BIC	1197421	
Log Likelihood	-598480	
Deviance	1196959	
Model Comparison		
Chi-square(df)	168.7(1)***	

*pvalue≤0.05; **pvalue≤0.01; ***pvalue≤0.001; SE: Standard Error.
β- regression coefficient; SE- Standard Error; σ- Variance; SD: Standard Deviation; AIC- Akaike information criterion; BIC- Bayesian information criterion; Chisq- Chi Square test; df- Degree of freedom.
This model was adjusted for age, education level, marital status, household income, occupation, setting and Gini.

Table 2 Appendix J: Multilevel multivariate linear regression analysis with individual and country level explanatory variables with inter-level interaction education level and national income (GNI-PPP)

	Model J2	
Fixed Effect	β	SE
Intercept	22.15	0.81***
Country Level		
GNI-PPP/10000	0.80	0.13*
Individual Level		
Education		
Primary	Reference category	
Intermediate	0.13	0.027***
Higher	-0.01	0.043
Education:GNIPPP		
Primary:GNIPPP	Reference category	
Intermediate:GNIPPP	-0.36	0.03**
Higher:GNIPPP	-0.53	0.03**
Random effect	σ	SD
Country	1.87	1.37
Residual	19.34	4.40
Fit Indices		
AIC	1196807	
BIC	1197053	
Log Likelihood	-598380	
Deviance	1196759	
Model Comparison		
Chi-square(df)	368.6(2)***	

*pvalue≤0.05; **pvalue≤0.01; ***pvalue≤0.001; SE: Standard Error.

β- regression coefficient; SE- Standard Error; σ- Variance; SD: Standard Deviation; AIC- Akaike information criterion; BIC- Bayesian information criterion; Chisq- Chi Square test; df- Degree of freedom.

This model was adjusted for age, education level, marital status, household income, occupation, setting and Gini.

Table 3 Appendix J: Multilevel multivariate linear regression analysis with individual and country level explanatory variables with inter-level interaction between occupation and national income (GNI-PPP)

	Model J3	
Fixed Effect	β	SE
Intercept	22.22	0.81***
Country Level		
GNI-PPP/10000	0.33	0.13*
Individual Level		
Occupation$^{\Psi}$		
High	Reference category	
Middle	-0.065	0.048
Low	-0.29	0.0471***
Elementary	0.016	0.061
	-0.35	0.041***
Occupation:GNIPPP		
High:GNIPPP	Reference category	
Middle:GNIPPP	-0.07	0.03
Low:GNIPPP	0.42	0.04***
Elementary:GNIPPP	-0.35	0.06***
	0.21	0.03***
Random effect	σ	SD
Country	1.86	1.37
Residual	19.36	4.40
Fit Indices		
AIC	1197172	
BIC	1197205	
Log Likelihood	-598443	
Deviance	1196886	
Model Comparison		
Chi-square(df)	241 (4)***	

*pvalue≤0.05; **pvalue≤0.01; ***pvalue≤0.001; SE: Standard Error.
β- regression coefficient; SE- Standard Error; σ- Variance; SD: Standard Deviation; AIC- Akaike information criterion; BIC- Bayesian information criterion; Chisq- Chi Square test; df- Degree of freedom.
$^{\Psi}$Occupation categories: High (1. Legislator, Senior Official, or Manager 2. Professional and 10.armed forces), medium (3.Technician or Associate Professional 4. Clerk 5. Service or sales worker), low (6. Agricultural or fishery worker 7. Craft or trades worker 8. Plant/machine operator or assembler) and elementary (elementary workers)
This model was adjusted for age, education level, marital status, household income, occupation, setting and Gini.

Table 4 Appendix J: Multilevel multivariate linear regression analysis with individual and country level explanatory variables with inter-level interaction between household wealth and national income (GNI-PPP)

		Model J4	
Fixed Effect		β	SE
Intercept		22.20	0.84***
Country Level			
GNI-PPP/10000		0.38	0.13**
Individual Level			
Setting			
	Urban	Reference category	
	Rural	-0.46	0.023***
Setting:GNIPPP			
	Urban:GNIPPP	Reference category	
	Rural:GNIPPP	0.04	0.02***
Random effect		σ	SD
	Country	1.94	1.39
	Residual	19.30	4.40
Fit Indices			
	AIC	1197166.6	
	BIC	1197432.8	
	Log Likelihood	-598557.3	
	Deviance	1197114.6	
Model Comparison			
	Chi-square(df)	105.77 (1)***	
R^2			
	Country Level R^2	0.276	
	Individual level R^2	0.050	
	Total R	0.077	

*pvalue≤0.05; **pvalue≤0.01; ***pvalue≤0.001; SE: Standard Error.

β- regression coefficient; SE- Standard Error; σ- Variance; SD: Standard Deviation; AIC- Akaike information criterion; BIC-Bayesian information criterion; Chisq- Chi Square test; df-Degree of freedom.

$^{\Psi}$Occupation categories: High (1. Legislator, Senior Official, or Manager 2. Professional and 10.armed forces), medium (3.Technician or Associate Professional 4. Clerk 5. Service or sales worker), low (6. Agricultural or fishery worker 7. Craft or trades worker 8. Plant/machine operator or assembler) and elementary (elementary workers)

Appendix L

Appendix J: Multilevel multivariate linear regression analysis for age with BMI as outcome variable in 70 countries.

		β	SE
Intercept		23.41	0.194***
Age groups			
	18-29 years	Reference category	
	30-39 years	1.05	0.028***
	40-49 years	1.60	0.030***
	50-59 years	1.86	0.35***
	60-69 years	1.65	0.039***
	70-79 years	1.27	4.92***
	80-89 years	0.40	8.90***

Monash University Human Research Ethics Committee (MUHREC)
Research Office

17 December 2014

Dear Researchers

Project Number: **CF14/3907 - 2014002034**

Project Title: **A Multilevel assessment of individual and country level predictors of individual level BMI in 70 countries**

Chief Investigator: **Prof Daniel Reidpath**

The above application has been reviewed by the Chairs of the Monash University Human Research Ethics Committee (MUHREC) who determined that the proposal satisfies section 5.1.22 of the National Statement on Ethical Conduct in Human Research.

Therefore, the Committee has granted an exemption from ethical review for the research as described in your proposal.

Thank you for your assistance.

[redacted]

Professor Nip Thomson
Chair, MUHREC

cc: Dr Mohd Masood

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