Trends in the socioeconomic patterning of overweight and obesity and predictions of the future prevalence of diabetes in India

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Abstract

The prevalence of overweight and obesity in India has increased substantially in recent decades, and Indians are particularly predisposed to diabetes. Despite this, recent trends in the socioeconomic patterning of overweight and obesity are currently unknown, and reliable future forecasts of overweight, obesity and diabetes to assist policy makers are over-simplistic. The main aims of this thesis were to: (I) examine recent trends in the socioeconomic patterning of overweight and obesity in India, (II) estimate the future prevalence of overweight, obesity and diabetes to 2040, and (III) estimate residual lifetime risk of diabetes.

The first objective was addressed using multilevel regression analysis, and the second and third by building dynamic simulation models. Input data were extracted from national surveys, census demographic data and community level cohort studies.

The research identified considerably greater increases in overweight and obesity prevalence between 1998 and 2016 in poorer, compared to richer, socioeconomic groups particularly in urban areas, the most economically developed states, and among women. Among 20-69-year-old Indians, overweight and obesity prevalence is forecast to reach 30% and 10% among men, and 27% and 14% among women by 2040. The resultant prevalence of diabetes among urban men and women, respectively, in 2040 is expected to reach 27% and 25%. The lifetime probability of developing diabetes at 20 years among urban men and women is 69% and 75%, respectively, however is considerably higher among the obese population.

This thesis marks the most recent attempt to identify the trends in the socioeconomic patterning of excess weight in India, the most thorough attempt to forecast future overweight, obesity and diabetes, and the first to examine the lifetime risk of diabetes. These findings are intended to guide future policy and monitor progress goals related to both excess weight and diabetes.

Abbreviations

- SEP - Socioeconomic Position
- BMI - Body Mass Index
- HIC - High Income Country
- LIC - Low Income Country
- LMIC - Low-Middle Income Country
- MIC - Middle Income Country
- GNI - Gross National Income
- PPS – Probability Proportional to Size
- PSU – Primary Sampling Unit
- CEB – Census Enumeration Block
- SIR – Standardised Incidence Ratio
- WC - Waist Circumference
- SoL - Standard of Living
- CVD - Cardiovascular Disease
- PCA - Principal Components Analysis
- HbA1c - Glycated haemoglobin
- NCD - Non-Communicable Diseases and Injuries
- DALY - Disability-Adjusted Life Years
- QALY - Quality-Adjusted Life Years
- YLL - Years of Life Lost
- LSI - Lifestyle intervention
- PCNSDP - Per capita net state domestic product
- UI - Uncertainty Interval
- CHD - Coronary Heart Disease
- GDP - Gross Domestic Product
- FPG - Fasting Plasma Glucose
- CBG - Capillary Blood Glucose
- IFG - Impaired Fasting Glucose
- IGT - Impaired Fasting Glucose
- WHO - World Health Organization
- SSB - Sugar Sweetened Beverage

- DHS - Demographic and Health Survey
- NFHS - National Family Health Survey
- SAGE - Study on Global AGEing and Adult Health
- NNMB - National Nutrition Monitoring Bureau
- ICMR - Indian Council of Medical Research
- INDIAB - INdia DIABetes study
- CARRS - cArdiometabolic Risk Reduction in South-Asia study
- CURES - Chennai Urban Rural Epidemiology Study
- SRS - Sample Registration System
- NHANES - National Health and Nutrition Examination Survey
- IDF - International Diabetes Federation
- NHIS - National Health Interview Survey
- MEDCHAMPS - Mediterranean Studies of Cardiovascular disease and Hyperglycaemia
- UN - United Nations
- MoHFW - Ministry of Health and Family Welfare
- IMS - Indian Migration Study
- SDG - Sustainable Development Goals
- NPCDCS - National Programme for Prevention and Control of Cancer, Diabetes, Cardiovascular Disease and Stroke
- NHP - National Health Policy
- GATS - Global Adult Tobacco Survey
- USAID - United States Agency for International Development
- UNICEF - United Nations International Children's Emergency Fund
- UNFPA - United Nations Population Fund
- DFID - Department for International Development
- GOI - Government of India
- CDC - Centers for Disease Control and Prevention
- OECD - Organisation for Economic Cooperation and Development
- IIPS - International Institute for Population Sciences
- NRHM - National Rural Health Mission
- NUHM - National Urban Health Mission

Relevant publications and conference presentations

Published research papers

- Luhar, S., Mallinson, P.A.C., Clarke, L. and Kinra, S., 2018. Trends in the socioeconomic patterning of overweight/obesity in India: a repeated cross-sectional study using nationally representative data. *BMJ open*, *8*(10), p.e023935.

- Luhar, S., Mallinson, P.A.C., Clarke, L. and Kinra, S., 2019. Do trends in the prevalence of overweight by socio-economic position differ between India's most and least economically developed states? *BMC Public Health*, *19*(1), p.783.

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Oral Presentation of research papers

- Luhar, S., Jones, R., Kondal, D., Mohan, A., Patel, S.A., Kinra, S., Clarke, L., Ali, M.K., Prabhakaran, D., Kadir, M., Tandon, N., Mohan, V., Narayan, V. Forecasting future diabetes in India to 2040. Paper presented at: 4th Asian Population Association (APA) Conference. 2018 July 11-14; Shanghai University, Shanghai, China.

- Luhar, S., Jones, R., Kondal, D., Mohan, A., Patel, S.A., Kinra, S., Clarke, L., Ali, M.K., Prabhakaran, D., Kadir, M., Tandon, N., Mohan, V., Narayan, V. Forecasting future diabetes in India to 2040. Paper presented at: Seminar at Global Diabetes Research Center. 2018 June 21;

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Chapter One. Background

1.1. Introduction

In 2016, of the 1.9 billion adults who were overweight or obese worldwide, 650 million were classified as obese. Globally, the pace of growth in the prevalence of overweight and obesity is alarming; increasing three-fold between 1975 and 2016[1] and increasing in every region of world[2]. The rapid increase in excess weight globally is caused by a combination of higher consumption of energy-dense fatty foods, and increasingly sedentary behaviour, driven by sectoral shifts in employment and urbanisation[1]. Overweight and obesity are important risk factors for certain non-communicable diseases (NCDs), including diabetes, coronary heart disease (CHD), stroke and some cancers[3].

The increasing prevalence of NCDs is consistent with theories of an epidemiological transition, whereby a predominance of infectious diseases is replaced by an increasing prevalence of 'man-made' or chronic disease[4,5]. This transition is known to occur as countries undergo economic development and shift from a previous state of high fertility and high mortality, to low fertility and low mortality (known as the demographic transition)[6,7]. The initial mortality declines, emanating from economic modernisation[7] leads to rapid population growth, population ageing, and considerable urbanisation. Between 1960 and 2015, whilst the global economy (in terms of Gross Domestic Product (GDP) per capita) approximately doubled[8], the proportion of the world's population living in obesogenic urban environments increased from 34% to 54%[9].

Currently, NCDs are responsible for around 71% of global mortality; claiming 41 million lives per year[10]. In low- and middle-income countries (LICs and MICs), approximately 85% of deaths between the ages 30 and 69 years are attributable to NCDs. Diabetes, a disease with a strong positive association with overweight and obesity[11], has witnessed almost a tripling in the number of cases between 2000 and 2017 (from 151 to 425 million people)[11]. Conservative estimates predict that the number of adults aged 20-79 with diabetes will increase from 425 million to 629 million between 2017 and 2045; a 48% increase[11]. Diabetes-related complications include cardiovascular disease (CVD), neuropathy, and eye-disease[11], and has also been found to increase the risk of heart attacks and stroke by two and three times, respectively[12]. Global trends in the future diabetes burden and prevalence are expected to vary considerably by broad regions. According to the International Diabetes Federation (IDF), whereas the expected increase in the diabetes burden between 2017 and 2045 in Europe (a region with a predominance of High Income Countries (HIC)) is 16%, the number of adults with diabetes in South East Asia is expected to increase by 84% over the same period[11].

Such is the public health challenge associated with the rising burden of NCDs and the threat it poses to global long-term development, the World Health Organization (WHO) has outlined targets for tackling the future burden. The 'Global Action Plan for the Prevention and Control of Non-communicable Diseases 2013-2020'[13] outlined its intention to reduce premature mortality from NCDs by a quarter by 2025, in addition to stopping further increases in global obesity beyond the 2010 level. The 2030 Agenda for Sustainable Development has since aimed to reduce premature mortality attributable to NCDs by 33% by 2030[14].

India is a Low-Middle Income Country (LMIC) with a population of 1.3 billion in 2015 according to the United Nations (UN) World Population Prospects. The country is experiencing a rapid epidemiological transition, whereby NCDs now account for 61.8% of all deaths[15]. At the same time infectious diseases still pose a significant health challenge, consistent with a 'non-Western' epidemiological transition model whereby rapid mortality declines occur at lower levels of economic development compared to when HICs went through the same transition[16,17].

The prevalence of overweight and obesity in India has increased considerably in recent decades. Whereas the prevalence of overweight and obesity combined approximately doubled among men aged 15-49 from 9.7% to 18.9% between 2005 and 2016[18,19], the prevalence increased among women between 1998 and 2016, from 10.6% to 20.7%[19,20]. Between 1990 and 2016, the prevalence of diabetes among Indian adults has increased from 5.5% to 7.7%[21], with a considerably higher prevalence in urban areas compared to rural areas[22].

Indians are also known to have an elevated predisposition to diabetes at comparatively lower levels of Body Mass Index (BMI) than in White European populations[23,24]; a metric commonly used to assign overweight and obesity status[1]. Indians have also been found to experience the onset of diabetes around a decade earlier than Europeans[25,26]. Furthermore, not only is India the second most populous country on earth, with a diverse disease profile and one of the lowest overall expenditures on health per capita globally[27], it is considerably heterogenous with regards economic development sub-nationally. For instance, the per capita net state domestic product (PCNSDP) in Goa is approximately ten times that of Bihar[28].

Socioeconomic position (SEP) is a commonly cited correlate of excess weight[29–32]. However the nature of this association changes with economic development, whereby it is commonly associated with affluence at earlier development levels, and poverty at later stages of development[29–32] Understanding the most vulnerable subpopulations within India's heterogenous makeup, for instance different socioeconomic groups within the country, will become increasingly important moving forward when deciding upon strategies to counter the growing prevalence of overweight and obesity, and the rising diabetes epidemic.

The increasing prevalence of diabetes, overweight and obesity in India also necessitates accurate and sophisticated forecasts that incorporate future demographic changes. The development of such models will be useful in testing future scenarios of interventions on the future prevalence. Additionally, it can aid in the monitoring of progress towards goals related to excess weight and diabetes; for instance, the National Health Policy (NHP) 2017 which targets the screening and treatment of 80% of diabetes cases and the reduction of premature mortality related to diabetes by 25% by 2025[33]. Finally, given that more than 50% of individuals with diabetes in India are not diagnosed[25,34], diabetes forecasts can help estimate the future burden of undiagnosed diabetes.

Finally, understanding the burden of diabetes above and beyond prevalence can offer new insights into potential challenges. The prevalence of diabetes is limited in that it solely expresses a population-level burden, without any reference to how diabetes impacts individuals[35]. Estimates of lifetime risk, that express the probability of individuals developing diabetes, is currently unknown in India, where there is a comparatively lower prevalence of overweight and obesity[36] and lower life expectancy[37], however a higher predisposition at all ages and BMI levels, compared to Western European populations[23,25,26,34,38]. Such evidence on the subpopulations at elevated risk of developing diabetes, and the extent of the increased risk, can identify the subpopulations in most urgent need of health policy attention in a setting with limited healthcare resources.

1.2. Aims and Objectives

The main aims of this thesis are to examine recent trends in the association of SEP and excess weight among Indian adults; provide estimates of the future prevalence of overweight, obesity, and diabetes among adults using easily understandable models with the most contemporary data; and estimate the life time risk of diabetes. By accomplishing these main objectives, I will provide a more detailed understanding of the current and future challenges related to excess weight and diabetes in India. I draw upon carefully collected and objectively measured data from geographically-representative cross-sectional data, community studies, and census demographic data.

The specific aims addressed in this thesis are as follows:

1. Examine trends in the socioeconomic patterning of overweight and obesity between 1998 and 2016 among women (15-49 years) and between 2005 and 2016 among men (15-54 years).
2. Assess how these socioeconomic patterning trends in overweight and obesity have differed between India's most and least economically developed states.

3. Forecast the future prevalence of overweight and obesity among Indian adults to 2040 by urban and rural residence (by age, sex and urban/rural residence).
4. Forecast the future prevalence of diabetes, in light of the forecasted overweight and obesity, among urban Indian adults, to 2040 (by age and sex).
5. Estimate the lifetime risk of diabetes among urban Indian adults (by age, sex, and BMI category).

Although it would be ideal to incorporate a measure of SEP into the forecasts of overweight and obesity (Aim 3), and consequently the forecasts of diabetes (Aim 4), I opt against this due to the expected changing nature of the association between excess weight and SEP throughout the forecasting period. This would add considerable uncertainty into a forecasting model as the future risk of overweight and obesity for different SEP groups would not be known, and consequently has the potential to make my forecast results less accurate. A number of systematic reviews have shown that in LMICs, the association between overweight and obesity and SEP changes substantially towards a negative association[29,30,32,39], and this is likely to happen at different speeds in different areas of the country, depending on subnational levels of economic development. Studies that have aimed to incorporate SEP into predictions of overweight and obesity assume the same probability of becoming overweight or obese within one SEP category over a forecasting period[40], which I expect to be untrue through objectives 1 and 2. To avoid such assumptions, I use a comprehensive but relatively parsimonious model.

Furthermore, for aims 4 and 5, I restrict my analysis to urban areas as the data required for the diabetes models, specifically the incidence of diabetes, is only available for urban areas. The CARRS study, with whom I have collaborated to achieve these aims, restrict data collection to two Indian cities (Delhi and Chennai) and one Pakistani city (Karachi).

1.3. Structure of the thesis

This thesis follows a research-paper based structure, with a total of ten chapters, and including five research papers. The first research paper (Chapter Five) has been published in BMJ Open, the second paper (Chapter Six) has been published in BMC Public Health. The third research paper (Chapter Seven) has been resubmitted with minor corrections to PLoS One. I have included the research papers in this thesis using standard formatting, rather than the journal formatting, however, the published articles are included in the Appendix.

In **Chapter One** (presented here) I have provided some very brief background to the overweight, obesity and diabetes challenge globally and in India before providing some rationale for the research that I have undertaken. I have outlined the main aims and objectives of the thesis, before breaking down the structure of the thesis. I then provide information on collaborating institutions and research funding, ethical clearance, and my role in the research.

Chapter Two contains a review of the relevant literature. In the first part I review the literature on the association between SEP and overweight and obesity. Specifically, I review the literature on the association observed in LICs and MICS; review possible reasons for the positive association in countries at early stages of development; and describe the literature on the negative association commonly seem in HICs. I then review the literature on this association in both nationally-representative and community-based studies in India. The second section of the review provides a detailed breakdown on models used to predict future overweight and obesity in a number of international contexts, following a logical order based on model complexity. This is followed by a review of the very limited forecasts on overweight and obesity in India. The third section of the literature review follows a similar structure to the second, however, focusing on forecasts of diabetes prevalence. Finally, in the fourth section I review the literature focused on providing estimates of lifetime risk of diabetes.

In **Chapter Three** I provide detailed context to the overall thesis. Firstly, I describe the demographic and epidemiological transition in India. I then describe recent trends in overweight and obesity in India, before discussing recent trends in global and India-specific diabetes prevalence. This is followed by a brief overview of current healthcare spending, in addition to national policy related to overweight and obesity, and diabetes. Finally, I explain why India is an important and relevant setting to explore my research questions.

Chapter Four contains an overview of the data and methods used in the thesis. In the first section, I provide a detailed description of the National Family Health Survey (NFHS), how the Standard of Living (SoL) index used as a proxy of SEP was calculated and describe a formalised version of the models to be used in Chapters Five and Six. In the next section, I provide a detailed description of the parameters I needed to obtain forecasts of future overweight and obesity prevalence. I then describe the process used to calculate the diabetes forecasts, before explaining how estimates of lifetime risk of diabetes were obtained.

Chapter Five is a research paper that analyses the socioeconomic patterning of overweight and obesity (combined) among urban and rural ever-married adults in India between 1998 and 2016 among women (15-49 years) and between 2005 and 2016 among men (15-54 years). Repeated cross-sectional data from the NFHS collected in 1998-99, 2005-06, and 2015-16 was used, and combined overweight and obesity was defined as a BMI$\geq$25kg/m^2. Two variables were used to proxy SEP: firstly, a measure of educational attainment and secondly a SoL index. Multilevel logistic regressions were adopted to examine trends in the prevalence of combined overweight and obesity by SEP.

In **Chapter Six** I include a research paper examining how trends in the socioeconomic patterning of overweight/obesity (combined) has varied between India's most and least economically developed states in recent decades. As in Chapter Five, the study used geographically-representative data from five of India's least and most developed states from the NFHS in 1998-99, 2005-06, and 2015-16. A measure of combined overweight and obesity was the main outcome (defined in the same way as in Chapter Five), educational attainment and a SoL index proxied SEP, and multilevel logistic regressions were used to assess the trends in the socioeconomic patterning over the study period.

Chapter Seven forecasts the future prevalence of overweight and obesity separately among Indian adults (20-69 years) by urban and rural areas, and by five-year age groups, through to 2040. In this study, multi-state lifetables were used. Transition parameters were derived from a range of sources: NFHS 3 (2005-06) and 4 (2015-16) were used to estimate the incidence of overweight and obesity among individuals aged 20-49 years, the Study on global AGEing and Adult Health (SAGE) waves 0 (2002-04) and 1 (2007-10) were used to estimate the incidence of overweight and obesity in older ages, and the Sample Registration System (SRS) abridged lifetables were used to estimate current and future mortality rates. I used relative risks derived from the literature to appropriately scale transition parameters. I additionally explore how the future prevalence of overweight and obesity will change under different future assumptions, such as high future urbanisation and annual increases in the incidence of overweight and obesity.

In **Chapter Eight**, I used a dynamic simulation model, using transition probabilities, to estimate the prevalence of diabetes among urban Indian adults (20-69 years) to 2040 using predicted overweight and obesity prevalence from Chapter Seven. I obtained estimates of diabetes prevalence from the Indian Council for Medical Research India Diabetes Study (ICMR-INDIAB) study (2008-13), diabetes incidence from the Centre for Cardiometabolic Risk Reduction in South-Asia study (CARRS); mortality rates from the SRS abridged lifetables; and smokeless tobacco consumption data from the Global Adult Tobacco Surveys (GATS) in 2009-10 and 2016-17. I tested the effect on future prevalence of diabetes of future changes to diabetes incidence, and future changes to overweight and obesity prevalence.

Chapter Nine includes the final research paper of this thesis which estimates the lifetime risk of diabetes for urban Indian adults aged 20 through 79 years, both overall and separately by BMI status. I used incidence data from the CARRS study and mortality rates derived from the SRS to build the model. Furthermore, I present estimates of diabetes-free life expectancy, by age and BMI, for urban Indian adults.

Finally, **Chapter Ten** discusses the findings of the thesis. This includes a summary of the main findings, an overview of the general limitations and strengths of the thesis, potential avenues for further research and recommendations for future survey data that would advance this research. I then discuss a number of implications of the findings, before providing a conclusion to the thesis.

1.4. Collaborating Institutions and Funding

The collaborating institutions for this research were the London School of Hygiene and Tropical Medicine (LSHTM) and The Emory Global Diabetes Research Centre at the Rollins School of Public Health, Emory University in Atlanta, Georgia. Research funding was obtained from the Economic and Social Research Council (ESRC) grant number: ES/J500021/1.

1.5. Ethical Clearance

Ethical clearance for the use of the secondary data sources were obtained from the ethics committee at the London School of Hygiene and Tropical Medicine. Secondary survey data was anonymised before I obtained it, and data for use in Chapters Eight and Nine were aggregated before I obtained it. I have included the ethics approval confirmation letters in the Appendix.

1.6. Role of the candidate

I, the candidate, designed all the studies in this thesis, with assistance from either my supervisors, the Advisory Committee, or external collaborators. I obtained non-publicly available data myself through either the Measure DHS website, or through co-authors. I conducted all of the data analysis and interpreted findings with input from co-authors. I produced the initial draft manuscripts for each of the research papers and the body of this thesis, and subsequently included revisions suggested by co-authors. A breakdown of my role in each of the research papers is included in the research paper cover sheet.

Chapter Two. Literature Review

In this chapter, I provide a review of the relevant literature related to the socioeconomic patterning of overweight and obesity, forecasts of future prevalence of overweight and obesity, forecasts of future diabetes prevalence, and existing research investigating the lifetime risk of diabetes. I provide an overview of literature from both international studies and research conducted in India.

2.1. Socioeconomic patterning of overweight and obesity

The association of overweight and obesity with SEP has been the subject of a number of studies and systematic reviews in recent decades. In 1989, Sobal and Stunkard reviewed over 144 published studies written on the association between SEP and obesity and concluded that this effect was considerably modified by the level of economic development of the society in question[41]. More specifically, in LICs, a positive association was observed among men, women and children, whereas a negative association was found among women in HICs. Another systematic review of 333 published studies up to 2004, identified similar trends in the association between obesity and SEP, however the strength of association varied by the indicator used[39]. In HICs, the negative association was found to be more common when using education or occupation as the indicator of SEP, whereas in LICs, a positive association was more often observed when using a measure of income as the main exposure.

A more detailed message was presented in Monteiro et al (2004), which reviewed 14 papers on the same association in LICs and MICs[32]. Among women, 10 of the 14 studies found a higher prevalence of obesity among lower SEP respondents, marking a negative relationship, and concluded that the association of obesity and SEP crosses over from a positive one to a negative one after a country achieves a Gross National Income (GNI) per capita of approximately US$2500. This threshold level of GNI per capita was revised down to US$1000 by Dinsa et al (2012) who reviewed 42 studies in LICs and MICs, and ultimately concluded that the association is either negative or mixed when examining the association among women and men, respectively, in MICs[30].

In Section 2.1 I review the literature on the socioeconomic patterning of overweight and obesity among adults in a number of international and India-specific studies. I will address posited reasons for the commonly observed positive association in LICs, and the negative association that is characteristic of HICs using examples from international studies. I subsequently review research reporting this association in studies using both nationally-representative surveys, and community-level studies in India.

2.1.1. The association between overweight and obesity and SEP in LICs and LMICs

2.1.1.1. Evidence from international studies

In LICs, the prevalence of overweight and obesity is commonly higher among individuals from a higher SEP compared to a lower SEP. Evidence for this positive association has been demonstrated consistently in literature from a number of studies.

A study using nationally-representative data from Brazil, collected in 1989 (when Brazil was considered a developing country and its GDP per capita was lower than the global average[8]), found that the prevalence of overweight and obesity was almost three times higher among men in the highest income quintile compared to the lowest[42]. Another study using nationally-representative population-based household survey data in Brazil found that the age-adjusted prevalence of obesity was around 1.5 times higher among the 25% richest Brazilians compared to the 25% poorest (measured by income), and that this association persisted in surveys conducted in both 1975 and 1989[43].

Demographic and Health Surveys (DHS) conducted in Sub-Saharan Africa have also detected similar socioeconomic disparities in overweight and obesity prevalence. A recent study using DHS data from Ghana in 2014 found that 75.3% of parous reproductive-aged women in the highest wealth quintile were either overweight or obese (BMI $\geq$25.0kg/m^2), compared to only 15.9% among those in the lowest wealth quintile. Similarly, the prevalence amongst those with secondary or higher education was 66.6%, compared to 27.5% among those with no education[44]. Another study examining the socio-demographic correlates of overweight and obesity (combined) using data from the 2011 Ethiopia DHS identified double the prevalence of combined overweight and obesity among reproductive-aged women in the highest wealth quintile, compared to the lowest[45]. Using seven DHS surveys between 1992 and 2005 to examine trends in the association of overweight and obesity with socioeconomic status in sub-Saharan Africa, Ziraba et al (2009) concluded that the odds of overweight and obesity was consistently higher among the urban rich population relative to the urban poor in all surveys (irrespective of whether household wealth or educational attainment was the exposure of interest), however the extent of the higher odds decreased over time[46].

Similar results have been found using different measures of SEP, for instance urban areas, compared to rural areas. Neuman et al (2013) conducted a study investigating the association of BMI with urban/rural residence using 38 DHS surveys between 1991 and 2010 and covering almost 700,000 women of reproductive-age. Their results for LICs identified 1.5 times higher mean BMI in urban areas compared to rural areas, which was fully accounted for after adjusting for household SEP[47].

2.1.1.2. Evidence from South Asian studies

A number of studies focused on South Asia have also investigated the association of overweight and obesity with SEP. A study in Bangladesh found an 8.1 times higher prevalence of combined overweight and obesity between 2000 and 2004 among rural women with higher education compared with women with no formal education[48]. Another study using the Bangladesh DHS in 2004 found 1.7 and 2.4 times higher odds of overweight and obesity (relative to normal weight), respectively among high, compared to low, socioeconomic status women[49]. A more recent study, using five pooled Bangladesh DHS surveys from 1999 to 2014, found a 5.6 times higher risk of obesity and 2.3 times higher risk of overweight (reference: normal weight) among urban women from the highest wealth quintile, compared to the lowest. In rural areas, the investigators found 7.9 times higher odds of obesity and 3.4 times higher odds of overweight between the highest and lowest wealth quintiles[50]. Janjua et al (2015) identified a similar association in Pakistan, where women from the highest wealth quintile had 6.8 times higher odds of obesity compared to women in the lowest quintile[51]. Using the Nepal DHS from 2006, Balarajan and Villamor (2009) identified a 4 times higher prevalence of overweight and obesity (combined) in the highest wealth quintile, compared to the middle quintile, whereas no significant difference in combined overweight and obesity prevalence was found at different levels of educational attainment. Conversely, the authors found positive associations between SEP and combined overweight and obesity in Bangladesh in 2004, irrespective of whether wealth quintile or educational attainment was used as the primary socioeconomic measure[52].

2.1.1.3. The changing association with economic development

Accompanying economic development, industrialisation and urbanisation, are shifts in the association between SEP and overweight and obesity. Literature from a number of transitioning LICs and LMICs have documented larger increases in the prevalence of overweight and obesity among lower socioeconomic groups compared to higher ones, leading to an attenuated positive association, and crucially at a certain level of development, a switch to a negative association[30,32,53].

A higher prevalence of combined overweight and obesity among women working in higher occupational classes, compared to agriculture and production, was found in one study analysing this association in 33 LICs and MICs[54]. The same study however found larger increases in overweight and obesity prevalence between 1992 and 2009 among the latter group[54]. Another study using anthropometric and socioeconomic data from 39 LICs and MICs identified a larger increase in the prevalence of combined overweight and obesity among low-income, relative to high-income, women between 1991 and 2008[53,55]. Ziraba et al's (2009) study that investigated the trends in the socioeconomic patterning of combined overweight and obesity in seven African countries also found that despite a positive association, the increase in prevalence between 1992 and 2005 among poorer individuals (measured using household wealth and education) was around 50%, compared to only 7% among the richest[46]. Monteiro et al (2004) reported that the 1.6 times higher age-adjusted prevalence of obesity among the richest 25% of Brazilians (measured by income), compared to the lowest, declined to a prevalence ratio of one between 1975 and 1997; a period of considerable economic development[43]. Large increases in the prevalence of excess weight among low-income women has also been reported in Vietnam between 1992 and 2002, a period over which Vietnam's economy doubled[56,57].

2.1.1.4. Differences in the association by sex

Literature has consistently reported that this changing association between overweight and obesity, and SEP, is found to happen at lower levels of economic development for women compared to men. A study investigating the socioeconomic patterning of obesity in South Africa, a MIC, found that higher SEP men have a higher risk of obesity compared to lower SEP men. On the other hand, women of different SEPs did not differ in their risk of obesity[58]. Similar results have been found in Brazil, where the prevalence of overweight and obesity has not been found to differ between women of different income quintiles[42]. In Zhejiang, a province of China undergoing a socioeconomic transformation, high-income men had a higher risk of obesity compared to low-income men. On the other hand, higher SEP women had a lower risk of obesity compared to women with lower SEP women[59]. Similar results were found by Zhang et al (2017) who reported a negative association between overweight and SEP among adult women (measured by higher levels educational attainment) in Tianjin, China, whereas a positive association was found among men[60]. Monteiro et al's (2004) review concluded that of the 13 papers that met their inclusion criteria (for instance, inclusion was contingent on the study sampling both men and women, and being conducted in a developing country), a positive association between SEP and obesity was observed in seven of the studies on men, and no negative associations were reported in any of the studies. On the other hand, among women, a positive association was observed in two studies, whereas a negative association observed in 10 of the 13 studies[32].

2.1.1.5. Why is SEP positively associated with overweight and obesity in LICs and some MICs?

The demographic transition (where a society transitions from having high fertility and mortality to low fertility and mortality), and the epidemiological transition (characterised by a transition from a high prevalence of infectious diseases to NCDs) are both accompanied by a concurrent nutrition transition[30,61,62]. Simply, urbanisation and increased incomes that accompany economic growth is associated with a reduced intake of carbohydrates and fibre, whilst consumption of fats and sugars increase[61,63]. However, although all countries are expected to progress through the nutrition transition, the cheaper cost of oils and fats in a more economically interdependent world, in addition to rapid rates of urbanisation, has meant that LICs are experiencing the nutrition transition at lower levels of aggregate economic development than countries that transitioned previously[61]. Shifting patterns of consumption in India are particularly characterised by increased intake of sugary foods and dairy products, an issue initially affecting high-income rural residents, and urban residents[64].

The reasons driving this socioeconomic disparity in overweight and obesity are not well explored. However, consistent with the theories around food availability and urbanisation in developing countries, papers reviewing the socioeconomic patterning of overweight and obesity have suggested that lower SEP individuals are protected from excess weight due to an inability to meet nutritional requirements. On the other hand, the relatively cheap prices of fatty, energy-dense foods for higher SEP individuals enables them to surpass their nutritional needs in environments characterised by relative food scarcity[30,32,46].

Other theories suggested to explain why the poor are protected against overweight or obesity include an increased likelihood of working in manual labour, with relatively high energy expenditure[30,32,41,43,47,65–68]. On the other hand, for higher SEP individuals, higher education among can improve both employment opportunities and opportunities for autonomy which can lead to less physical activity and increased consumption of fatty foods[32,69].

These mechanisms have been explained to happen at times when there are generally favourable impressions of larger body sizes in LICs[30,32] which may encourage excess food consumption among higher SEP individuals. Fernald (2009) reports evidence of this phenomenon across number of middle-income countries[30,70]. Additionally, Holdsworth et al (2004) also found, in a study among urban Senegalese women, that overweight was considered as a positive and desirable body size[30,71].

2.1.2. Association of overweight and obesity with SEP in HICs

2.1.2.1. Evidence from international studies

In contrast to the positive association between overweight and obesity and SEP in societies at early stages of economic development, in HICs overweight and obesity is associated with a lower SEP[30,32,39,41].

Nationally-representative data from three birth cohorts (1946, 1958 and 1970) in the United Kingdom, has been shown to find evidence of a higher mean BMI (consistently above the BMI threshold for overweight classification) among individuals in the lowest occupational social class, compared to the highest, in all of the waves analysed. Additionally, a continuing divergence in mean BMI over time between the highest and lowest occupational social classes among women has been documented[72]. In Organisation for Economic Cooperation and Development (OECD) countries, lower rates of education have been found to be strongly associated with higher rates of obesity. One study using national health surveys from 11 OECD countries found absolute differences in the obesity prevalence between the highest and lowest educational group as high as 18.3% points and 18.9% points, among Hungarian and Spanish women, respectively. The authors further concluded larger inequalities among women compared to men[73].

Using the Centers for Disease Control and Prevention's (CDC) Behavioural Risk Factor Surveillance System data between 1995 and 2008, a study investigating the effect of socioeconomic factors on obesity in Southern States in the US have identified positive independent associations, in all states, between the overall obesity rate and the percentage of people living below the poverty line, the percentage receiving food stamps, the unemployment rate, and the income level. The authors further concluded that higher BMI was driven by economic factors, in addition to consumption of, and expenditure on, low-quality foods[74]. Another study identified a three-times higher odds of obesity among adult German women in the lowest income bracket (relative to the highest), and 1.7 times higher odds of obesity among women in the lowest educational group (relative to the highest)[75].

Another European-focused study, using cross-sectional data on over 3000 middle-aged and elderly men, identified a significantly higher odds of having a large waist circumference (WC) - used sometimes to measure obesity - among men with below high school education relative to those with college education, and that both smoking, and physical inactivity predicted large WC[76].

2.1.2.2. Why is SEP negatively associated with overweight and obesity in HICs?

In HICs, affording a healthy low-calorie diet has been found to be a more pressing concern than food scarcity, among lower SEP individuals[30]. For instance, one study has reported that in rural South Africa, healthy food choices cost 30% more per month than an average diet for a five-person household[77]. Another study has reported socioeconomic inequalities in the energy cost of foods purchased in supermarkets in the United States, and found that being from a lower SEP, defined by education and household income, is associated with purchasing cheap high-calorie foods with high fat content[78]. In their review on the association between obesity, quality of diet and food costs, Drewnowski and Specter (2004) not only reported a negative association between affluence and rates of obesity, but that this may be associated with the low cost of energy-dense foods that are relatively affordable to lower SEP individuals[79]. Such assertions are supported by a report by the European Commission which stated that in the European Union, up to 60% of manual workers and 57% of unemployed people struggle to afford healthy diets[80]. The increasing affordability of high-energy diets along with media and fast food commercialisation reaching lower SEP individuals in transitioning countries, may partly explain why the association of overweight and obesity with SEP reverses on economic development[81].

Conversely, higher SEP individuals in countries at more advanced stages of the epidemiological transition are able to afford and consume low-calorie healthy diets, where fat intake is reduced and consumption of fruits and vegetables are more commonplace[39,79,82–85]. This increased ability to afford healthier foods among higher SEP individuals, has also been suggested to occur due to thinner body sizes, rather than larger bodies, being favoured to project an image of higher social status[39].

Changes in the nature of work and cheap energy-dense diets available in countries undergoing rapid development are also driven by fast urbanisation rates – for instance, in India, the proportion of the population living in urban areas is projected to increase from 32.8% to 52.8% between now and 2050[9]. In their review of the association between excess weight and SEP in Sub-Saharan Africa, Ziraba et al (2009) report that rapid urbanisation can reduce risk of underweight and increase overweight prevalence through exposure to less physically exerting jobs and increased access to energy-dense diets, which can replace jobs previously undertaken by lower SEP manual workers. Additionally, susceptibility of lower SEP individuals to overweight may be further promoted by both a lack of means, and knowledge to adopt healthier behaviours[46,66].

2.1.3. Association of overweight and obesity with SEP: Evidence from India

Although currently outdated, past associations between SEP and overweight and obesity in India have been explored in the literature, with evidence from both community studies and nationally-representative studies using survey data.

2.1.3.1. Results from nationally-representative surveys

Large nationally-representative surveys have been used to examine the association between overweight or obesity and SEP in India. One or more NFHS data sets - repeated nationally-representative cross-sections which collected anthropometric data in 1998-99, 2005-06 and 2015-16 - have been used in a number of studies.

Using a single cross-section from 2005-06, Siddiqui and Donato (2016) reported an increasing probability of being classified as either overweight or obese with increasing levels of wealth, determined using an asset-based wealth index. A particularly large measure of effect was observed in rural areas. This result was consistent among men and women in both urban and rural areas. Using years of education as a proxy of SEP, the authors also found a declining probability of combined overweight and obesity after the seventh year of education among urban women. This finding is in line with literature demonstrating that among women in economically developing areas, the association of SEP with overweight and obesity turns negative earlier than amongst men[86]. Another study using the same data found double the risk of being overweight and a three -times higher risk of being obese among 'non-poor' urban participants (classified using an asset-based wealth index)[87]. Similar results have been reported elsewhere[52].

Furthermore, pooled NFHS datasets has been used in analyses to examine trends in the socioeconomic patterning of overweight and obesity over time. Given India's economic development since economic liberalisation in the early 1990s[88], one might expect any positive association of overweight and obesity with SEP to approach a negative association in subsequent surveys. Subramanian et al (2009) however reported no change in the association between BMI and SEP (measured using an asset index) between 1998-99 and 2005-06 among reproductive-aged women in both urban and rural areas, and ultimately concluded that overnutrition remains a disease primarily affecting higher SEP individuals (data for men was not available in 1998-99 to assess trends in the association)[89]. Another study reported a reduction in the positive association between overweight and obesity in a selection of Indian states defined by an overall high prevalence of overweight, whereas they found an increase in the positive association in states with high levels of underweight[90]. This is consistent with the literature stating that more economically developed areas are likely to have a negative or smaller positive association when compared to less economically developed areas.

Studies using other nationally-representative data sets have found an increased risk of overweight and obesity among higher SEP individuals, measured in a variety of ways. A study using the first wave of the Study on global AGEing and adult health (SAGE) in 2007-10 found increased odds of obesity (using waist circumference (WC) to define central adiposity and BMI to define excess weight) among participants aged 50 years or more from a privileged caste, or among those with higher education[91]. Another study using the nationally-representative National Nutrition Monitoring Bureau (NNMB) national survey in 2011-12 found similar results, whereby the odds of central adiposity and excess weight was highest among adult women living in high quality housing, with a high level of literacy, working in the business sector, and with a high individual income[92].

2.1.3.2. Results from community/cohort studies

In addition to nationwide studies, many smaller scale community-level studies have been conducted exploring the same associations.

A cross-sectional survey of around 4000 adults from 1154 households in rural and peri-urban Telangana state in 2012 found that men with a higher SoL had more than double the prevalence of BMI-defined obesity (23.3%) compared to men with a lower SoL (10.6%). A similar relative prevalence of obesity between high and low SEP women was also identified (25.9% vs 12.8%). Contrastingly, the same study identified a larger WC (sometimes used as an alternative measure of overweight or obesity) among both men and women with lower education compared to participants with some education[93]. Similar positive associations of obesity and SEP were found in a study using data from the Indian Migration Study (IMS), collected between 2005 and 2007, whereby around 2000 individuals, primarily from rural areas of four large Indian states were included for analysis. The study reported an almost three times higher prevalence of obesity among high SEP women (39.0%) compared to lower SEP counterparts (13.0%)[94]. These findings are supported by other community studies in rural India. One study in rural West Bengal found 4.4 and 5.8 higher odds of overweight (defined as BMI>23kg/m^2) among men and women respectively in the highest wealth quintile compared to the lowest in 2017. Slightly attenuated results were found when using education as the main exposure. Men with 11+ years of education had 3.3 times higher odds of overweight relative to participants with no schooling[95]. Another study in rural South India found increased odds of overweight (BMI≥23kg/m^2 and <25kg/m^2), obesity class I (BMI≥25kg/m^2 and <30kg/m^2), obesity class II (BMI≥30kg/m^2), and higher BMI among adults aged 20-80 years who were from higher wealth quintiles compared to lower wealth quintiles. On the other hand, higher prevalence of underweight was found among poorer individuals, representing a dual burden of over and under-nutrition split along socioeconomic lines[96].

This association has been found to persist in community studies focused on urban areas. One study aiming to determine the association of socioeconomic indicators with CVD risk factors in 11 cities in urban India found a higher prevalence of overweight and obesity among individuals with perceived high, compared to low, SEP. Similarly, the prevalence of overweight and obesity was reported to be lower among adults with fewer years of education. Individuals with lower levels of education were also found to be less likely to consume a high fat diet[97].

2.2. Forecasts of overweight and obesity

Estimates of future trends in the prevalence of overweight and obesity is likely to increase in importance as the world continues to become more urbanised[9] and people reside in more obesogenic environments. Previous trends suggest that the total number of adult women classified as obese has increased five-fold, from 69 million to 390 million between 1975 and 2016. Moreover, the number of obese men has increased almost nine-fold over the same period (31 million to 281 million)[2]. Predictions of future overweight and obesity can be useful in identifying subpopulations that are particularly vulnerable, in addition to providing evidence upon which future health decisions, particularly regarding resource allocation, can be based[98]. In this section, I will review the literature on forecasts of excess weight both globally and in India and will discuss the various models in order of their complexity.

2.2.1. Simple prediction models

One of the simplest methods used to forecast future overweight and obesity is to firstly estimate age-specific prevalence rates in a particular baseline period and make future estimations of *total* future prevalence and absolute burden by applying those age-specific prevalence values to future age-specific population projections. Adopting this approach, Kelly et al (2008) estimated that 23.9% (1350.4 million people) and 10.1% (573.0 million people) of the global population will be overweight and obese, respectively, by 2030, with the highest future prevalence expected to be in the 'Established market economies' (mostly HICs)[99]. Although simple to calculate, this approach can lead to a substantial underestimation of the future prevalence of overweight and obesity as age-specific prevalence is not likely to remain constant over a forecast period. For instance, urbanicity (which is expected to increase from 53.9% to 68.4% between 2015 and 2050[9]) may be associated with an increasing incidence rate of overweight and obesity as consumption of energy-dense foods and sedentary lifestyles become more prevalent. A positive association between sedentary behaviour and increased risk of obesity has been demonstrated in India[100].

2.2.2. Forecast models applying annual rates of change

Another approach used in several studies has involved modelling future trends in overweight and obesity as a function of previous trends. In addition to assuming constant age-specific prevalence, Kelly et al (2008) used the most recent secular trends in the prevalence of overweight and obesity and concluded that 38.1% of the world's population would be overweight in 2030, whereas 19.7% would be classified as obese. This assumption also suggested that China would be the world region with the highest prevalence of overweight (59.7%), whereas Latin America and the Caribbean would have the highest overall prevalence of obesity (38.3%), by 2030[99]. Wang et al (2008) estimated the future prevalence of overweight and obesity in the United States based on the continuation of an annual average increase in prevalence over the past three decades, using data from the nationally representative National Health and Nutrition Examination Survey (NHANES). Their model predicted that by 2048, *all* American adults would be either overweight or obese, and the prevalence among black women would reach 100% by 2034[101].

Such models are limited by the problematic assumption that as the proportion of a population who becomes overweight or obese increases, the proportion of the population at risk of becoming overweight or obese remains constant. In reality, the proportion of the population at risk of becoming overweight or obese declines as a larger proportion become overweight or obese[102]. This is likely to lead to considerably overestimated findings, for instance, Wang et al's (2008) finding that 100% of US adults will be overweight or obese by 2048[101]. Unrealistic findings are particularly more common the longer into the future the predictions are made[102].

A compositional approach in a regression framework has been adopted in by some studies[103,104]. This approach is similar to using annual rates of change, however, transformed prevalence for multiple BMI categories (for instance, underweight, normal weight, overweight, and obese) are projected simultaneously, not allowing the sum of the prevalence across BMI groups to exceed one[104]. Transformed prevalence can subsequently be projected using either a linear or non-linear time trend. One study adopting the compositional approach found that the prevalence of obesity will increase from 18.0% to 22.2% between 2013 and 2030, assuming a non-linear time trend, and 19.4% to 30.4% using a linear time trend, among men in Quebec, Canada, aged 18 years or more. The equivalent results among women was an increase from 15.5% to 18.2% assuming non-linearity of future trends, and 16.3% to 22.4% under the linear assumption[104]. This model has also been used to estimate the projected morbid obesity prevalence in the UK to 2035[103].

Rather than forecast the future prevalence of overweight or obesity, other studies have focused on predicting future mean BMI. Wang et al (2007) adopted a regression model for the USA whereby birth cohort and survey year were used as covariates against a mean BMI dependent variable, enabling age-specific predicted values to be extracted for future time periods and applied to a simulated population. Their findings suggested wide variation in 2010 prevalence of obesity by ethnicity, whereby the prevalence of obesity was highest among black women (55%)[105]. Another study using a similar approach to forecast future overweight prevalence in Australia from 2005 to 2025 found that the prevalence among men and women aged 20 years or more will reach 83% and 75%, respectively[106].

A limitation of forecasting mean BMI is the lack of accommodation for changes in BMI at other points across the BMI distribution which have been found to increase more at higher BMI values[106,107]. A model addressing this limitation conducted separate quantile regressions for BMI percentiles 1 to 99 and projected future BMI at particular percentiles using the time trend extracted from the regression. Using this method, the authors predicted that 77.6% of US adult men and 71.7% of adult women aged 20-74, respectively are predicted to be overweight by 2020, whereas 40.2% and 43.3% of men and women aged 20-74 years, respectively are expected to be obese[107]. Another study used a similar method to project future obesity rates in OECD countries to 2019 and found large increases in obesity in Australia, Canada, England and the United States between 2010 and 2019, at the same time as overweight prevalence was expected to remain stable or even decline. On the other hand, obesity was expected to grow at a comparatively much slower rate in Austria, France, Italy and Spain, whereas large increases in overweight were predicted[73].

2.2.3. Forecasts of overweight and obesity using covariate extrapolation

Another approach used to forecast overweight and obesity involves using a regression model to examine the relationship between the probability of overweight or obesity with a number of covariates, and subsequently apply the associations identified to extrapolations of covariates[73,102,108]. Finkelstein et al (2012) used this framework in forecasting future obesity and severe obesity in the United States to 2030 among adults aged 18 years or more. Specifically, the investigators regressed a number of individual-level, characteristics, state-level characteristics, and a non-linear time-trend against the probability of being classified as being obese or severely obese. State-level characteristics included the annual unemployment rate, prices of gas, alcohol and fast food, access to the internet, in addition to many others. To produce the forecasts, synthetic cohorts of the population were created and the coefficients from the regressions applied. Their findings suggested that 42.19% of the adult population would be obese by 2030, whereas 11.08% would be severely obese[108].

Such models are based on the assumption that the association between the probability of obesity with the covariates chosen will continue to hold into the forecast period, an unlikely assumption, for instance if government policies are introduced to changes such associations[73,102,108]. In the context of this thesis, it may be inappropriate to forecast future overweight and obesity based on the proportion of the population in different SEP categories, as various studies have reported a constantly changing association between SEP and overweight and obesity in LMICs, from a positive one to a negative one, over time[29,30,32,39]. Assuming a constant association between SEP and overweight and obesity could potentially lead to the underestimation of forecasted prevalence, especially if lower SEP individuals continue to constitute a substantial proportion of the total population in the future. This limitation is also likely to be more problematic with more covariates that need extrapolating, as each extrapolation will introduce additional uncertainty[102].

2.2.4. Dynamic simulation models

Dynamic simulation models are designed to track changes in an outcome over a specified time period. Groups of individuals, or simulated individuals themselves, are followed, with transitions through different BMI groups, ages, or migration routes determined by transition probabilities or rates[98]. They are useful in that future demographic changes, changes in incidence of a condition and parameter uncertainty can be packaged in a fashion whereby these various dynamics operate simultaneously and internally within the model, and different future scenarios can be tested with relative ease. Dynamic simulation models work well in the prediction of future overweight and obesity due to its ability to simultaneously incorporate non-linear trends, the delay between changes in past incidence and its effect on total prevalence, in addition to feedback loops[98]. A feedback loop, in the context of forecasting future overweight and obesity, could involve a reduction in future incidence of overweight and obesity in response to increased awareness of excess weight as the prevalence increases[109]. The packaging of epidemiological, societal (for instance urbanisation) and policy related effects in such a framework has made simulation modelling an appealing method in the forecasting of overweight and obesity.

2.2.4.1. Microsimulation models

One family of dynamic simulation models are microsimulation models. Microsimulation approaches in overweight and obesity forecasting generally begin with a simulated population with a particular BMI distribution at a baseline time point. This population is designed to represent a real population[98]. The model's forecasts are based on the random simulation of the population's BMI trajectory as they age up to a pre-determined forecast year[110]. Estimated transition parameters from one BMI value to another, based on a starting BMI, age and cohort, are then applied to the simulated population to inform an individual's BMI trajectory over the life course. Mortality rates for individuals based on one's sex, age, cohort and BMI are usually introduced as a competing transition for any simulated individual, and probabilities of giving birth are usually added to make the simulated population as realistic as possible[110]. Commonly, models operate in discrete-time and adopt a simplifying Markov assumption (that an individual's risk of transitioning to a different BMI, remaining at the same BMI, or dying, are based on current characteristics rather than any previous transitions)[98].

Microsimulation has been adopted in a number of overweight and obesity forecasting studies in HICs[110–114]. The Foresight team, affiliated with the Government Office for Science in the UK, estimated that the proportion of men aged 21-60 years classified as overweight will decline from around 44% in 1993 to 35% in 2050, whereas the proportion of women who are overweight will increase from 30% to 33% over the same period[110]. On the other hand, the proportion of adult men who are obese is expected to reach 60% in 2050, from 13% in 1993; among women the prevalence will increase from 16% to 54%, although a larger proportion of obese women are expected to have a BMI greater than 40kg/m^2[110].

Similarly, another microsimulation study in Australia found that the prevalence of overweight through 2025 is likely to remain relatively stable among adults. On the other hand, the prevalence of obesity is predicted to increase from 19% to 35% among adults between 1995 and 2025, whereas the prevalence of severe obesity was projected to almost triple, from 5% in 1995 to 13% in 2025[113].

Simulation models offer an easily interpretable framework within which one can test the effects of interventions designed to tackle overweight or obesity. Webber et al (2014) used microsimulation resembling the Foresight team's model to forecast the future burden of obesity and obesity related diseases in 53 countries, primarily in Europe. In 2030 their model projected that 4.0%, 4.6% and 2.1% of people across the 53 countries would have diabetes, CHD and stroke and cancer, respectively. Furthermore, the authors established that a reduction in the population BMI of 1% would cause around 365 incident cases per 100000 of CHD and stoke to be avoided, whereas a 5% reduction in population BMI would result in 1317 incident cases per 10000 of CHD and stroke being averted[114].

2.2.4.2. Macrosimulation models

In contrast to microsimulation models, macrosimulation models group individuals by particular characteristics, for instance, age, BMI group or urban/rural residence. Rather than track individuals, macrosimulation models track proportions of the population in each group; sometimes referred to as health states. Similar to microsimulations, transitions between health states or a death state, are determined based on a set of transition rates and mortality rates. Macrosimulation models generally use the proportions of the population in each health state, an estimate of the total population in the baseline period, the number of individuals entering the model at each discrete time step (in addition to their distribution across the states) and an understanding of how the transition (including mortality) rates are likely to evolve over the forecast period as input parameters. Uncertainty is often incorporated into the models by running multiple simulations, each time selecting a random set of parameter values from a specified range and distribution, also known as Monte Carlo simulations[98].

Basu's (2010) age-classified macrosimulation model, forecasting BMI distributions between 2004 and 2014 in the United States among children/adolescents and people aged 17 years or more, found that obesity levels are expected to remain relatively constant among US adults, whereas the prevalence of overweight is expected to increase over the period. One-year transitions between BMI groups were estimated using longitudinal data from the Medical Expenditure Panel Survey[115].

Simple macrosimulation models are usually sufficiently flexible to expand and answer more nuanced research questions. A study aiming to examine the reasons for a plateauing obesity prevalence in the United States for instance, expanded the Basu (2010) model to compartmentalise the population below the BMI classification for overweight into groups with different risks of transitioning to overweight (susceptible, exposed, and recovered). This expansion aimed to account for some diversity in the probability of becoming overweight among those who are not overweight (for instance, the exposed category represented individuals born into or residing in an obesogenic environment). Their results provided a particularly detailed understanding of the dynamics of future obesity in the United States, particularly the fact that the future level at which obesity will plateau is primarily driven by a combination of the probability of being born into an obesogenic environment and the birth rate. Additionally, the study found that obesity prevalence is likely to plateau around 2030, irrespective of any interventions. Such findings can play a crucial role in accurately monitoring the impact of future interventions[116].

Similar models have also been used to explore predicted future socioeconomic inequalities in obesity. In Australia, one study found that if all educational groups had the same probabilities of becoming obese, the projected difference in prevalence in 2025 between the lowest and highest educational group would decrease from 14% to 6%[40]. Another study incorporated an indicator of caloric imbalance to influence transition rates between BMI categories, which were determined by changes affecting the food environment or activity environments or changes to either the effectiveness or the use of services to regulate one's weight. Their findings suggested that efforts to maintain caloric balance among school children would do little to halt the increase in adult obesity[117].

2.2.5. Overweight and obesity forecasts for India

There is a considerable lack of studies aiming to forecast future overweight and obesity prevalence in India. Kelly et al's (2008) global forecasts, assuming age- and sex-specific prevalence of overweight and obesity estimated that 12.9% (134.8 million) adults would be overweight and 4.0% (42.2 million) adults would be obese by 2030 in India under the constant prevalence assumption. On the other hand, assuming a continuation of past prevalence trends pre-2005, they estimated that 27.8% (290.7 million) and 5.0% (52.1 million) of Indian adults would be overweight and obese, respectively, by 2030[99]. The extent of the underestimation in these previous estimates are demonstrated by the fact that 5.1% of women (15-49 years) and 3.2% of men (15-54 years) are *currently* classified as obese[19].

A more recent study using pooled nationally representative data from the nationally representative NNMB between 1991 and 2011, and the 2014-15 NFHS aimed to predict combined overweight and obesity among rural adults in six Indian states to 2035. The study adopted a linear model after visually examining 25 years of past trends, which they concluded best fit the data used. Their forecasts suggested that the prevalence of combined overweight and obesity would increase to approximately 20% among men and just over 20% among women. Their results also demonstrate considerable heterogeneity by state, whereby the prevalence in 2035 is predicted to reach 40% among men in Kerala, double what is expected among men in rural Gujarat[118].

2.3. Diabetes models

In this section, I will review selected literature related to models of diabetes that aim to forecast future trends in prevalence or estimate the lifetime risk of diabetes.

2.3.1. Forecasts of diabetes

Future increases in overweight and obesity are likely to contribute to an increasing proportion of the Indian population developing diabetes. This is of particular concern given the association of diabetes with conditions such as CVD and eye disease[11]. Reliable and accurate forecasting models of future diabetes prevalence can be useful in monitoring a country's progress in meeting diabetes related targets and predicting future resource requirements to tackle the growing challenge. In this section, I will review research aiming to predict future diabetes in a number of global studies before reviewing India specific studies. As in section 2.2, I review the literature in order of the complexity of methodology.

2.3.1.1. Results from international studies

Diabetes forecasts or projections have been employed by a number of studies globally. One of the most cited predictions of future diabetes are the estimates produced by the International Diabetes Federation (IDF) who aim to regularly report current estimates of the global burden and prevalence of diabetes. The IDF 8th Diabetes Atlas, released in 2017, report both current estimates of the diabetic population (aged 20-79 years) and projections to 2045, assuming constant age-specific prevalence and letting future estimates be a function of demographic change[11]. They estimate that the largest percentage growth in the number of people with diabetes will be in Africa, where the number will increase from 16 to 41 million, a 156% increase. In contrast, in Europe the number of adults with diabetes is expected to increase by only 16%, from 58 to 67 million adults. In South East Asia, the IDF region including India, the increase in the number of people with diabetes is expected to reach 151 million by 2045, up from 82 million in 2017 (an increase of 84%)[11]. Wild et al (2004)[119] applied a similar method using national survey estimates of diabetes prevalence, applying the estimates to similar countries (based on geographical proximity or socioeconomic standing), and used the baseline age-specific prevalence to estimate the 2030 population with diabetes based on a population projection. They found that the Middle East is the global region that is expected to have the largest increase in the number of people with diabetes (161% between 2000 and 2030), whereas the former socialist economies are predicted to have the smallest growth. India is the area of the world in this study with the highest expected number of people with diabetes, with over 79 million people in 2030. Globally, Wild et al (2004) project that the number of people with diabetes in 2000 will more than double by 2030, increasing from 171 to 366 million[119].

Although a useful starting point for global predictions, assuming a constant age-specific prevalence of diabetes, and modelling the future trends solely as a function of demographic changes is problematic as the age-specific prevalence is expected to change in line with previous changes in incidence of diabetes and mortality. Failure to account for this can lead to large underestimations in predictions. This is evident when comparing these studies as Wild et al (2004) predict that 366 million people 20-79 will have diabetes by 2030; a figure already surpassed by 2017 (the IDF estimate the global number of people with diabetes to be 425 million)[11,119].

Macrosimulation models using a Markov assumption[1], and incorporating diabetes incidence, baseline prevalence and future mortality in future prevalence estimates have been used in a number of studies. For instance, simple three state models (partitioning the population into 2 alive states – Diabetes and No diabetes, and one 'Dead' state) have been used to forecast future diabetes prevalence studies focused on the USA.[120,121] Using estimated incidence from the National Health Interview survey (NHIS) in 2000 to probabilistically pass individuals to the

[1] The commonly adopted Markov assumption, is a simplifying assumption, implying that the following state of a process is dependent on the current state, and not on previous states. In the context of diabetes forecasts, the probability of developing diabetes is dependent on an individual's *current* characterisitcs rather than characterisitcs in prior periods.

‘Diabetes’ state, Honeycutt et al (2003) estimated that the number of people in the United States with diabetes would increase from 12 million in 2000 to 39 million by 2050 (9.7% of the total population). The authors also reported that applying age-, sex-, and ethnicity-specific prevalence in 2000 to the 2050 projected population, would predict 24.4 million people with diabetes, 14.6 million fewer people than was predicted in the Markov model[120]. An updated model, using a baseline year of 2005, predicted that the number of people in the USA with diabetes will increase from 16.2 to 48.3 million between 2005 and 2050[121], 9.3 million more people than in the older model[120], driven by an increase in the incidence rate and a reduction in the relative risk of dying between 2000 and 2005[121]. Using more recent NHIS data, Lin et al (2018) found that the number of people with diagnosed diabetes will reach 60.6 million by 2060, up from 22.3 million in 2014; a doubling in prevalence from 9.1% to 17.9%[122].

More recent models, adding extra health states, for example informed by glycaemic level (placing individuals at relatively higher or lower risk of developing diabetes), have been conducted in different contexts. Boyle et al (2010), using data from the CDC in the USA, found that the prevalence of diabetes can expect to reach between 25-28% by 2050, from 14% in 2010. This was found to be primarily driven by increases in high-risk minority ethnic groups, population ageing and increasing longevity of people with diabetes[109]. A similar study using data from national health surveys to inform transitions in Iran, and partitioning diabetes those with diabetes by whether they were diagnosed or not, found a doubling of undiagnosed cases of diabetes between 2009 and 2030 (1 to 2.5 million), and a more than threefold increase in diagnosed cases, from 2.7 to 9.2 million over the same period[123]. Another study in Germany estimated that the prevalence of diabetes among individuals aged 40 years or more can expect to increase from 10.5% to 16.3% between 2010 and 2040. Additionally, using data on the cost ratio for an individual with diabetes compared to an individual without diabetes, the direct medical cost of diabetes will almost double from €11.8 to €21.1 billion between 2010 and 2040[124].

An appealing feature of dynamic simulation models to forecast future diabetes is the flexibility in testing future scenarios impacting a number of input parameters on the future prevalence or burden. Boyle et al (2010) for instance, modelled different future incidence scenarios to describe the sensitivity of their estimates to the inputs. The authors found that whereas a medium incidence/low mortality scenario was associated with an increased prevalence from approximately 14% to 32.8% between 2010 and 2050, a low incidence/high mortality alternative, could reduce the extent of this increase to 20.5% by 2050[109]. A similar study using longitudinal data from the Mexican Health and Aging Study found that without any intervention targeting future diabetes incidence in Mexico, the prevalence of diabetes among the population aged 50 years or more will increase from 19.3% to 34.0% between 2012 and 2050, whereas a reduction in incidence by 30% would reduce future prevalence by 5.4 percentage points, to 28.6%[125]. Another study tested a variety of different future intervention scenarios in the United States and found that an intervention, wherein broad diabetes risk reduction efforts were introduced, in combination with a structured lifestyle intervention (LSI) targeting individuals with impaired fasting glucose (IFG) would reduce the projected prevalence of diabetes from 22.7% to 21.3% in 2030. On the other hand, a strategy targeting high-risk individuals (with IFG and Impaired Glucose Tolerance (IGT)) would reduce the projected prevalence to 22.2% by 2030[126].

2.3.1.2. Using predicted overweight and obesity to estimate the future prevalence of diabetes

Future incidence of diabetes will be largely impacted by future trends in overweight and obesity. A number of models have directly incorporated future trends in overweight or obesity into models forecasting future diabetes. One advantage of such models is that data driven models predicting future overweight and obesity can be directly used in informing future population incidence of diabetes, rather than merely testing hypothetical scenarios. A study commissioned by the CDC designed a dynamic simulation model that directly examined effects on future diabetes of interventions targeting future obesity in the USA. Their estimates of future obesity were driven by both caloric balance (determined by caloric intake, physical activity and resting metabolism), and found that interventions reducing caloric intake by 3% between 2005 and 2015 can reduce the projected 2050 prevalence down from approximately 6% to 5%. Similar effects on future prevalence were also predicted if caloric intake was reduced by 2% and clinical management of diagnosed cases between 2005 and 2015 was increased from 70% to 85%[127].

Rather than using data driven estimates of future obesity, Al-Quwaidhi et al (2014) assumed a linear increase in obesity prevalence to inform predictions of 2022 prevalence of diabetes in Saudi Arabia[128]. The model they used was designed for the Mediterranean Studies of Cardiovascular disease and Hyperglycaemia (MEDCHAMPS) project whose overall aim was to examine the CVD burden in the Mediterranean, in addition to analysing cost-effective interventions to counter the growing CVD burden[129]. With obesity prevalence estimated to reach over 70% among women and over 40% in men, the model predicted that the prevalence of diabetes would increase from 11.1% in 1995 to 44.1% in 2022[128]. Additionally, their model verified a considerable underestimation in diabetes prevalence when using the constant age-specific prevalence method adopted by the IDF. Similar studies using the same obesity driven model has been used in other settings in the region, including Syria[130], Palestine[131], Turkey[132], and Tunisia[132]. This model additionally allows the testing of policies targeting reductions in obesity increases, in addition to changes in the proportion of the population who smoke, on future diabetes. Sozmen et al (2015) reported a predicted increase in type 2 diabetes in Turkey from 7.5% in 1997 to 31.5% in 2025 in the absence of policy targeting future obesity and smoking. Were the prevalence of obesity to decline by 10% and the prevalence of smoking to decline by 20% between 2010 and 2020, the model predicted a 10% relative decline in the diabetes prevalence by 2025[132].

Other models used to assess the impact of predicted obesity trends on future diabetes include microsimulation models in the United States and the United Kingdom (where collectively an additional 71 million people with obesity will lead to a further 6 million to 8.5 million additional people with diabetes by

2030)[111]. Another study focusing on 53 WHO European region members found a projected population prevalence of 4399 per 100000 population in the absence of future policy targeting BMI reductions; in contrast the prevalence in 2030 assuming a 5% decrease in population BMI is predicted to decline to 3771 cases per 100000[114].

2.3.1.3. Forecasts of diabetes: Results from studies in India

I identified very few studies predicting future diabetes trends in India. The IDF estimate, using the constant age- and sex-specific prevalence approach, has found that the number of Indians aged 20-79 years is expected to increase almost two-fold between 2017 and 2045, from 72.9 (55.5-90.2) million to 134.3 (103.4-165.2) million, making India the country with the highest number of people with diabetes globally[11]. Using a similar methodology however also including urbanicity as an additional driver of diabetes prevalence, Bommer et al (2018) estimated that the total prevalence of diabetes would reach 9.9% in 2030, from 8.7% in 2015. On the other hand, when merely applying a mean annual rate of change in the age and sex-specific prevalence of diabetes observed in all LMICs to India, the 2030 prevalence was predicted to be an additional 2.8 percentage points higher than under the assumption of a constant age-specific prevalence[133].

Using a dynamic three-state macrosimulation model adopting a Markov assumption, one study predicted that the prevalence of diabetes in India will increase from 5.4% in 2016 to 6.7% by 2030[134]. A key limitation of the model is the use of transition probabilities between states that did not vary by age and sex; a problematic assumption given variation in the incidence of diabetes by age found elsewhere[135]. Additionally, the adoption of a time-constant probability of developing diabetes is unrealistic given that overweight and obesity prevalence (combined) has increased considerably in recent years[18–20], and can be expected to continue. A sophisticated model initially conceived by Homer et al (2004)[127] including health states at different glycaemic levels was also adopted by Mishra et al (2018) to forecast the future prevalence of diabetes in the city of Varanasi, predicting a diabetes prevalence of 35.6% by 2030[136].

Microsimulation studies have also modelled future diabetes indirectly in India. Basu et al (2014) investigated the effect of a Sugar Sweetened Beverage (SSB) tax on future overweight and obesity prevalence, and diabetes incidence, and concluded that a 20% SSB tax would reduce overall diabetes incidence by 1.6% via a 3.0% reduction in the prevalence of overweight and obesity between 2014 and 2023. The effect of the tax was expected to increase if SSB consumption increased at a faster rate, leading to a reduction of 2.5% of incident type 2 diabetes cases between 2014 and 2023[137].

2.3.2. Models of lifetime risk of diabetes

The final objective of this thesis is the estimation of the lifetime risk of diabetes in India. Lifetime risk of diabetes is a useful measure that is easily interpretable and is able to communicate the remaining probability of developing diabetes for an individual without diabetes at a given age and set of risk factors[138]. Below I review the very limited literature on the lifetime risk of diabetes globally. All studies that explicitly aim to estimate lifetime risk of diabetes are limited to HICs using incidence-based models.

One of the first studies to estimate the remaining life time risk of diabetes used data from the NHIS (1984-2000) to estimate residual lifetime risk at various ages in the United States. The study identified a remaining lifetime risk of diabetes of 32.8% and 38.5% for men and women, respectively, at birth[35]. Using a system of multi-state lifetables and incidence data from a national study in Australia, Magliano et al (2008) estimated a remaining lifetime risk of diabetes among 25-year-olds of 38.8%[139].

Estimates of lifetime risk can vary significantly between different subpopulations, for instance ethnic/racial groups, groups with different glucose levels, and groups with different risk factors. Narayan et al (2003) identified considerably higher lifetime risks among the Hispanic population in the United States (45.4% and 52.5% among men and women at birth, respectively) compared to the White population (26.7% and 31.2% among men and women at birth, respectively)[35]. In Canada, among the 20-year-old First Nations population the lifetime risk of diabetes was 75.6% and 87.3% among men and women, respectively. On the other hand, the remaining risk was 55.6% for men not in the First Nations category, and 46.5% among female counterparts[138].

As would be expected, the remaining lifetime risk of diabetes has been found to be considerably higher among people with more risk factors for diabetes, compared to those without, or with fewer risk factors. A study in the United States estimated the remaining lifetime risk among individuals in different BMI classes and found significantly higher remaining risk among higher BMI groups. The remaining lifetime risk among 18-year-old men with a BMI greater than 35kg/m^2 was found to be almost ten times higher than among underweight men (70.3% vs 7.6%)[140]. Similarly, among underweight women, the lifetime risk at 18 years is 12.2% compared with 74.4% for those with a BMI greater than 35kg/m^2. The authors found similar variation between BMI groups when additionally stratifying by ethnicity, whereby the highest lifetime risk at every age was observed among the Hispanic population[140].

Expanding on this idea, Djoussé et al (2011) estimated the remaining lifetime risk of diabetes among groups with different clustering of risk factors for diabetes, including an individual's physical activity, smoking behaviour, weight status, and dietary intake. Among men with none of the risk factors, the remaining lifetime risk at age 45 years was 7.3%, whereas the men with four or more of the risk factors had a 30.5% probability of developing diabetes in their remaining life. The remaining risk was similar among women, whereby there was a 6.4% probability of developing diabetes among 45-year-olds with no risk factors, compared to 31.4% for women with four or more risk factors. Similar results of increasing lifetime risk with excess weight, measured by both BMI and WC, were found in the Netherlands[141].

Lifetime risk of progression to diabetes has also been found to vary by baseline glucose levels. A study in the Netherlands, using data from the population-based Rotterdam study, estimated the remaining lifetime risk among individuals with Normal glucose tolerance (NGT), prediabetes, diabetes. The remaining risk of progressing from NGT to prediabetes at age 45 years was 48.7%, whereas the probability of progressing to diabetes was 31.3% among adults with NGT, and 74.0% among those with prediabetes[141].

Trends in the lifetime risk of diabetes have also been assessed using a Markov matrix model framework by using trends in incidence among different cohorts in the NHIS. Findings show the importance of using the most-up-to-date data to estimate lifetime risk as the most recent cohort (2000-11) of men had a 20 percentage point higher lifetime risk at 20 years compared to the 1985-89 cohort[142], and women had a 13 percentage point higher lifetime risk.

2.4. Conclusion

In this chapter I have provided an overview of the existing literature relating to the general themes of this thesis. Regarding the socioeconomic patterning of overweight and obesity, there is consistent evidence of a positive association between SEP and overweight and obesity in LICs, and an inverse association in HICs. Posited reasons for this initial positive association are the ability for higher SEP individuals to exceed nutritional requirements, and greater uptake of a less physically active lifestyle. On the other hand, in HICs the higher prevalence among the poor is driven by the ability to afford high calorie energy-dense diets but not low-calorie nutritious diets. The reversal in the association between overweight and obesity and SEP that occurs with economic development appears to occur at lower levels of economic development among women compared to men. Although research from both nationally-representative and community studies in India show a consistently higher prevalence of overweight and obesity among higher SEP individuals, recent economic development and diversity in economic development nationwide would imply that the current socioeconomic patterning is still unknown, and the association may now be negative among certain subpopulations.

The next subsection of this chapter reviewed various models used to predict the future prevalence of overweight and obesity globally, in addition to their limitations. The models vary in their sophistication and inputs required. Simulation models appear to offer a particularly elegant and flexible mechanism through which future overweight and obesity can be modelled, in addition to easily testing future scenarios of input behaviour on future predictions. Furthermore, the ability of simulation models to reflect both future expected demographic change in the future predictions of overweight and obesity, and model the real-life lag between past changes in incidence on future prevalence appear to make them preferable to models discussed earlier in the section. Despite this, no attempt to model future overweight and obesity in such a way has been attempted for India, and previous efforts rely solely on the extrapolation of previous trends.

In my review of models used to predict the future prevalence of diabetes, I firstly reviewed results from international studies, before covering the very limited models used to predict diabetes in India. Although in all studies, diabetes is predicted to continue to increase into the future, studies using the simplistic assumption of a constant age-specific prevalence of diabetes (using demographic change as the sole driver of future increases in population prevalence) can lead to considerable underestimates of future diabetes prevalence. Nevertheless, under this assumption, India is predicted to have the highest number of people with diabetes worldwide by 2045[11]. Simulation models incorporating estimates of diabetes incidence offer greater flexibility whereby the effect on future prevalence of future changes to incidence and future overweight and obesity can be easily incorporated. Despite Indians having a predisposition to developing diabetes, and currently having the second highest number of people with diabetes worldwide, there is a notable gap in the literature, whereby long term forecasting of the future prevalence of diabetes using both carefully collected up-to-date data and incorporating overweight and obesity inputs in a coherent and flexible model, has not been properly explored.

Finally, models of lifetime risk of diabetes offer a depth of understanding beyond what prevalence estimates are able to provide, with information on how the disease impacts an individual, and alluding to whether high-risk subpopulations or the whole population should be targeted in interventions. My review of the very limited literature on the lifetime risk of diabetes demonstrates a generally high risk in HICs which is likely driven by a high BMI distribution and high life expectancy. Residual lifetime risk of diabetes has been found to decrease with age and can vary considerably between populations with different risk factors for developing diabetes, or different races/ethnicities. Although a useful measure to communicate the probability of developing diabetes, the lifetime risk of diabetes among South Asians, where there is a relatively high propensity to develop diabetes[23,25,26,34,38] and a lower BMI distribution, has not been appropriately investigated.

Chapter Three. Thesis Context

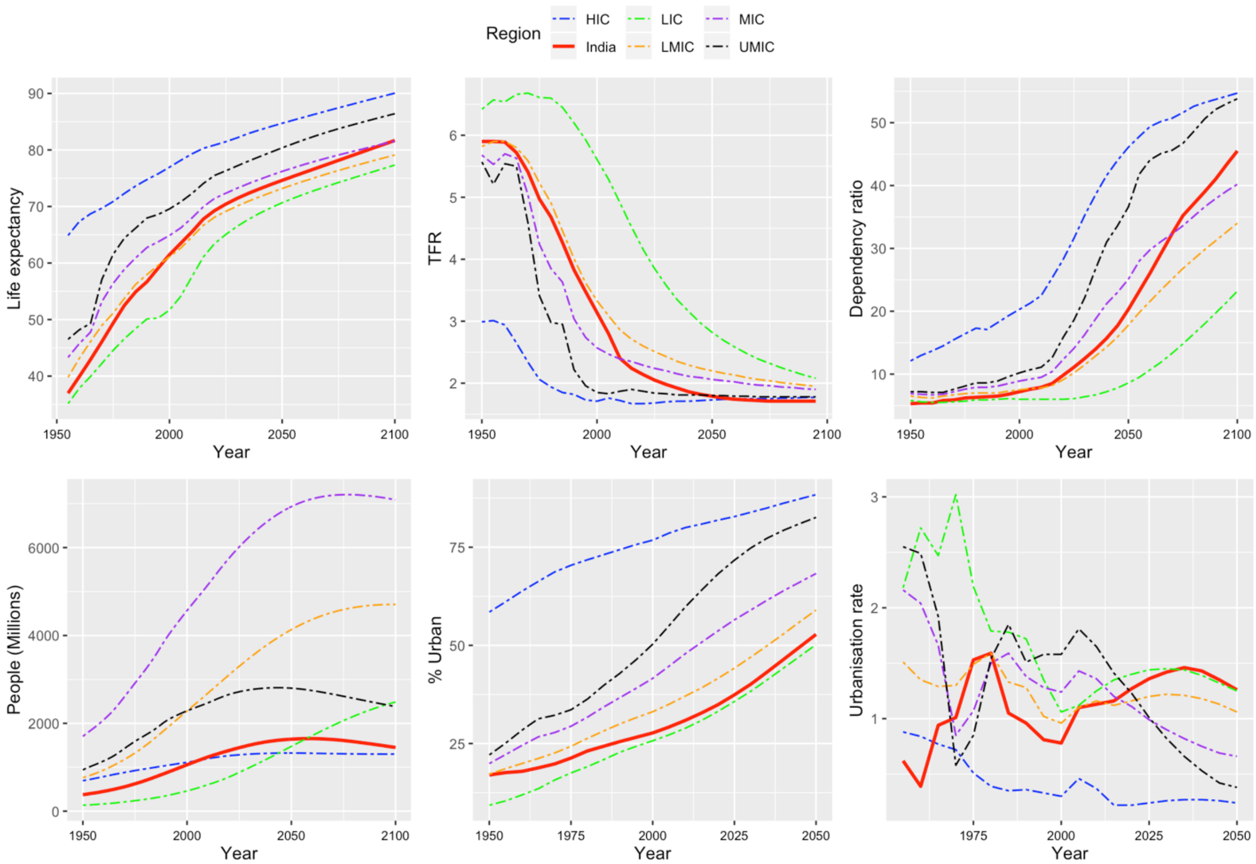
In this section, I will provide some context to the overall thesis. I will firstly describe the demographic and epidemiological transition in India before describing recent and forecasted trends in urbanisation. I will then move on to describing past trends and the current picture of overweight, obesity, and diabetes using evidence from recent studies, before giving a brief description of strategies employed in India to control these conditions. I then conclude by explaining how India provides an ideal context to explore the research questions.

3.1. The demographic and epidemiological transition

3.1.1. Transition theory

The classic demographic transition model, which was first developed by Frank W. Notestein[7], describes a process undergone by almost all societies. In the pre-transition phase, a society is characterised by a state of high fertility and high mortality. In the middle stages, initial mortality improvements lead to population growth before declines in fertility are observed. Finally, in the post-transition phase, where most HICs are placed, society is characterised by both low levels of fertility and mortality.

Figure 1. Past, current and projected** future global demographic processes* by World Bank defined regions



*Panel 1 - Life expectancy at birth (1950-2100); Panel 2 – Total Fertility Rate (1950-2100); Panel 3 - Dependency Ratio (1950-2100); Panel 4 – Population size (millions); Panel 5 – Percentage of total population living in Urban areas (1950-2050); Panel 6 – Urbanisation rate (%) (1950-2050)

** All projections are based on the United Nations Medium Fertility scenario

3.1.2. Global trends in the demographic transition

The mortality declines that initiate the demographic transition are positively related to economic development, and serve as a catalyst to declines in the fertility rate[143]. Globally, there is considerable diversity between regions in the extent of their progression through the demographic and epidemiological transitions dependent on their overall levels of economic development (Figure 1). In panels 1, 2 and 4 of Figure 1, I present global trends since 1950, in addition to projections, of life expectancy at birth[2], Total Fertility Rate (TFR)[3], and population size, and show that regions defined by higher levels of economic development appear to have progressed further through the transition. For instance, the life expectancy at birth in HICs is 23.5 years higher in HICs compared to LICs in 2015-20 (86.9 years in HICs and 63.4 years in LICs). On the other hand, the TFR, was 1.67 children in HICs, compared to 4.52 in LICs in 2015-20.

Despite higher mortality and fertility relative to HICs, the speed of progression experienced in some of the world's poorer regions is dramatic. In LMICs, between 1950 and 2015, life expectancy at birth has almost doubled, from 39.8 to 68.1 years. On the other hand, notable declines in the TFR have also been observed, plummeting from 5.82 children to 2.71 children between 1950 and 2015. Consequently, the growth in the size of the population of LMICs has been considerable. Whereas the population of HICs has increased from 0.69 billion to 1.23 billion people between 1950 and 2015, the population of LMICs has dramatically risen from 0.76 billion in 1950, to over double that in HICs (2.9 billion).

As people live longer and the number of births in a society declines, the proportion of the population living in older ages inevitably increases. Although in 2015, there were approximately 8 people aged 65 or more years for every 100 people aged 15-64 (Panel 3) in LMICs, compared to almost 25 in HICs, this ratio is expected to increase to almost 35 in LMICs by 2100.

[2] Life expectancy at birth refers to the total number of years a new born can expect to live, based on a set of age-specific death rates at a single point in time.
[3] TFR is defined as the total number of children, on average, that a woman can expect to have throughout her reproductive years.

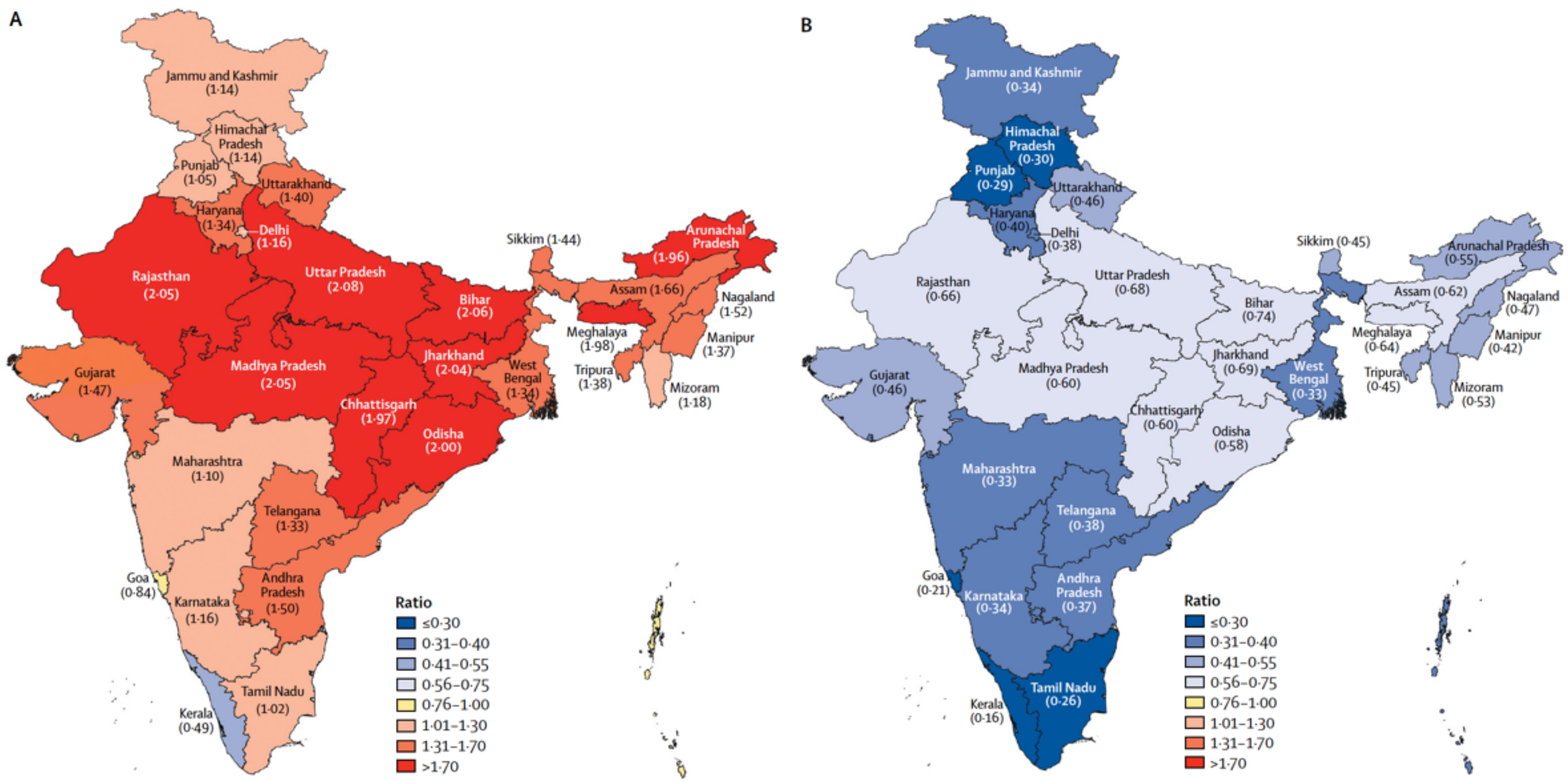
3.1.3. India's demographic and epidemiological transition

India is considered a LMIC according to the World Bank and is still undergoing its demographic transition. Between 1960 and 2018, the Indian economy has increased from a GDP (current US$) of $37 billion to $2.7 trillion[8]. Between 1950 and 2015, the life expectancy at birth has increased from 37 years to 69 years; the TFR has more than halved from 5.9 children to 2.2; and India has added a further 1 billion individuals to its population (an increase from 0.37 billion to 1.3 billion). Over the same period, the number of Indians aged 65 years or more per 100 Indians aged 15-64 increased from approximately 5 to 10, however is projected to reach 45 by 2100.

Progression through the demographic transition has been associated with rapid urbanisation, with an increasing proportion of the population living in urban areas. Dyson's (2011) more nuanced 'sector-specific' take on the demographic transition explains that the crude death rate of urban areas initially exceeds that of the crude birth rate, whereas the opposite is true in rural areas[144,145]. However, due to rapid mortality improvements in urban areas, particularly related to reductions in infectious disease mortality, the urban population increases, which can be additionally buoyed by rural to urban migration prompted by economic growth[144]. India has observed a doubling in the proportion of the population residing in urban areas from, 17% in 1950 to 33% in 2015, and is projected to reach 53% by 2050. Whereas in HICs the urbanisation rate has been consistently declining since 1950, the opposite is true in India and other LMICs since 2000.

Omran's formalisation of a concurrent epidemiological transition, alongside the demographic transition, describes the declining mortality as a result of 'receding pandemics' before an "Age of Degenerative and Man-Made Diseases" whereby communicable diseases are overtaken by 'man-made' or 'anthropogenic' primary causes of death[5]. In India, accompanying these demographic shifts, increasing urban population, and economic growth, have been radical changes in the disease profile. As mortality, particularly related to infectious diseases has declined, India has experienced an upsurge in the proportion of deaths attributable to NCDs[146], notably among older Indians and among the urban population[146]. Although wide heterogeneity in the speed of this epidemiological transition exists between India's states, between 1990 and 2016 NCDs have surpassed communicable diseases as the main contributor to Disability-Adjusted Life Years (DALYs) across the country[15]. Over this period the all-age death rate for diabetes has risen by 130.8% between 1990 and 2016, whereas the age-standardised death rate increased by 63.7%[15]. On the other hand, the all-age and age-standardised mortality rates associated with diarrhoea, respiratory infections and tuberculosis have all declined over the same period. Figure 2 demonstrates the switch over from the predominance of communicable to NCDs in all Indian states, using the ratio of DALYs lost to communicable diseases to DALYs lost to NCDs.

Figure 2. Ratios of DALYs due to Communicable causes relative to Non-Communicable causes across India's states



*Source: Dandona et al (2017)[15]

3.2. Overweight and obesity in India

Urbanisation and industrialisation are positively associated with the increased consumption of processed foods, cheap vegetable oils and sugar-sweetened beverages, all of which are associated with an increasing prevalence of overweight and obesity[147]. Moreover, urbanisation is linked to increasingly sedentary behaviour and a reduction in physical activity[147]. Globally, the age-standardised prevalence of obesity has increased more than three-fold in men (3.2% to 10.8%) and more than doubled among women (6.4% to 14.9%) between 1975 and 2014[36], and if previous trends continue, by 2025 the global prevalence of obesity is expected to be greater than that of underweight[36].

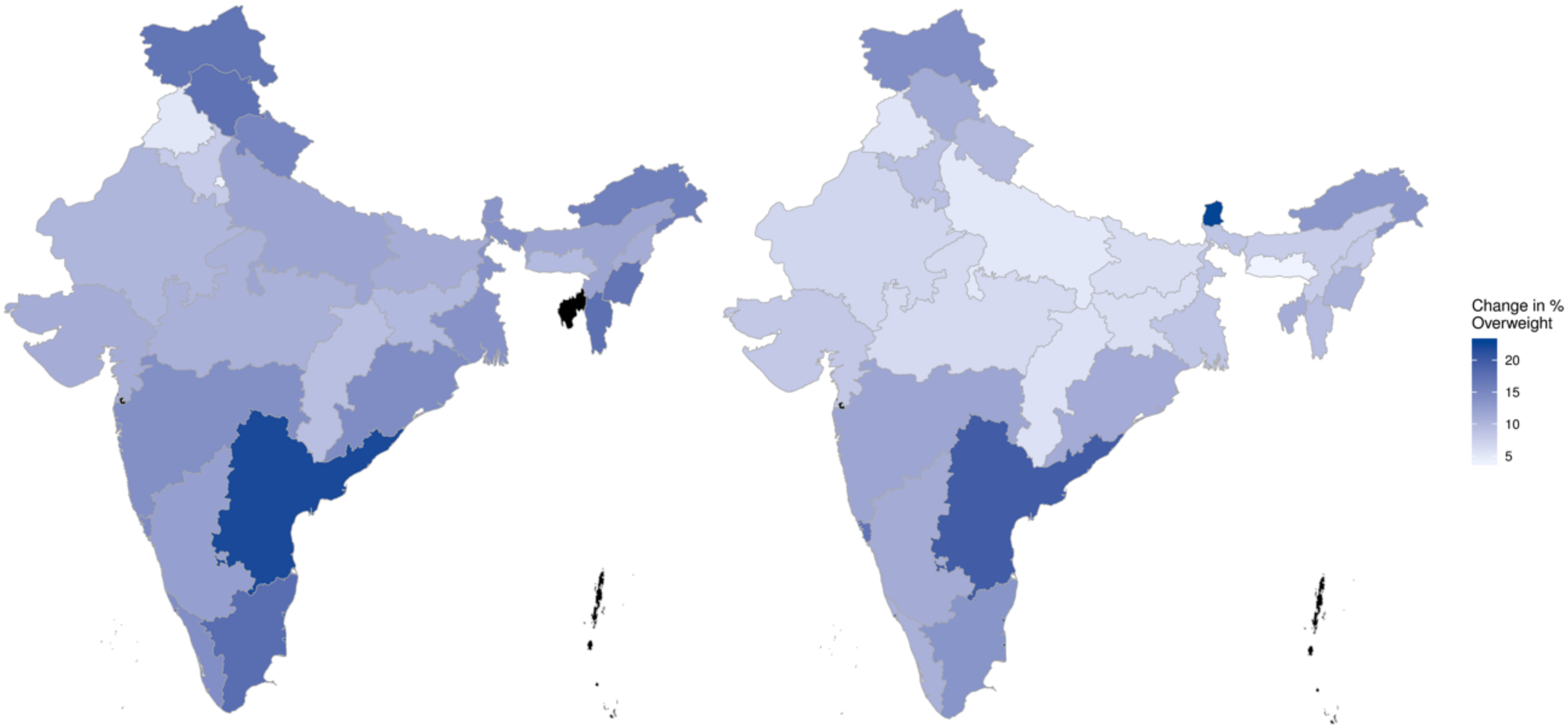
In India, the prevalence of combined overweight and obesity has increased from 9.7% to 18.9% between 2005 and 2016 among men (15-49 years), and from 10.6% to 20.7% between 1998 and 2016 among women (15-49 years). On the other hand, the prevalence of underweight has decreased from 35.8% to 22.9% among women and 33.7% to 20.2% among men over the same period[18–20]. The extent of the overweight and obesity challenge varies considerably within India. Whereas the prevalence of overweight and obesity in 2016 was 12.0% and 3.1%, respectively among women in rural areas, the prevalence was 22.2% and 9.1% among urban women. The prevalence of overweight and obesity is also higher among women, compared to men, with a recent systematic review on obesity in India reporting a higher prevalence in a majority of recent state-level studies[148].

The significant heterogeneity in economic development between India's states is accompanied by considerable variation in the state-level prevalence of overweight and obesity[18–20,28]. Consistent with theory around the epidemiological transition and economic development, India's most economically developed states generally have a higher prevalence of overweight and obesity, compared to India's least developed states. The NFHS-4 (2015-16) state-representative data report a higher prevalence of combined overweight and obesity in more economically developed states/union territories Punjab (31.3% in women), Goa (33.5%), Delhi (33.5%), Andhra Pradesh (33.2%), Telangana (28.7%) and Puducherry (36.7%), compared to relatively lesser economically developed states, such as Jharkhand (10.3%), Bihar (11.7%), Madhya Pradesh (13.6%) and Chhattisgarh (11.9%)[19,148]. Additionally, the states that have experienced a more marked economic growth in recent decades have also experienced the largest percentage point increases in overweight and obesity prevalence. For instance, whereas the prevalence of combined overweight and obesity in Tamil Nadu has increased from 14.7% to 30.9% between 1998 and 2016 among women, it has increased from 3.7% to 11.7% in Bihar. In Figure 3, I map demonstrate the extent of the variation in the increase in combined overweight and obesity between India's states in recent decades.

A particularly staggering increase in combined overweight and obesity prevalence in India was observed in the South Eastern state of Andhra Pradesh (separate states of Andhra Pradesh and Telangana since 2014). Whilst the percentage of reproductive aged women classified as either overweight or obese was 12.0% in 1998-99, this increased to 33.2% by 2015-16[19,20]. Among men, between 2005-06 and 2015-16, the prevalence of combined overweight and obesity increased from 13.6% to 33.5% [18,19]. A likely important determinant of this increasing overweight and obesity prevalence is the proportion of the population residing in urban areas. Between 2001 and 2011, the percentage of the population of Andhra Pradesh living in urban areas increased from 27.3% to 33.5%, representing a relative increase of 22.7%, the second highest of India's major states over the intercensal period[149]. Even in rural areas, however, a considerable increase in the consumption of fats and oils has been observed since the turn of the century. The National Nutritional Monitoring Bureau (NNMB) report an increase from 38.7% to 42.7% in percentage of the sedentary adult female population consuming 70% or more of their daily recommended intake of fats and oils between 2001 and 2012. Among men, this percentage increased from 13.1% to 46.2% over the same period[150,151]. On the other hand, considerably smaller increases were observed in states where relatively high percentages of women met 70% or more of their recommended daily intake of fats and oils in the initial period. Furthermore, Andhra Pradesh was one of the only major states in which the percentage consuming 70% or more of the recommended daily intake of sugar or jaggery increased between 2001 and 2012 [150,151].

Heterogeneity in overweight and obesity prevalence also exists by age in India. A study by the Indian Council for Medical Research India Diabetes Study (ICMR-INDIAB) in four Indian states established a general trend of increasing prevalence of combined general and abdominal obesity with age, before a slight decline in ages 65 years or more.

Figure 3. Percentage point change in combined overweight and obesity among women (1998-2016) (left panel) and men (2005-2016) (right panel)



*Source: National Family Health Surveys 2[20], 3[18], and 4[19]

Nutritional status, such as overweight and obesity can be measured in a number of ways. A commonly used measure typical of surveys in LMICs and India in particular is BMI, defined by the division of an individual's height in metres (m) by the square of their weight in kilograms (kg). According to WHO recommendations, an adult with a BMI between 25.0kg/m^2 and 29.9kg/m^2 is generally considered overweight, whereas an adult with BMI greater than or equal to 30kg/m^2 is defined as obese[1]. Alternatively, abdominal obesity is commonly measured using one's WC measured in centimetres (cm), whereby a WC greater than 80cm is considered obese among men, and a WC greater than 90cm is defined as obese among men[152,153].

A particular feature of the overweight and obesity profile among Indians is higher abdominal obesity (using WC) and body fat for any given BMI when compared to White Caucasians or Black Africans[34,154]. This implies a higher proportion of Indians classified as overweight or obese using abdominal overweight or obesity as the primary measure, when compared to generalised overweight or obesity (using BMI). One study in New Delhi determined a prevalence of abdominal obesity nearly 20 percentage points lower, compared to generalised obesity (68.9% compared to 50.1%)[155]. Additionally, in both urban and rural areas of Tamil Nadu, Jharkhand, Maharashtra, and Chandigarh, the ICMR-INDIAB study found consistently higher prevalence of abdominal obesity, compared to generalised obesity[152].

3.3. Diabetes

According to the WHO, diabetes mellitus, or diabetes, is a "chronic disease that occurs either when the pancreas does not produce enough insulin or when the body cannot effectively use the insulin it produces[12]." Insulin is an important hormone that is firstly produced in the pancreas and transports glucose in the blood to body cells to be converted to energy. Resistance of cells to insulin, or the lack of insulin, leads to raised blood sugar, or hyperglycaemia, which if uncontrolled, can cause substantial damage to vital organs and serious health complications including CVD, neuropathy, and eye disease[11].

The two most common forms of diabetes are Type 1 and Type 2 diabetes, the latter of which constitutes the majority of all diabetes cases[11]. Type 2 diabetes is caused by the inability of the body to use the insulin it produces, and the most important risk factor for Type 2 diabetes is excess body weight[12].

3.3.1. Diabetes globally

Globally, 425 million people aged 20-79 years had diabetes in 2017, which is expected to rise to 629 million by 2045 according to the IDF[11]; an increase of 48% within the next three decades. The WHO report that in 2014, 8.5% of all adults aged 18 years or more had diabetes[12]. The global region with the largest expected increase in the number of people with diabetes is Africa, whereby the current 16 million people is projected to increase to 41 million between 2017 and 2045[11]. However, the region projected to experience the largest absolute increase in the number of people with diabetes is the IDF South East Asia region, which includes India. In this region, the number of people with diabetes is expected to increase from 82 million people (10.1%) to 151 million by 2045, an absolute increase of 69 million, and a percentage increase of 84%[11].

3.3.2. Diabetes in India

India is the country containing the second highest number of adults (20-79 years) with diabetes (72.9 million in 2017). IDF projections suggest that by 2045, India will be the country with the most people with diabetes globally, with 134.3 million individuals, compared to a projected 119.8 million in China[11]. Studies in India since the 1970s that have estimated the prevalence of diabetes (using measured blood samples or self-reports) have shown considerable heterogeneity in results[25]. A study using data from a cross-sectional population-based survey of over 41,000 adults aged 25 years or more, measured an age-standardised prevalence of diabetes of 3.3% across India, with considerably higher prevalence in urban India (4.6%) compared to rural areas (1.9%)[156]. Evidence from the National Urban

Diabetes Survey in 2001, containing objective measurements from approximately 11,000 people aged 20 years or more, found an age-adjusted prevalence of diabetes and prediabetes of 12.1% and 14.0%, respectively[157]. One of the most recent studies estimating diabetes and prediabetes prevalence is the ICMR-INDIAB study, based on blood tests of around 57,000 adults aged 20 years or more. The population-based study found a prevalence of 7.3% across the 15 states between 2008 and 2015[22]. In India, diabetes was reported to be responsible for 3.3% of deaths in 2016 and 2.2% of DALYs, the majority of which were due to years of life lost to death rather than years of life lost to disability[21].

The increased predisposition of central obesity in South Asians implies a higher insulin resistance at lower levels of BMI, and consequently an elevated risk of developing diabetes[23,24]. This has even been observed among adolescents[38], whereby South Asians have been found generally experience the onset of diabetes more than a decade before Europeans[25,26]. A possible explanation for this higher predisposition involves maladaptation of South Asians to an increasingly 'Western diet'[38,158], in addition to the high consumption of refined carbohydrates, which can lead to high blood sugar levels[38,159–161].

This may interact considerably with the 'thrifty genotype' and 'thrifty phenotype' hypotheses. The 'thrifty genotype' hypothesis implies that South Asians have evolved to cope in environments with scarce food supplies, and consequently, their introduction into environments with moderately high consumption of calories, and sedentarism, may rapidly lead to the development of diabetes[162,163].

On the other hand, the 'thrifty phenotype' hypothesis[164–166] suggests that the underconsumption of nutrients during foetal formation can lead to low birth weight, which in turn, increases the likelihood of later life diabetes and visceral fat accumulation. This is explained by the fact that foetuses in malnourished mothers make their muscles relatively insulin resistant in order to take all the glucose necessary for development, leading to a relatively high level of glucose circulating in the blood[167]. In the Netherlands, a study found that women facing the Dutch famine of the mid 1940s early into their pregnancy had male offspring at considerably higher risk of obesity[166–169] . A recent study in Switzerland has found lower birth weight to be associated with higher prevalence of obesity and diabetes in adulthood[170]. Evidence from India includes the Pune Children's study, which found a negative association between childhood BMI and birth weight after having adjusted for current weight, in addition to body fat percentage and central adiposity[168,171,172]. Using data from the Andhra Pradesh Children and Parents Study (APCAPS) near Hyderabad, Kinra and colleagues found lower resistance to insulin among children born to mothers who were given a local breakfast composing of corn soya blend and soybean oil during pregnancy[166].

Were the 'thrifty genotype' and 'thrifty phenotype' hypotheses the sole explanations for the high predisposition among South Asians, one may expect the prevalence of diabetes or overweight and obesity to be higher in rural areas, which may be more likely to be burdened with greater food insecurity[163]. The interaction of these explanations with obesogenic urban environments is likely to account for the higher prevalence of diabetes[22] and obesity[152] in urban areas, compared to rural areas.

The overall prevalence of diabetes is considerably higher in urban India compared to rural India. Joshi et al (2008)[25] reports that a number of national and subnational studies in India since 1970 find consistently higher diabetes prevalence in urban areas, compared to rural areas. The ICMR-INDIAB study across 14 Indian states and one Union Territory reports double the prevalence in urban India (11.2%) compared to rural India (5.2%) in 2008-2015. This study also reports a slightly higher prevalence of diabetes among men compared to women[22]. Another study using measured blood samples of 1.32 million participants collected by nationally representative household cross sectional surveys the Annual Health Survey (AHS) in 2012-13 and District Level health Survey (DLHS) in 2012-14 found a national age-standardised prevalence of 6.1% among women and 6.5% among men[173]. Diabetes prevalence also increases with age. The India State-Level Disease Burden Initiative Diabetes Collaborators reported that in 2016, the prevalence among women 20-24 years old was 1.5% in 2016, compared to 15.4% among women aged 65-69 years. Among men, the prevalence among 20-24-year olds was 1.8%, compared to 18.8 among 65-69-year olds[21].

There is considerable heterogeneity in the prevalence of diabetes at the level of the state, whereby states at more advanced stages of the epidemiological transition have generally higher prevalence. A recent study by the India State-Level Disease Burden Initiative Diabetes Collaborators estimated an age-standardised prevalence of 12.5% among states at relatively later stages of the epidemiological transition, compared to 7.7% among states at earlier stages[21]. Although at the national-level, being in higher socioeconomic groups only slightly increases an individual's risk of having diabetes[173], in some high GDP states a negative association between SEP and diabetes prevalence has been observed[22].

Diabetes is associated with diabetes-related complications including retinopathy and kidney damage[11]. Using population-based data among individuals aged 20 years or more from the Chennai Urban Rural Epidemiology Study (CURES), one study reported that 17.6% of participants had diabetic retinopathy[34,174]. In the same population, the prevalence of CHD was twice as high among the population with diabetes (21.4%) compared to individuals with normal glucose tolerance (9.1%)[34,175,176]

Regarding past and current trends in the burden of diabetes, the India State-Level Disease Burden Initiative Diabetes Collaborators estimate an increase in overall prevalence between 1990 and 2016 of 2.2 percentage points, from 5.5% to 7.7%, and a more than doubling in the total number of Indian adults with diabetes from 26 million in 1990 to 65 million in 2016[21]. Over the same period, the crude death rate from diabetes rose from 10.0 to 23.1 per 100,000, the age standardised DALY rate for diabetes increased in every state over the same period; and the increase in DALYS to diabetes was the largest among all the NCDs (an increase of 39.6%).

3.4. Strategies to counter increasing excess weight, and diabetes

India is a participating country in the UN Decade of Action on nutrition (2016-2025) in which Member States have committed to implement long term, reasoned programmes that focus on tackling malnutrition in all forms, including both underweight and excess weight[177]. Although the National Health Policy (2017) aims to 'reduce premature mortality from CVDs, cancer, diabetes or chronic respiratory diseases by 25% by 2025' and have 80% of the known individuals with diabetes to have a 'controlled disease status' by 2025[33], there is no explicit mention about the control of overweight and obesity, the primary driver of type 2 diabetes globally.

Given that India is the country currently with the second highest number of people with diabetes[11], the healthcare expenditure on diabetes is alarmingly low. Using the WHO definition of healthcare expenditure[178], which encompasses public and private expenditure on both preventative and curative care, in addition to expenditure on nutrition activities, for the 73 billion people with diabetes currently, a mere $32 billion is spent on their healthcare; approximately $438 per individual annually[11]. In contrast, the United States spends $11,638 annually per individual with diabetes[11,178]; equivalent to $348 billion for the 30 million people with diabetes. Using the IDF projections, even maintaining this low per capita expenditure will result in an annual expenditure of 63 billion dollars by 2045[11].

The only government initiative with a specific focus on diabetes and diabetes risk factors such as excess weight is the National Programme for Prevention and Control of Cancer, Diabetes, Cardiovascular Disease and Stroke (NPCDCS)[179]. Established in 2010, the NPCDCS is designed to support state efforts in controlling and tackling the increasing NCD burden in India by providing both technical and financial assistance. Moreover, it is intended to be integrated with the overall National Health Mission[4] to allow the optimal use of scarce healthcare resources through the establishment of small health centres called NCD cells. The overall aims of the NPCDCS includes the prevention of NCDs through promoting lifestyle changes; building of NCD related healthcare capacity to boost prevention, diagnosis and treatment of NCDs; promotion of early diabetes

[4] The National Health Mission is an initiative aimed at providing good quality and affordable healthcare to the population of India, with a particular emphasis on marginalised groups. The preceding National Rural Health Mission (NRHM) was initiated in 2005 by former Prime Minister Manmohan Singh to provide affordable healthcare to underprivileged rural populations. The NRHM along with its equivalent in urban areas, the National Urban Health Mission (NUHM) are both sub-missions of the National Health Mission[323].

detection to prevent the development of complications; improvement of healthcare staff quality to respond to the increasing NCD prevalence rates; and capacity building for both palliative and rehabilitative care. Moreover, the programme aims to increase awareness of diabetes and its risk factors in order to boost prevention and reduce the proportion of cases going undetected[179].

Rollout of the National Programme has been steady. By March 2017, approximately 45% of districts across India were without NCD cells, and in rural India particularly, there remains a deficit in human resources and drugs required to control the increasing diabetes prevalence, leading many to pay out-of-pocket for diabetes care[21]. Studies have also found coverage of training of healthcare personnel and a shortfall in necessary equipment and information to carry out the NPCDCS[180].

3.5. Summary of Context

India is undergoing a rapid demographic and epidemiological transition; with rising life expectancy at birth, large population growth, and rates of urbanisation that are faster than what has been experienced in many of the world's HICs[37]. This has led to an explosion in the prevalence of NCDs, in particular diseases such as diabetes that are driven by the rising prevalence of overweight and obesity. The expected continuation in life expectancy improvements, urbanisation rates, and population ageing[37], implies a continuation in the rising prevalence of both overweight and obesity and diabetes for the foreseeable future. In this Chapter I have also touched on the higher propensity for South Asian Indians to have a higher body fat content at any BMI when compared to White Caucasians, implying a higher insulin resistance and propensity to develop diabetes at all BMI levels. Coupled with an earlier onset of diabetes relative to Europeans, by at least a decade[25], the profile of overweight and obesity, and diabetes in India is particularly unique.

Given high current and future rates of urbanisation and projected increases to longevity and population size, India presents an ideal setting for answering the research questions I posed in Chapter One. By 2023 India is projected to become the world's most populous country[37], and consequently, even relatively small increases in future overweight and obesity prevalence will imply a comparatively larger number of people developing diabetes, when compared to smaller populations.

India is also one of the world's most diverse places, especially with regards geography, and socioeconomic inequality. Therefore, a more nuanced understanding of which areas and which subpopulations are increasingly at risk, for instance SEP groups or urban/rural residents, is particularly warranted when quantifying the disease and excess weight distribution in India.

Constant monitoring of the socioeconomic patterning of overweight and obesity is necessitated in light of firstly the faster speed of the epidemiological transition in India compared to many HICs that preceded it (implying a relatively faster paced shift from a positive to negative association in India), and the considerable differences in state-level economic development (implying wide variation in the socioeconomic patterning trends sub-nationally).

Despite the availability of population-based survey data objectively measuring individual level and aggregate-level excess weight and diabetes, in addition to past and current demographic information for India, attempts to estimate trends in the socioeconomic patterning of overweight and obesity are outdated by almost a decade[89,90], forecasts of future overweight and obesity[118,181] and diabetes[11,133,134] are overly simplistic and inflexible, and estimates of lifetime risk are limited solely to HICs. Carefully addressing this dearth in the body of literature is important for the following reasons: first, designing future policies; second, testing how realistic current targets outlined in Health Policy Plans are; third, providing a platform for understanding both the extent in the funding shortfall dedicated to diabetes related healthcare; fourth, quantifying the future burden of diabetes-related complications; and fifth, to paint a more accurate picture of the number of undiagnosed cases in India[34,182].

Chapter Four. Methods

This thesis contains five quantitative studies using a range of data sources with information on morbidity, health, and demography across India, over recent decades. Some of the data sources used were designed to be nationally-representative, and others are community-level studies. This chapter is split into 4 separate sections. Section 4.1 focuses on the studies in Chapters Five and Six, where I estimate trends in the socioeconomic patterning of overweight and obesity both nationally and sub-nationally, respectively. In section 4.2, I describe in detail the calculation of certain parameters used in the forecasts of overweight and obesity. In section 4.3, I describe in detail the calculation of future prevalence of diabetes based on predictions of overweight and obesity, and in section 4.4, I demonstrate the calculation of measures of lifetime risk and diabetes-free life expectancy in this thesis.

4.1. Socioeconomic patterning of overweight and obesity

This section has been written to provide more detail to the nationally-representative NFHS data, calculation of the wealth index used as a proxy of SEP, and the regression model adopted in the research papers in Chapters Five and Six.

4.1.1. The National Family Health Surveys (NFHS)

The NFHS comprises a set of multiple, large sized data sets which are designed to be nationally-representative and state-representative samples of households across India. The surveys collect data and report information on morbidity, nutrition, and demography throughout India, in addition to a range of indicators pertaining to women and children, including, fertility, infant and child mortality, and reproductive health. Although the Ministry of Health and Family Welfare (MOHFW) of the Government of India is the organisation in charge of the NFHS, specific guidance for the collection of the survey data is overseen by the International Institute for Population Sciences (IIPS) based in Mumbai. In each of the states or union territories covered in the NFHS, a Field Organization working in collaboration with the IIPS, is in charge of undertaking the survey data collection[183].

The NFHS comprises four nationally-representative surveys collected between 1992 and 2016. The first round was collected in 1992-93, the second in 1998-99, the third in 2005-06 and the fourth in 2015-16. The various rounds have been funded by various organisations, including the United States Agency for International Development (USAID), the Bill and Melinda Gates Foundation, United Nations International Children's Emergency Fund (UNICEF), United Nations Population Fund (UNFPA), Department for International Development (DFID), Government of India (GOI) and the MOHFW[183].

4.1.1.1. Number of respondents

Table 1 contains the total number of respondents, by sex, in NFHS-2, 3 and 4, the three surveys used in this thesis that collected data on the respondent's height and weight. Whereas NFHS-2 only collected data on ever-married women, the NFHS-3 and 4 samples included both ever-married and never-married women.

Table 1. Number of households, respondents, and response rates in NFHS surveys

	NFHS-2 (1998-99)	*NFHS-3 (2005-06)*	*NFHS-4 (2015-16)*
Number of households	91,196	109,041	601,509
Urban	30,435	50,236	175,946
Rural	60,761	58,805	425,563
Number of respondents	89,199	213,584	811,808
Men	-	74,369	112,122
Urban	-	38,199	35,526
Rural	-	36,170	76,596
Women	89,199	124,385	699,686
Urban	27,862	56,961	204,735
Rural	61,337	67,424	494,951
Response (%)			
Households	97.5	97.7	97.6
Respondents			
Men	-	87.1	91.9
Women	95.5	94.5	96.7

Source: NFHS reports 2[20]; 3[18]; and 4[19]

4.1.1.2. Survey design

In the surveys, urban and rural samples were selected separately, and where necessary, smaller geographical areas, for instance urban slum areas, were oversampled. The samples selected in each of India's states were proportional to the population size.

In NFHS-2, 3 and 4, rural samples were selected using a two-stage sampling procedure. The first stage involved selecting villages, or Primary Sampling Units (PSUs), with a probability proportional to size (PPS). In the second stage, random households were selected from each PSU[18–20]. In urban areas, NFHS-2 and 3 used a three-stage procedure, in which the first stage involved selecting wards with a PPS, the second stage involved randomly selecting a census enumeration block (CEB) from each of the wards, and the final stage involved randomly selecting households within each CEB[18,20]. In NFHS-4, using the 2011 census to inform the sampling frame for the selection of PSUs, a two-stage procedure was adopted in urban areas, where CEBs were the PSUs selected with a PPS, and households within these areas randomly selected. In both urban and rural areas in NFHS-4, if PSUs contained less than 40 households, the PSU was joined to the nearest PSU[19].

In NFHS-2 and 3, an average of 30 households per cluster (PSU) were selected with equal probability[18,20]. Upper and lower limits of 60 and 15 households to be selected were set in order not to avoid substantial workload differences between clusters. In NFHS-4, a fixed number of 22 households per cluster were selected using systematic sampling[19]. The overall probability of a household being selected – which is the product of the probability of a household being selected within a cluster and the probability of a cluster being selected –therefore differs between clusters. To account for the uneven selection probabilities, I use sampling weights provided in the data sets. I use sampling weights in all the substantive analysis, for instance, cross tabulations of prevalence and in all regression analysis. Unweighted values are only reported when merely describing the data i.e. number of respondents in certain variable categories in Table 8, Table 9 and Table 12.

4.1.1.3. Variable definitions

Body Mass Index (BMI): Height and weight information on women aged 15-49 years in NFHS-2, 3 and 4, and men aged 15-54 years in NFHS-3 and 4, were collected by specially trained investigators. A solar-powered SECA digital scale was used to measure the weight of respondents, with the NFHS-2 report claiming an accuracy of ±100 grams[20]. The height of respondents in NFHS-2 and 3 was measured using a measuring board designed for use in survey data collection[18,20]. In NFHS-4, the Seca 213 stadiometer was used to collect the respondent's height information[19]. Measured height and weight is used to produce a measure of BMI. BMI can be used to categorise people into groups of nutritional status and is calculated as the individual's height (meters) divided by the square of their weight (kilograms)[184]. The WHO recommends the following cut-offs to allocate individuals to different nutritional categories[1]:

- <18.50 kg/m^2: Underweight
- 18.50 kg/m^2 - 24.99 kg/m^2: Normal Weight
- 25.00 kg/m^2 - 29.99 kg/m^2: Overweight
- ≥ 30.00 kg/m^2: Obese

BMI is commonly used as the variable to determine an individual's nutritional status in population studies using survey data in LMICs. However, criticisms of the variable exist, for instance, BMI does not allude to an individual's body fat content, nor the distribution of body fat, which are risk factors for NCDs[184]. Additionally, South Asians may have higher body fat content for a given BMI, when compared to White Caucasians[185,186], a reason for which some have suggested different cut-off values for South Asians[15,187]. In Chapters Five and Six, I used a combined measure of overweight and obesity, hereon referred to overweight/obesity (BMI$\geq$25.0kg/m^2). I opted to use the global cut-offs for BMI in this thesis to ensure comparability with studies, and because the relative risk I extracted for use in my models in Chapters Seven and Eight, only apply to global BMI cut-offs.

Residence: The census definition of what constitutes an urban area was adopted in this thesis (and informed the sampling frame in the data sets used)[188]. The Office of the Registrar General and Census Commissioner define an urban area as "places with a municipality, corporation, cantonment board or notified town area committee, etc" or places with at least 5000 inhabitants; an area where the population density is, at minimum, 400 per km^2; and where, at minimum, three quarters of employed adult males are involved in non-farming related activities[188].

4.1.2. Calculation of the wealth index

Reliably collecting data on monetary income or consumption spending is considerably more challenging[189,190] than collecting information on ownership of assets, in part due to the fact that in many LMICs, income may either be derived from a number of sources or received in-kind[190,191]. Asset, or wealth, indices are therefore commonly used to proxy SEP in low resource settings.

The NFHS Wealth Index aims to capture a household's economic status that mirrors their expenditure and income position[18,192]. Using principal components analysis (PCA), household assets/attributes (for example, type of roofing and car ownership) are assigned weightings based on variability between households[190]. After assigning a score for each asset and summing up the scores for each household, individuals are then ranked by their household final wealth index and split into quintiles, each containing a fifth of the total study population. The wealth index in a particular survey, however, is a relative measure of wealth, and is specific to the country and the time in which the survey was conducted[193]. Consequently, it is not appropriate for comparison between surveys. For example, the absolute wealth of individuals in upper quintiles in earlier surveys may be similar to those in lower quintiles in later surveys if a country undergoes rapid economic development.

To overcome this limitation of comparability of wealth indices, a separate Wealth Index was calculated after having pooled the surveys over time. Using PCA, I used the household answers to the following questions collected in the NFHS surveys to calculate a separate wealth score for each household:

- Does the household have electricity?
- Does the household have a pressure cooker?
- Does the household have a mattress?
- Does the household have a chair?
- Does the household have a cot bed?

- Does the household have a table?
- Does the household have a fan?
- Does the household have a radio?
- Does the household have a black and white television?
- Does the household have colour television?
- Does the household have a phone?
- Does the household have a fridge?
- Does the household have a watch?
- Does the household have a bike?
- Does the household have a motorbike?
- Does the household have an animal cart?
- Does the household have a car?
- Does the household have a water pump?
- Does the household have a thresher?
- Does the household have a tractor?
- Does the household have agricultural land?
- How many persons per sleeping room live in the household?
- What is the source of drinking water?
- What is the house made of?
- What is the main cooking fuel?
- What is the type of toilet facility?

Due to the differences in the importance of the household assets and characteristics between urban and rural areas, partly demonstrated by ownership of assets (Table 2), I calculated separate urban and rural-specific Wealth Indices. Using the final index, I allocated individuals within the bottom third of wealth index values to the lower SEP group, the middle third to the middle SEP group, and the upper third to the higher SEP group.

Table 2. Percentage (%) of households with the following assets/characteristics by survey and urban/rural residence

	1998-99		*2005-06*		*2015-16*	
	Urban	***Rural***	***Urban***	***Rural***	***Urban***	***Rural***
Asset						
Mattress	71.7	38.1	75.4	48.7	82.3	58.4
Pressure cooker	65.2	16.0	69.9	22.1	83.6	42.2
Chair	71.3	356.0	76.1	43.8	86.5	70.7
Cot/bed	86.1	79.4	86.3	81.2	88.5	88.3
Table	64.9	30.0	65.0	32.9	72.1	46.5
Clock/watch	90.1	57.5	91.0	71.4	90.8	71.4
Electric fan	82.2	31.4	84.7	38.6	95.1	69.1
Bike	53.5	45.7	50.1	51.6	45.0	55.9
Radio	53.2	32.2	38.9	27.0	10.3	7.0
Sewing Machine	35.5	11.9	30.9	12.6	33.5	19.0
Telephone	20.1	2.6	36.3	7.4	96.1	87.3
Refrigerator	28.8	3.7	33.5	6.6	54.2	16.4
Television (B+W)	44.8	17.0	25.6	18.7	3.1	3.5
Television (Colour)	27.3	3.5	51.5	12.5	86.0	51.5
Moped/Scooter/Motorcycle	25.0	6.0	30.5	10.8	51.5	30.3
Car	4.4	0.6	6.1	1.0	11.4	3.2
Water Pump	9.3	8.2	11.0	9.9	21.5	14.9
Thresher	0.7	2.5	0.4	2.2	0.6	1.9
Tractor	0.8	2.0	0.5	2.3	0.7	3.4
Characteristics						
Flush toilet/pit latrine	63.9	8.8	79.9	20.8	81.1	36.2
High quality house material	66.0	19.0	81.2	28.8	84.5	41.3
LPG/Electricity for cooking	47.7	5.3	59.6	8.3	79.3	23.4
Piped/handpump water source	92.6	72.3	92.3	81.1	86.4	84.6

Sources: NFHS 2; NFHS 3; NFHS 4

The effectiveness of Wealth Indices in capturing household wealth has been questioned in the literature. Criticisms of the wealth index include its lack of comparability between different surveys[193], and that, unless explicitly specified, it does not incorporate the quality of assets owned[194]. Additionally, score misclassification and underestimation of results may arise due to inconsistencies in the collection of asset ownership data between interviewers[195,196]. Additionally, the lack of ownership of certain assets may not be associated with wealth, but rather preference, credit access, or general availability in certain areas[197].

When deciding upon the SEP variables to analyse, I opted against the use of occupation as it was only collected on a very limited subsample of the respondents in the NFHS 4 (around 5% of women respondents). I also opted against the use of caste as one of my main SEP exposure variables. Caste is a social structure exclusive to India, whereby an individual's positioning is pre-determined at birth. Despite there being many different castes along this hierarchy, the grouping of caste in the NFHS is based on the government definitions and individuals fall into four very broad categories, with some subjectivity on the allocation of castes to these broad groups. Additionally, the definition of the four broad categories are subject to change over time and may differ between states, making it somewhat inappropriate for analysis of time trends. For instance, 17 castes were removed from the 'Scheduled Caste' category and included as part of the 'Other Backward Caste' in Uttar Pradesh prior to the 2019 General Election[198].

4.1.3 The multilevel model

Due to the deliberate clustering of sampling units in the NFHS multi-staged sampling procedure, the use of a standard regression model to assess the association of SEP with overweight/obesity was likely to produce underestimated standard errors. Underestimating the standard errors implies that the model does not recognise the full extent of the variance in the association, and consequently I risked identifying false statistical associations. In order to correct for this, I adopted multilevel logistic regression models.

In the study examining trends in the association of overweight/obesity and SEP at the national level, I adopted a three-level model (Chapter Five). In this particular multilevel model, individuals represented the first level, PSUs were the second level and states were the third. For the subnational analysis (Chapter Six) I adopted a two-level model – in this model, individuals represented the first level and PSUs the second. To examine the changing association between surveys, the SEP variables were interacted with a categorical variable representing survey year. In the fully adjusted model, I controlled for other socioeconomic variables, age and marital status.

Multilevel models are commonly used when the outcome, in my case overweight/obesity, is expected to be influenced by membership of a PSU or state[73]. In brief, multilevel models enabled me to decompose the overall variance in overweight/obesity into variance between PSUs or states and variance within PSUs or states. A higher level of correlation between respondents within a state or PSU in terms of likelihood of being overweight or obese would imply a higher proportion of the total variance being due to variance between PSUs and states. Failure to accommodate this potential correlation within clusters would lead to underestimated standard errors. Examination of the proportion of total variance attributable to variance between levels in the NFHS data suggested considerable variation in average overweight/obesity prevalence between PSUs and states, and consequently, I deemed it appropriate to allow the intercept of the model to vary between PSUs and states.

For the three-level model in Chapter Five, I made no *a priori* assumption that the association between overweight/obesity and SEP varied by sampling units, and therefore elected not to model a random slope. I estimated a separate intercept parameter for the overweight/obesity category. Formally, the three-level regression model was modelled as follows:

$$P(y_{ijs} = Y) = (\beta_1 x * T) + \beta_2 \theta + \varphi_{js} + \omega_s$$

Equation 1

$$P(y_{ijs} = Y) = log\left(\frac{\pi_{ijs}^{Y}}{\pi_{ijs}^{!Y}}\right)$$

Equation 2

The outcome variable in this model was the probability that individual *i* in PSU *j* in state *s* is classified as overweight/obese, as opposed to being classified as not overweight/obese. This probability is denoted as $P(y_{ijs} = Y)$. β_1 represents the effect of being in SEP group x relative to the baseline SEP category (in this case, the lowest SEP group), in survey period *T*, on the log odds of being overweight/obese compared to being not overweight/obese.

For interpretability, I translated the log odds into predicted probabilities of overweight/obesity. To do this, I selected a random sample of the population, and passed them through the model, predicting their individual probability of overweight/obesity in time period *T*. I used the mean predicted probability to denote the final predicted probability by SEP category.

4.2. Forecasts of overweight and obesity

In this section I provide details on the estimation of the parameters used in the forecasts of future overweight and obesity prevalence, in addition to a detailed breakdown of how the system of multi-status lifetables operate.

4.2.1. Estimation of incidence using Intracohort Interpolation

A key parameter in my forecasts of future overweight and obesity prevalence in India was the incidence of overweight and obesity. I estimated incidence among individuals aged 20-49 using two cross-sections of the NFHS (2005-06 and 2015-16) as they are designed to be nationally-representative. Both of these NFHS rounds collected data on an adult's height and weight, and reported BMI, to which I applied the WHO recommended cut-offs[1] to assign individuals one of the following three mutually exclusive nutritional status groups: underweight/normal weight; overweight; and obese.

I used the prevalence of overweight and obesity in the two surveys, in conjunction with mortality rates calculated from the Sample Registration System (SRS) to estimate the net rate of incidence of overweight and obesity using the iterative intra-cohort interpolation procedure[199] developed by Stupp (1988). Using this procedure, I converted the changes in the prevalence of overweight and obesity among specific cohorts into to age-specific transition rates using an iterative procedure. Assuming that age-specific incidence is constant over the inter-survey period (in my case, 10 years), the final iteration provides age-specific incidence that has the highest likelihood of resembling the actual changes to each cohort[199].

In order to calculate the rates in the inter-survey period, for men and women in urban and rural areas separately, I required the following three inputs:

- The prevalence of overweight and obesity in 2005-06 and 2015-16 separately for men and women in urban and rural areas by five-year age groups.

- The central age-specific mortality rates in 2005 and 2015 separately for men and women in urban and rural areas.

- The relative risk of dying for individuals classified as overweight relative to the underweight/normal weight category; and the relative risk of dying for individuals who are obese relative to overweight.

In brief, the procedure is carried out using the following steps:

Calculate the cohort incidence rates $I_k(c)$, indicating the change in status (in my case nutritional status) occurring to cohort c, during the inter-survey period.

$$I_k(c) = F_k(c, c+T) - F_k(c, c) \qquad \text{for } c = \alpha \text{ } to \text{ } \beta - T$$

Equation 3

Where $F_k(c,c)$ and $F_k(c,c+T)$ refer to the prevalence of the nutritional status, k, in question amongst age cohort c in the initial period and the succeeding survey, respectively, with T denoting the length of the inter-survey period. The cohorts α and β refer to the youngest and oldest cohort for which initial data is available. If P_k is the proportion that have not yet experienced nutritional status k, one can rewrite the equation above as:

$$I_k(c) = ln[P_k(c, c)] - ln[P_k(c, c+T)]$$

Equation 4

One can then obtain an initial estimate of the age-schedule by weighting the cohort rates ($I_k(c)$) by the amount of time spent in a particular age-group. For instance, when calculating the rates for the 25-29 ages group, I added the product of the cohort incidence rate for the 15-19-year age group and the time spent they spent aged 25-29 years in the 10 years following the initial survey (2.5 years), to the product of the cohort rate among 20-24 year olds and the time spent aged 25-29 this cohort (5 years), and the product of the cohort rate among 25-29 year olds and the time spent aged 25-29 this cohort (2.5 years). This summation is subsequently divided by the length of the inter-survey period (10 years). Finally, I adjusted this calculation by adding the difference in the mortality rates between those with and without nutritional status *k*, in order to account for the fact that they are likely to die at different rates. Formally:

$$f_0(a) = \frac{\sum_{a-T}^{a} I_k(c) * p(c,a)}{\sum_{c}^{c+T} p(c,a)} + [m_k(a) - m_{!k}(a)]$$

Equation 5

Using the example of the first iteration of the rate for age group 25-29, successive iterations of the age-specific incidence rate are calculated in the following way:

1. Calculate the products of the cohort incidence rate for each cohort passing through age-group 25-29 with the initial age-specific rate estimate. Subsequently, calculate a weighted sum of these products by the time spent by each cohort in the five-year age-group for which the rate is required. For the age group 25-29 years between surveys ten years apart, this is calculated as follows:

$$[I_k(15-19) * f_0(20-24) * 2.5] + [I_k(20-24) * f_0(25-29) * 5] + [I_k(25-29) * f_0(30-34) * 2.5]$$

2. Calculate the sum of the age-specific rates from iteration 0, weighted by the time spent in each age group in the inter-survey period:

$$[f_0(20-24) * 2.5] + [f_0(25-29) * 5] + [f_0(30-34) * 2.5]$$

3. Divide the sum obtained in step 1 by the sum obtained in step 2, and as in Equation 5, adjust this by adding the difference in the mortality rates between those with and without nutritional status *k*.

Table 3 and Table 4 present an example of the calculation of age-specific annualised incidence of obesity among the overweight population of women in urban areas. In the table of inputs (Table 3), the first column refers to the age groups; the second and third contain the proportion *not* having experienced event *k* in 2005 and 2015, i.e. the proportion of the population who are overweight among those who are either overweight or obese. The fourth column contains the geometric average prevalence of overweight, which is used in the calculation of the average difference between the mortality rates of the obese and overweight populations. The fifth and sixth columns contain age-specific central death rates in 2005 and 2015 (expressed per 100,000-person years) estimated from SRS lifetables, the seventh column contains the age-specific relative risks of dying among obese women, relative to overweight women, and the final column contains the average difference in age-specific mortality between the obese and overweight population.

Table 3. Inputs needed to calculate obesity incidence using the Iterative Intracohort Interpolation method (women in urban areas) (5 d.p)

Age group (years)	*F (2005)*	*F (2015)*	*S*(a)*	*m(a) 2005*	*m(a) 2015*	*RR**	*Δ m(a)*
15-19	0.87824	0.79185	0.83393	0.00119	0.00089	1.2	0.00017
20-24	0.82741	0.78232	0.80455	0.00139	0.00100	1.2	0.00019
25-29	0.78938	0.75698	0.77301	0.00146	0.00089	1.2	0.00019
30-34	0.76670	0.72160	0.74380	0.00144	0.00089	1.2	0.00019
35-39	0.71938	0.69080	0.70495	0.00175	0.00123	1.2	0.00023
40-44	0.67842	0.67549	0.67695	0.00218	0.00171	1.2	0.00031
45-49	0.69618	0.66826	0.68208	0.00349	0.00260	1.2	0.00048

Table 4, is calculated using the formulae above and shows that the age-schedule of age-specific overweight incidence converges after approximately three iterations.

Table 4. Iterations of the intracohort interpolation using inputs from Table 3 (expressed per person-year) (5 d.p)

Age group (years)	*I(c)*	$f_0(a)$	$f_1(a)$	$f_2(a)$	$f_3(a)$
15-19	0.01486	0.01502	0.01502	0.01502	0.01502
20-24	0.01368	0.01466	0.01467	0.01467	0.01467
25-29	0.01334	0.01408	0.01409	0.01409	0.01409
30-34	0.01267	0.01344	0.01347	0.01347	0.01347
35-39	0.00737	0.01174	0.01181	0.01181	0.01181

This procedure was repeated for men and women in urban and rural areas aged 20-49 years. Separate sets of incidence rates were calculated for the transition from underweight/normal weight to overweight, and overweight to obesity.

One limitation of this procedure is that it calculates net transition rates, rather than gross rates, i.e. calculates the overall flow from state *!k* to *k*, rather than separate gross rates in and out of the nutritional states. In order to accommodate this in my final model, fixed remission rates were introduced on the rates of transition back to lower weight classes. These were added to the net rates of transition to overweight and obesity to convert the net rates into gross ones.

4.2.2 Calculation of the incidence of overweight and obesity in old age

For individuals aged 50-69 years, I calculated the number of incident cases, over all ages, of overweight and obesity among the population classified as initially underweight/normal weight and overweight, respectively, using longitudinal data from the Study on Global Ageing and Adult Health (SAGE) waves 0 (2002-04) and 1 (2007-10). This calculation was carried out for men and women separately. In order to estimate the approximate person-time at risk of transitioning, I assumed that incident cases occurred at the halfway-point between the waves.

As there were too few incident cases to reliably estimate age-specific rates directly from these data, I used indirect standardisation to estimate risk in India and obtained the detailed age pattern of incidence from an external standard. I identified a study conducted in the United States that estimated the following age-pattern of obesity incidence using data from the Behavioural Risk Factor Surveillance System[200]:

Table 5. Incidence of obesity in the United States reported in Pan et al (2011)

Age group (years)	*Incidence rate (%)*
18-29	6.4
30-49	4.8
50-59	3.3
70+	1.5

In order to obtain rates for the age-groups I needed (50-54; 55-59; 60-64; and 64-69), I fitted a spline to the above data, which I refer to as the standard rates, assuming that the above incidence rates pertained to the mid-point of each age-group.

Indirect standardisation involved scaling these standard rates by a standardised incidence ratio (SIR), which is defined as the ratio of the observed number of incident cases in India (estimated using SAGE data) to the expected number of events (how many incident cases one could expect to see if the standard rates was exposed to the same amount of person-time at risk as in the Indian data). Confidence intervals (95%) were obtained by multiplying the standard rates for the 50-54; 55-59; 60-64; and 64-69 age groups by upper and lower bounds of the SIR, which were obtained in the following way:

$$SIR_{95\%ci} = SIR \pm (1.96 * \frac{\sqrt{O}}{E})$$

Equation 6

Where O and E refer to the number of observed and expected incident cases, respectively. After obtaining a set of incidence rates of overweight and obesity among men and women, I obtained urban- and rural-specific incidence estimates using a scalar of the average association between urban and rural incidence and overall incidence that I estimated using the NFHS data.

4.2.3 Forecasting the central mortality rate using the Lee-Carter model

Rather than remaining constant over the forecast period, the age-specific mortality rates of the Indian population are likely to decline. Failure to account for future declines in mortality is likely to produce underestimates of the future prevalence of overweight and obesity.

In order to forecast future age–specific mortality, I used the Lee-Carter model[201–203]. This model summarises a series of historic age-specific mortality schedules over time using the following three parameters[204]:

Two age-specific (a) parameters:

- The average historic log age-specific mortality schedule (a_a)
- Age-specific deviations from this centred log mortality schedule (b_a)

One time-specific (t) parameter:

- Overall level of mortality (κ_t).

The Lee-Carter model proposes that any set of age-specific log mortality rates can be summarised as follows:

$$log(m_{a,t}) = a_a + b_a\kappa_t$$

Equation 7

Fitting the model involves subtracting the average log mortality curve (a_a) from the log mortality rates and performing a singular value decomposition (SVD) on the resulting centred mortality surface. From the SVD one can calculate b_a and K_t as follows[204]:

$$b_a = \frac{v}{\sum v} \quad \text{and} \quad \kappa_t = sU \sum v$$

Equation 8

Where v and u refer to the left and right singular vectors that correspond to the largest singular value (s).

The Lee-Carter model forecast depends entirely on the extrapolation of the κ_t parameter which I obtained using a random walk with a drift, which is estimated using maximum likelihood in ARIMA (0,1,0):

$$\tilde{d} = \frac{\kappa_T - \kappa_1}{T - 1}$$

Equation 9

The drift parameter is used to predict the mortality schedule in all succeeding periods after the last year for which recorded mortality data is available.

I obtained input mortality data for the Lee-Carter mortality forecast from the SRS (explained in detail in Chapter Seven), which contains lifetable data for every year from 1997 to 2013 for men and women separately in both urban and rural India. Using the ${}_nq_a$ values contained in the abridged lifetables, which denotes the conditional probability that an individual aged a will die between exact ages a and $a+n$, I calculated age-specific mortality rates using a rearrangement of Chiang's (1968) formula[205,206] This formula was initially designed to calculate this conditional probability using age-specific mortality rates. Specifically,

$$
{}_{n}^{k}m_{a} = \frac{{}_{n}^{k}q_{a}}{n + \left({}_{n}^{k}a'_{a} - n\right){}_{n}^{k}q_{a}}
$$

Equation 10

Where *k* refers to the subpopulation the central mortality rate relates to, i.e. urban men, urban women, rural men, or rural women. Additionally, ${}_{n}a'_{a}$ refers to the proportion of the interval lived by those who die between ages a and $a+n$. The parameter values obtained from the series of age-specific mortality schedules from 1997 to 2013 are shown in Figure 4 using the example of women in urban areas.

Using these parameters, I forecasted future mortality using the **forecast** function in R, which also produced 95% confidence intervals[207,208]. Figure 5 shows the forecasted log mortality rates for the ages of interest between 1997 and 2050.

Figure 4. Plot of the a_a (Panel 1), b_a (Panel 2) and k_t (Panel 3) parameters used in the Lee-Carter Mortality forecast (Women in Urban India aged 20-69 years)

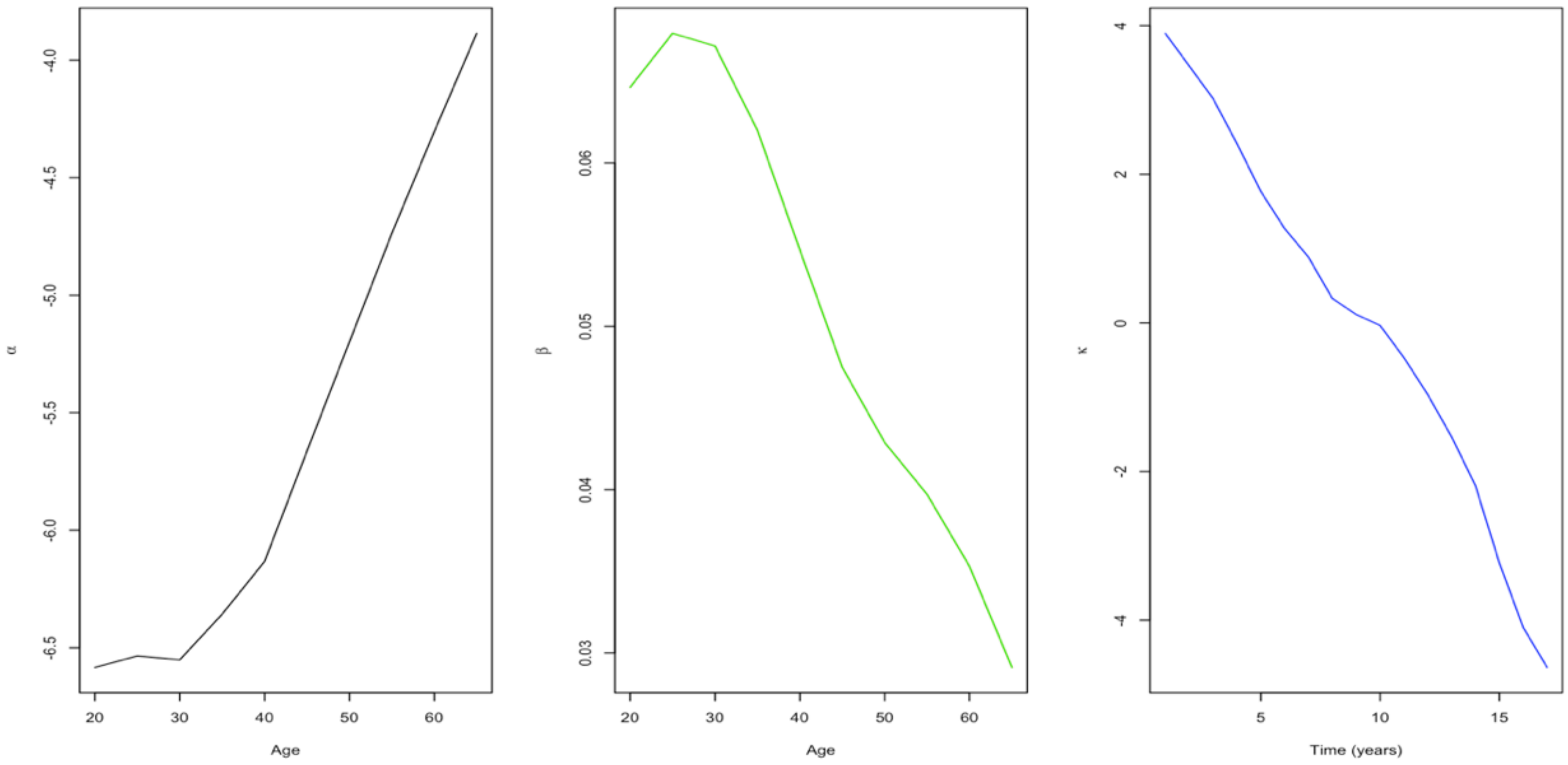
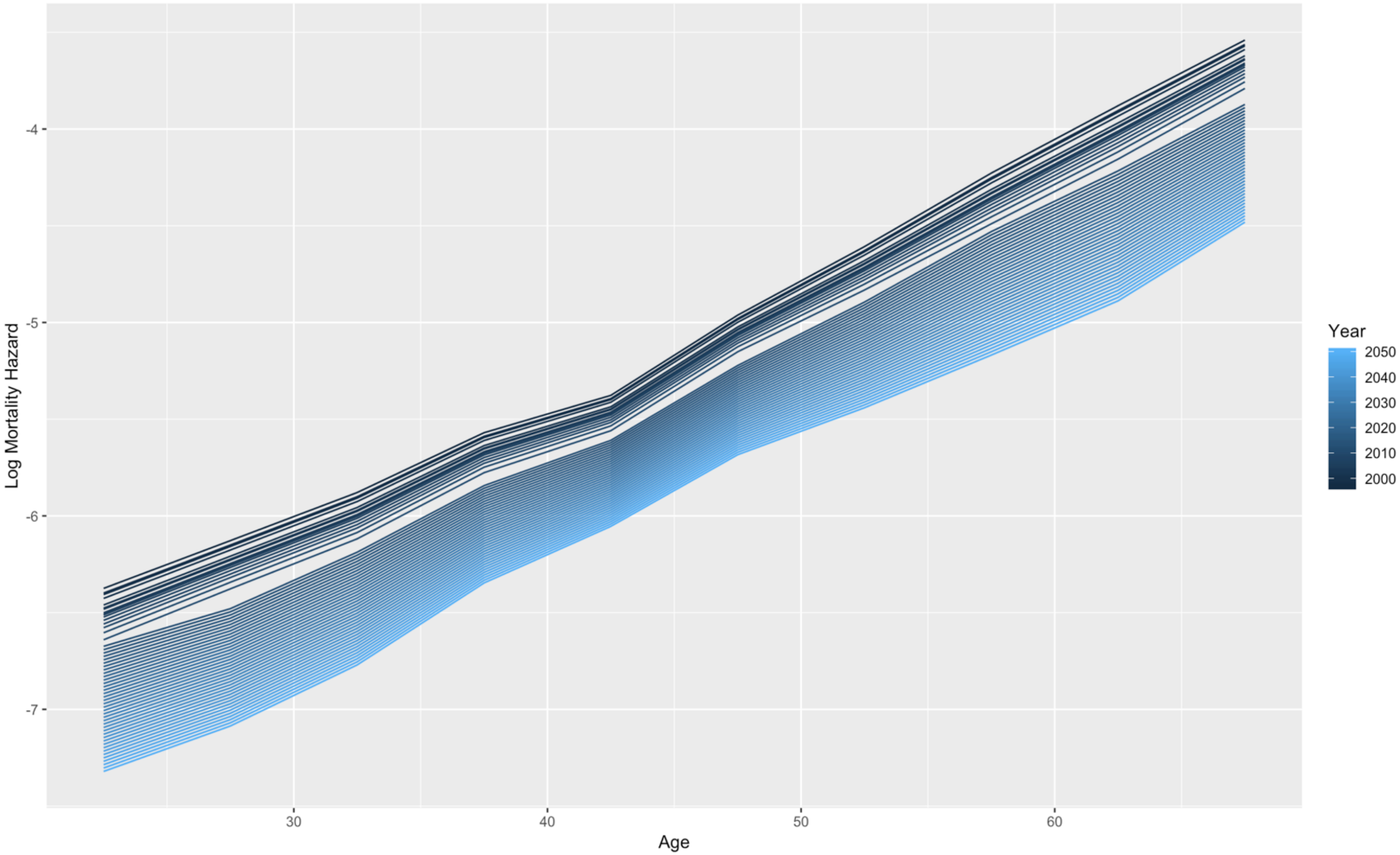


Figure 5. Age-specific log mortality rates (20-69 years) among women in urban India (1997-2013 actual; 2014-2050 forecast)



*Source: SRS Abridged lifetables

4.2.4. Differential mortality by nutritional status

Individuals classified as underweight/normal weight, overweight, and obese are all likely to have different risks of mortality, and failure to account for this may bias my final estimates of the future prevalence of various nutritional statuses. Using relative risks of mortality for different BMI categories, relative to a specified baseline, one can adjust the central mortality rate to obtain BMI group-specific mortality rates. I used the relative risks of dying by BMI group, relative to the normal weight category, reported in Pednekar et al. (2008)[209]. This study examined the association of body weight with mortality in Mumbai in a prospective cohort study that followed up 148,173 individuals aged 35 and above, recruited in 1991-97 through to 1997-2003. As the study reported relative risks for men and women aged 35-59 and 60+, I used the relative risks for the 35-59 age group for individuals aged 20-34 years.

Table 6. Relative risks of dying by BMI group in India (reference group: Normal weight 18.5-24.9kg/m^2)

BMI Group	***Age (years)***	***Women***			***Men***		
		RR	*Lower*	*Upper*	*RR*	*Lower*	*Upper*
Underweight	*35-59*	1.7	1.5	1.9	1.5	1.9	2.2
	60+	2.0	1.3	1.6	1.4	1.3	1.4
Overweight	*35-59*	1.0	0.9	1.2	0.9	0.8	1.0
	60+	0.8	0.7	0.9	0.9	0.8	0.9
Obese	*35-59*	1.2	1.0	1.5	1.2	1.0	1.5
	60+	0.8	0.7	1.0	0.9	0.8	1.1

Source: Pednekar et al (2008) page 528

I obtained separate mortality rates for individuals in the obese and overweight BMI categories and updated them at every interval as the apportioning of the central mortality rate to various BMI categories is dependent on the proportion of the population in those categories. For example, I obtained the mortality rate of the obese population in the following way:

1. Obtain the relative risk of dying for the obese population relative to the non-obese population.

$$ {}_{!OB}^{OB}R_{a,t} = \frac{{}_{N}^{OB}R_{a,t}}{({}_{N}^{UW}R_{a,t} * {}_{-OB}^{UW}\theta_{a,t}) + ({}_{N}^{OW}R_{a,t} * {}_{-OB}^{OW}\theta_{a,t}) + {}_{-OB}^{N}\theta_{a,t}} $$

Equation 11

Where ${}_{N}^{OB}R_{a,t}$, ${}_{N}^{UW}R_{a,t}$, and ${}_{N}^{OW}R_{a,t}$ represent the relative risks of dying among the population who are obese, underweight, and overweight, respectively, relative to the normal weight reference category, reported in Table 6. The terms ${}_{-OB}^{OW}\theta_{a,t}$, ${}_{-OB}^{UW}\theta_{a,t}$, and ${}_{-OB}^{N}\theta_{a,t}$ denote the proportion of the total population that excludes the obese population, who are overweight, underweight and normal weight, respectively.

2. Obtain the mortality rate among the non-obese population.

$$ m_{a,t}^{!OB} = \frac{\overline{m}_{a,t}}{(\gamma_{a,t}^{OB} * {}_{!OB}^{OB}R_{a,t}) - \gamma_{a,t}^{OB} + 1} $$

Equation 12

Where $\overline{m}_{a,t}$ and $\gamma_{a,t}^{OB}$ denote the central death rate and the prevalence of obesity, respectively, for age group *a* at time *t*.

3. Use the mortality rate among the non-obese population to obtain the mortality rate among the obese population, using the following formula:

$$m_{a,t}^{OB} = m_{a,t}^{!OB} * {}_{!OB}^{OB}R_{a,t}$$

Equation 13

These calculations were repeated to obtain the relative risk of dying among the overweight population relative to those who are not.

The mortality rate among the underweight/normal weight population was subsequently obtained with the knowledge that the central death rate ($\overline{m}_{a,t}$) is a weighted sum of the death rates in each of the *k* lifetables. Specifically,

$$m_{a,t}^{UW/N} = \overline{m}_{a,t} - \left(m_{a,t}^{OB} * \gamma_{x,t}^{OB}\right) + \left(m_{a,t}^{OW} * \gamma_{a,t}^{OW}\right)$$

Equation 14

4.2.5. Calculation of multi-status lifetables

The incidence-based model used to forecast the future prevalence of overweight and obesity in India is presented in Figure 15 in Chapter Seven. In brief, the future predicted prevalence of overweight and obesity in urban and rural India are determined by a set of age-specific rates of flow into these BMI groups, which I refer to as health states, rates of flow out of these groups back to lower BMI groups, rates of urbanisation and age- and health state- specific mortality rates.

A common way of forecasting in this framework is to populate a matrix of transition rates before converting it to a matrix of transition probabilities. In this case, each cell of a transition matrix denotes the probability that an individual will be in a particular health state in a succeeding period, dependent on the state in which they started. However, most studies apply transition probabilities to the population at risk of a transition *at the beginning* of a time period to determine the distribution of the population across health states in a succeeding time period. Importantly, the models do not take account of a changing population-at-risk within a time period, for instance, allowing people to follow various pathways within a five-year forecast step, albeit determined by discrete age-period rates. This may become more problematic when working with relatively wider age-groups. In order to fully account for this, I employed a multi-state lifetable system developed by Schoen and Nelson (1974) who addressed questions about flows in and out of marriage in the UK and USA using a system of lifetables[210]. Rather than work with transition probabilities derived from the rates, this model directly uses the rates to calculate the forecast.

The forecast was carried out using a system of six interconnected increment-decrement lifetables; one for each of the transient health states (for example, overweight (rural) and obese (urban)). If the number of individuals alive at age a in state k is l_a^k, then the number of individuals in state k in age group $a+n$, whereby n denotes the interval width, can be formally written as:

$$l_{a+n}^k = l_a^k + \sum_{i \neq k}^{k} {}_n^i d_a^k - \sum_{i \neq k}^{k} {}_n^k d_a^i - {}_n^k d_a^m$$

Equation 15

Whereby $\sum_{i \neq k}^{k} {}_n^i d_a^k$ refers to the total number of decrements from state i to state k, $\sum_{i \neq k}^{k} {}_n^k d_a^i$ refers to the total number of decrements from state k to other states i, and ${}_n^k d_a^m$ the total number of deaths from state k between exact ages a and $a+n$. For instance, in this system, the population of obese women in urban India in 2015 will depend on the number of women entering this state from the overweight rural, overweight urban and obese rural lifetables between 2010 and 2015, the number exiting to the overweight urban state between 2010 and 2015, and the number of deaths among urban obese women between 2010 and 2015.

The total person-years of exposure for a cohort in lifetable k between ages a and $a+n$ to a particular decrement is denoted by the standard lifetable notation ${}_n^k L_a$. The number of decrements needed to calculate the total number of entries in and out of a particular health state is therefore:

$$ {}_{n}^{i}d_{a}^{k} = {}_{n}^{i}r_{a}^{k} * {}_{n}^{k}L_{a} $$

Equation 16

Where *r* represents the rate of transition (incidence, mortality, remission or urbanisation).

After repeating the above equation for the total number of transitions between ages a and $a+n$, and substituting the values into l_{a+n}^{k} to obtain an initial estimate of the number of individuals in state *k* at age $a+n$, I obtained an updated estimate of the number of person-years of exposure using the formula below, which expresses the total number of person-years in terms of initial and subsequent people in each health state.

$$ \widehat{{}_{n}^{k}L_{a}} = \frac{n}{2}(l_{a}^{k}+l_{a+n}^{k}) $$

Equation 17

Using this new estimate of person-years of exposure to a particular decrement, I recalculated the number of decrements expected and the number of individuals alive at age $a+n$ in each lifetable *k*. I repeated this iterative procedure until the $\widehat{{}_{n}^{k}L_{a}}$ converged, ensuring that the appropriate population at risk of a decrement was considered at each time step of the forecast.

4.3. Forecasts of future diabetes prevalence in urban India

4.3.1. The model

In order to forecast the future prevalence of diabetes in urban India, I adopted a dynamic macrosimulation model, which estimates the future prevalence of diabetes as a function of diabetes incidence and demographic change. The model was based on the MEDCHAMPS IMPACT model that has been used to forecast type-2 diabetes in a number of countries[128–132,211].

The model I employed operates by partitioning the population into four separate living health states, and one absorbing state, death (Figure 6). The living health states are broken down further into the Diabetes (blue) and non-Diabetes (green) states. A criterion of the modelling approach adopted is the mutual exclusivity of health states i.e. nobody can occupy more than one state at any one time. Therefore, the diabetes state contained all individuals classified as having diabetes; the state 'Overweight/Obese' contained all overweight and obese individuals who did not have diabetes; the 'Tobacco Consumer' state contained all tobacco consuming individuals who neither had diabetes nor were classified as overweight or obese; and the 'Healthy' state contained all the remaining living people.

The model I adopted differed from the original MEDCHAMPS IMPACT model in a number of ways[128,131,132,211,212]. Firstly, I did not include two separate death states (one for deaths related to diabetes and deaths from other causes), as estimating the future number of diabetes-related deaths was not an objective of this study. On the other hand, I included just one death state, with differential probabilities of dying based on age and starting state. Secondly, the MEDCHAMPS IMPACT model included predictions of future smoking prevalence, which was assumed to increase linearly into the forecasting period. On the other hand, I used smokeless tobacco consumption, as it is a more common form of tobacco consumption in India. For instance, in the 2016-17 Global Adult Tobacco Survey reported that 29.6% of men and 12.8% of women were smokeless tobacco consumers[213]. Finally, whereas the MEDCHAMPS IMPACT model incorporates future obesity to drive future diabetes, I include a measure of both overweight and obesity, as overweight individuals are also at a higher, albeit attenuated, risk of developing diabetes compared to underweight/normal weight individuals[214,215].

The model operated in discrete time (5-year intervals) and used a Markov assumption, in that the probability of transitioning from one of the health states to another or remaining in the same health state in a subsequent period, was conditional only on the starting state.

Table 7 includes a list of the parameters needed to run the model, the data source of the parameters, how they were calculated, and how the data source measured the variables necessary.

Figure 6. Compartmental model used to forecast future diabetes prevalence in India

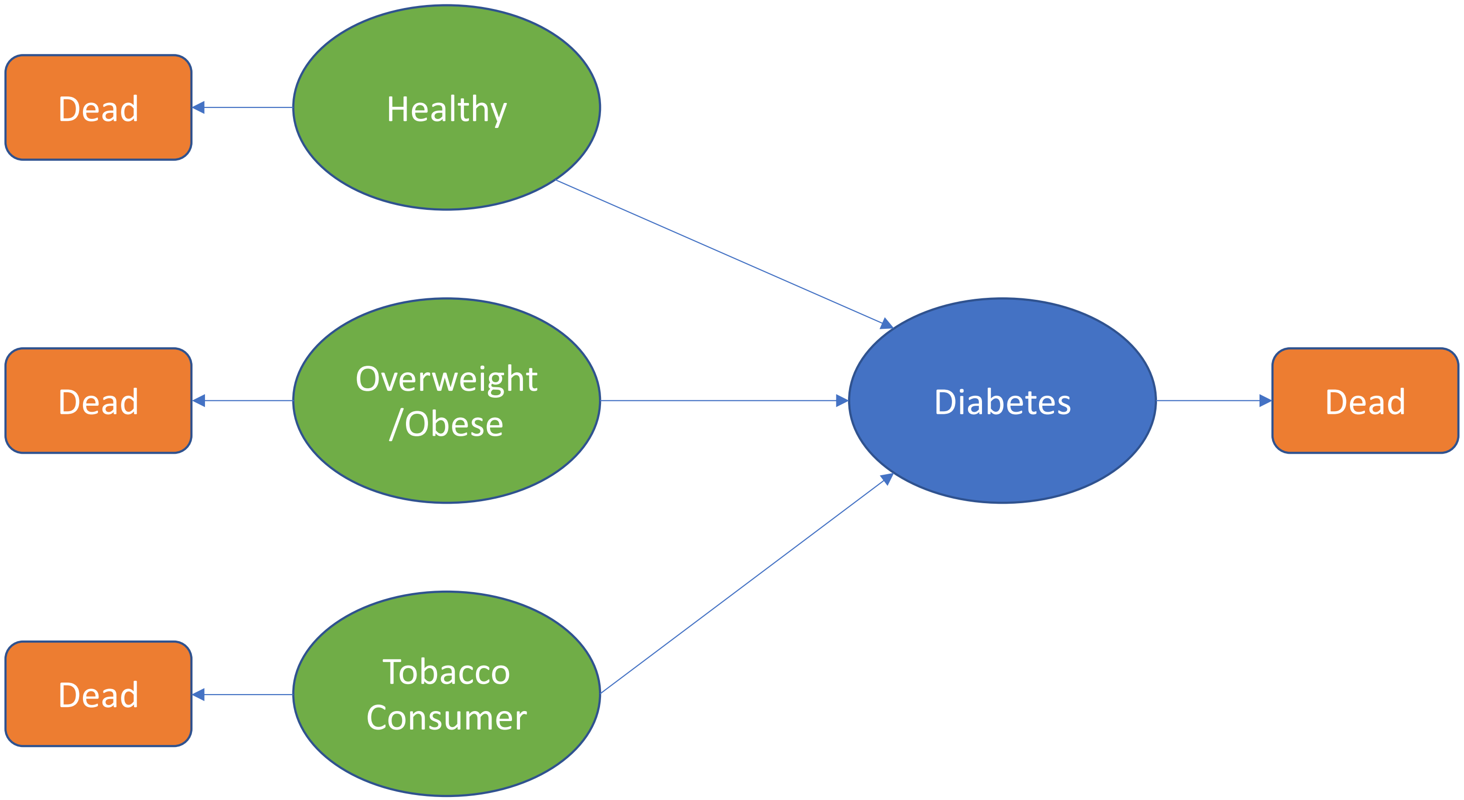


Table 7. Parameters used in the diabetes forecasting model

	Source	***Calculation***	***Definitions***
Initial Population	United Nations World Population prospects (2017)[37]; UN world Urbanization prospects (2018)[9]	Sex-stratified population multiplied by urban/rural proportions	
Prevalence of diabetes	Indian Council for Medical Research-India Diabetes Study (ICMR-INDIAB) prevalence of diabetes in 14 of 28 Indian states between 2008 and 2013 (57117 individuals)		Capillary Blood Glucose (CBG) ≥126mg/dl; 2hr post glucose load CBG≥ 220mg/dl, or both[22].
Prevalence of overweight/obesity (BMI≥25.0kg/m^2)	NFHS-3 2005-06; NFHS-4 2015-16[18,19]	Linear interpolation of the prevalence in the two surveys	25.0-29.9kg/m^2 = Overweight; ≥30.0kg/m^2=Obese
Forecast of overweight/obesity		Dynamic Markov model in Luhar et al (Chapter Seven)	25.0-29.9kg/m^2 = Overweight; ≥30.0kg/m^2=Obese
Prevalence of smokeless tobacco consumption	Global Adult Tobacco Survey (GATS) 2009-10[213]		
Forecast of smokeless tobacco consumption	GATS 2009-10; GATS 2016-17[213]	Application of relative change between surveys to subsequent years	

Table 7 continued…

	Source	*Calculation*	*Definitions*
Incidence of diabetes	Centre for Cardiometabolic Risk Reduction in South Asia Study (CARRS) baseline (2010); CARRS 2018	Cox Poisson regression	Diabetes treatment *or* Fasting Plasma Glucose (FPG) ≥ 126kg/m^2 *or* Glycated Haemoglobin (Ha1C)>6.5%
Central mortality rate	Sample Registration System (SRS) Abridged lifetables 1997-2013[216–221]	Standard lifetable techniques	
Forecasted mortality rate		Lee-Carter Model	
New entrants aged 20-24 years	United Nations World Population prospects (2017)[37]; UN world Urbanization prospects (2018)[9]		

4.3.2. Differential transition rates

I calculated separate rates of diabetes incidence and mortality depending on the non-diabetes living state one was in. For instance, the incidence rate of diabetes among those who are overweight or obese is likely to be considerably higher than the incidence rate among the population who are neither overweight nor obese as it is the primary risk factor for diabetes. A meta-analysis by Abdullah et al (2010) found that across 18 published prospective cohort studies, the risk of diabetes for obese people, relative to the normal weight population, was 7.2 times higher (95%CI: 5.7-9.0), whereas overweight people had three times the rate of diabetes compared to normal weight people[222]. Incidence rates in the CARRS study (refer to Table 7 and Chapter Eight) were calculated separately for individuals who were neither overweight nor obese, those who were overweight, and those who were obese. The overall incidence rate among the overweight/obese population was weighted depending on the proportion of the overweight/obese population that were overweight and obese respectively. Formally:

$$i_{a,t}^{O} = (i_{a,t}^{OW} * \theta_{a,t}^{OW\prime}) + (i_{a,t}^{OB} * \theta_{a,t}^{OB\prime})$$

Equation 18

Where $\theta_{a,t}^{k\prime}$ represents the proportion of the overweight/obese people at age *a* at time *t* that are either overweight or obese, and $i_{a,t}^{OW}$, $i_{a,t}^{OB}$, and $i_{a,t}^{O}$ represent the incidence of diabetes among the overweight, obese and overweight/obese population, respectively.

The incidence rate of diabetes among the remaining living non-diabetes states was obtained by partitioning the incidence among the non-overweight/obese population ($i_{a,t}^{-O}$) into separate incidence rates for the 'Healthy' and 'Tobacco consumer' states. Specifically, the incidence rate among the non-overweight/obese population can be partitioned in the following way:

$$i_{a,t}^{-O} = (i_{a,t}^{TC} * \theta_{a,t}^{TC}) + (i_{a,t}^{H} * \theta_{a,t}^{H})$$

Equation 19

Whereby $\theta_{a,t}^{TC}$ and $\theta_{a,t}^{H}$ represent the proportion of the population who are neither overweight/obese nor have diabetes who are tobacco consumers, and not tobacco consumers, respectively. Similar to the equations used in Section 4.2.4, I partitioned $i_{a,t}^{-O}$using the relative risk of diabetes among tobacco users relative to non-tobacco users. A recent study conducted in Sweden has found that adults consuming smokeless tobacco have a 15% (95% CI: 0%-32%) greater risk of dying, relative to those who do not consume smokeless tobacco[223].

Similarly, I used relative risks of dying from the literature to inform differential mortality rates for those who are tobacco consumers, those who are overweight/obese and individuals with diabetes. A brief overview of the studies used for this calculation is included in Chapter Eight.

4.3.3. Transition matrix used to forecast diabetes

After obtaining the parameters, I populated an intensity matrix of rates ($\mathbf{Q}_{a,t}$), which contained the rates of transition to different health states depending on the starting state and age, and time period. The matrix $\mathbf{Q}_{a,t}$ was then converted to a matrix of transition probabilities ($\mathbf{P}_{a,t}$) by calculating the matrix exponential. To do this, I used the 'expm' package[224] in R version 3.5.1.

In the matrices below, the first row (state at time *t*) and first column (state at time *t+n,* where *n* is the length of the time step) refer to the 'Healthy' state, the second refers to the 'Overweight/Obese' state, the third refers to the 'Tobacco Consumer' state, the fourth is the 'Diabetes' state, and the fifth represents the 'Death' state.

$$\mathbf{Q}_{a,t} = \begin{pmatrix} -i_{a,t}^{H} - m_{a,t}^{H} & 0 & 0 & i_{a,t}^{H} & m_{a,t}^{H} \\ 0 & -i_{a,t}^{O} - m_{a,t}^{O} & 0 & i_{a,t}^{O} & m_{a,t}^{O} \\ 0 & 0 & -i_{a,t}^{TC} - m_{a,t}^{TC} & i_{a,t}^{TC} & m_{a,t}^{TC} \\ 0 & 0 & 0 & -m_{a,t}^{D} & m_{a,t}^{D} \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

$$\mathbf{P}_{a,t} = \begin{pmatrix} 1 - p_{a,t}^{H} - q_{a,t}^{H} & 0 & 0 & p_{a,t}^{H} & q_{a,t}^{H} \\ 0 & 1 - p_{a,t}^{O} - q_{a,t}^{O} & 0 & p_{a,t}^{O} & q_{a,t}^{O} \\ 0 & 0 & 1 - p_{a,t}^{TC} - q_{a,t}^{TC} & p_{a,t}^{TC} & q_{a,t}^{TC} \\ 0 & 0 & 0 & 1 - q_{a,t}^{D} & q_{a,t}^{D} \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

In matrix $\mathbf{Q}_{a,t}$, the terms $m_{a,t}^{k}$ and $i_{a,t}^{k}$ refer to the rates of mortality and incidence of diabetes, depending on the state *k* one is in at the beginning of the time step. Terms *p* and *q* in the transition matrix $\mathbf{P}_{a,t}$ refer to the probability that one will occupy the 'Diabetes' state or 'Death' state, respectively, at the end of the time step, dependent on the starting state.

In order to forecast diabetes in subsequent time periods, I used π_t, a vector of the population distributed between the five states in time *t*. The matrix multiplication of this vector with the transition matrix $\mathbf{P}_{a,t}$ yields the population distribution across the five health states in period *t+n*.

$$\pi_{a+n,t+n} = \boldsymbol{P}_{a,t} * \pi_{a,t}$$

Equation 20

In order for external forecasts of the prevalence of overweight/obesity and tobacco consumption to be fed into the model, without adjusting the 'Diabetes' state, as per the MEDCHAMPS IMPACT method[128,130–132,211], I reallocated the living population across the three remaining living health states before each time step. This procedure is outlined in detail below and refers to any age group of individuals in the model:

1. Calculate the adjusted prevalence of tobacco consumption, after the removal of tobacco consumers who are overweight or obese ($P_t^{T\prime}$), where P_t^{O} and P_t^{T} are the prevalence of overweight/obesity and tobacco consumption, respectively:

$$P_t^{T\prime} = P_t^{T} - (P_t^{T} * P_t^{O})$$

Equation 21

2. Calculate the size of the Diabetes State in $t+n$ for a particular cohort:

$$D_{t+n} = (D_t * (1 - q_t^D)) + (T_t * p_t^{TC}) + \ (H_t * p_t^H) + \ (O_t * p_t^O)$$

Equation 22

Where D_t is the number of individuals with diabetes in time *t*; $T_t$is the number of individuals in the 'Tobacco consumer' state in time *t*; H_t is the number of individuals in the 'Healthy' state in time *t*; and O_t is the number of individuals in the 'Overweight/Obese' state in time *t*.

3. Calculate the Population size (N) in $t+n$:

$$N_{t+n} = N_t - M_t$$

Equation 23

Where $M_t$is represents the number of people who die between *t* and $t+n$.

4. Calculate the size of the 'Tobacco Consumer' state in preparation for next time step:

$$T_{t+n} = (N_{t+n} * P_{t+n}^{T\prime}) - D_{t+n} * \left\{ \frac{P_{t+n}^{T\prime} * (RR^T - 1)}{1 + (P_{t+n}^{T\prime} * (RR^T - 1))} \right\}$$

Equation 24

Where RR^Trepresents the risk of diabetes among tobacco consumers relative to those who are not.

5. Calculate the size of the 'Overweight/Obesity' state in preparation for next time step:

$$O_{t+n} = (N_{t+n} * P_{t+n}^{O}) - D_{t+1} * \left\{ \frac{P_{t+n}^{O} * (RR^{O} - 1)}{1 + (P_{t+n}^{O} * (RR^{O} - 1))} \right\}$$

Equation 25

Where RR^{O} represents the relative risk of diabetes among overweight/obese people, relative to those who are not.

6. Calculate the size of the Healthy State in time *t+n*:

$$H_{t+n} = N_{t+n} - (D_{t+n} + T_{t+n} + O_{t+n})$$

Equation 26

4.4. Estimates of Life time risk, diabetes-free life expectancy, and Years of Life Lost to diabetes

In Chapter Nine, I sought to estimate the lifetime risk of diabetes in India using a matrix model by age, sex and BMI and estimate diabetes-free life expectancy by age and sex. In the Appendix, I also report results from calculations of the Years of Life Lost (YLL) to diabetes by age and sex. In this section I provide a detailed description of the methodology adopted in the chapter.

4.4.1. The transition matrix

The starting point of the analysis was populating a transition matrix, structured by age and sex separately for each BMI category (Not Overweight/Obese; Overweight; and Obese), whereby living individuals can either be classified as having diabetes or not. A typical transition matrix, whereby transition probabilities are assigned based on an initial state, is formally shown as[225,226]:

$$\boldsymbol{P} = \begin{pmatrix} \boldsymbol{U} & \boldsymbol{M} \\ \boldsymbol{0} & \boldsymbol{I} \end{pmatrix}$$

Where the separate cells represent submatrices. The submatrix denoted by **U** represents transitions among the transient (living) states, the **M** submatrix denotes the transitions from living states to death, and submatrix **I** represent an identity matrix populated with values of 1 across the diagonal. Note that in contrast to the diabetes forecasts which modelled five-year age groups, the estimates of lifetime risk were obtained for individual ages from 20-79 years. The expanded form of the matrices **U** and **M** are as follows:

$$\boldsymbol{U} = \begin{pmatrix} 0 & 0 & \gamma_a & \mu_a & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 0 & d_i & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 0 & 0 & \gamma_{a+1} & \mu_{a+1} & \cdots & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & d_{a+1} & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \cdots & \gamma_X & \mu_X \\ 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & d_X \\ 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 \end{pmatrix}$$

$$\boldsymbol{M} = \begin{pmatrix} \delta_a & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & \varphi_a & 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 0 & \delta_{a+1} & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \varphi_{a+1} & \cdots & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & \delta_X & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \cdots & 0 & \varphi_X & 0 & 0 \\ 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 1 \end{pmatrix}$$

In the matrix **U**, γ_a is the probability of an individual not having diabetes in time *t+1* if they did not have diabetes in time *t*; μ_a represents the probability of an individual who does not have diabetes in time *t* developing diabetes by time *t+1*; and d_a represents the probability of somebody with diabetes in time *t* still having diabetes in $t+1$. Although in the model I assume no remission from diabetes, this probability is not equal to 1 due to the competing risk of mortality.

In the mortality submatrix, $\mathbf{M}$, δ_a denotes the probability of dying among those without diabetes aged *a* at time *t*, and φ_a represents the probability of dying among those with diabetes aged *a* at time *t*.

From the transition matrix, I obtained estimates of the time spent in each of the transient states, or occupancy time, by calculating the fundamental matrix of the transition matrix[225–227]. The fundamental matrix ($\mathbf{N}_1$) of matrix $\mathbf{U}$ is calculated in the following way:

$$\boldsymbol{N}_1 = (\boldsymbol{I}_s - \boldsymbol{U})^{-1}$$

Equation 27

Each cell in $\mathbf{N}_1$ represents the expected occupancy times, or number of years, an individual can expect to live in a particular health state (i.e. with or without diabetes), given their starting state. From a matrix of times spent in each state given a particular starting state and age, one can calculate the following statistics:

- Years of life lost (YLL) to diabetes
- Diabetes-free life expectancy

4.4.2. Years of life lost (YLL) to diabetes

$$\boldsymbol{N}_1 = E\begin{pmatrix} \omega_{ND\to ND} & \omega_{ND\to D} \\ 0 & \omega_{D\to D} \end{pmatrix}$$

Above I present a condensed fundamental matrix of occupancy times, for any age, whereby $\omega_{ND\to ND}$ represents the proportion of the time between time *t* and *t+1* that a person can expect to live without diabetes, assuming they start without diabetes, $\omega_{ND\rightarrow D}$ represents the amount of time one can expect to live with diabetes, given they started out without diabetes, and $\omega_{D\rightarrow D}$ represents the amount of time one can expect to live with diabetes, given they started out with diabetes. In an age-classified model, stratified by single years, each cell contains the proportion of the coming year one can expect to live in each state, depending on starting state and age.

It follows that the sum of each row, therefore, will represent the average remaining life expectancy, conditional on the starting state and starting age.

In order to obtain the life expectancy of the average individual at starting age *a* without diabetes (η_a^{ND}), I calculated the sum of the odd rows. Similarly, the life expectancy of the average individual at any age with diabetes was calculated as the sum of the even rows (η_a^{D}). This was conducted for ages 20 through 79. The notation *p* in the equations below refer to the columns of fundamental matrix ($\mathbf{N}_1$), and ω represents the elements of $\mathbf{N}_1$.

$$\eta_a^{ND} = \sum_{p\geq 1} \omega_{2(a-19)-1,p}$$

Equation 28

$$\eta_a^{D} = \sum_{p\geq 1} \omega_{2(a-19),p}$$

Equation 29

The YLL lost to diabetes at age *a* was calculated as the excess number of expected years an individual at age *a* without diabetes can expect to live compared to someone of the same age without diabetes.

$$YLL_a = \eta_a^{ND} - \eta_a^{D}$$

Equation 30

4.4.3. Diabetes-free life expectancy

The amount of time a person who does not have diabetes at any age, can expect to live with diabetes throughout their lifetime, was calculated as the sum of the cells in odd rows, excluding the odd columns (which refer to the time spent without diabetes depending on starting state)[140,225]. I denote the time spent with diabetes among those without diabetes at age a as ψ_a.

$$\psi_a = \sum_{p \geq 1} \omega_{2(a-19)-1,2p}$$

Equation 31

The proportion of life lived diabetes-free if one did not have diabetes at age a is equal to:

$$\theta_a = \frac{\psi_a}{\eta_a^{ND}}$$

Equation 32

And diabetes-free life expectancy is measured as the difference between the denominator and numerator in Equation 32.

4.4.4. Remaining lifetime risk of diabetes

The remaining lifetime risk of diabetes is defined as the probability that an individual without diabetes at any age will develop diabetes before death. This statistic was obtained by firstly calculating probability matrix, **B**, which refers to the probability distribution of the age at death[225]. Matrix **B** is calculated as the product of the fundamental matrix $\mathbf{N}_1$ and mortality matrix **M**.

$$\boldsymbol{B} = \boldsymbol{M}\boldsymbol{N}_{\mathbf{1}}$$

Equation 33

In matrix **B**, cells $b_{2(a-19)-1,2p}$ represents the probability of dying with diabetes if one did not have diabetes at age *a*. As a key assumption of my model is that an individual with diabetes cannot transition back from having diabetes, the lifetime risk of developing diabetes at any age can be defined as the probability that an individual without diabetes will eventually die with diabetes. Formally,

$$LTR_a = \sum_{p \geq 2(a-19)-1} b_{2(a-19)-1,2p}$$

Equation 34

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Student ID Number	1300428	**Title**	Mr
First Name(s)	Shammi		
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Thesis Title	Trends in the socioeconomic patterning of overweight and obesity and predictions of the future prevalence of diabetes in India		
Primary Supervisor	Lynda Clarke		

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Chapter Five. Trends in the socioeconomic patterning of overweight/obesity in India: a repeated cross-sectional study using nationally representative data

5.1. Abstract

Objectives: I aimed to examine trends in prevalence of overweight/obesity among adults in India by socioeconomic position (SEP) between 1998 and 2016.

Design: Repeated cross-sectional study using nationally representative data from India collected in 1998/1999, 2005/2006 and 2015/16. Multilevel regressions were used to assess trends in prevalence of overweight/obesity by SEP.

Setting: 26, 29 and 36 Indian states or union territories, in 1998/99, 2005/06 and 2015/16, respectively.

Participants: 628,795 ever-married women aged 15–49 years and 93,618 men aged 15-54.

Primary outcome measure: Overweight/obesity defined by BMI >24.9 kg/m^2.

Results: Between 1998 and 2016, overweight/obesity prevalence increased among men and women in both urban and rural areas. In all periods, overweight/obesity prevalence was consistently highest among higher SEP individuals. In urban areas, overweight/obesity prevalence increased considerably over the study period among lower SEP adults. For instance, between 1998 and 2016, overweight/obesity prevalence increased from approximately 15% to 32% among urban women with no education. Whereas the prevalence among urban men with higher education increased from 26% to 34% between 2005 and 2016, I did not observe any notable changes among high SEP urban women between 1998 and 2016. In rural areas, more similar increases in overweight/obesity prevalence were found among all individuals across the study period, irrespective of SEP. Among rural women with higher education, overweight/obesity increased from 16 to 25% between 1998 and 2016, whilst the prevalence among rural women with no education increased from 4% to 14%.

Conclusions: I identified some convergence of overweight/obesity prevalence across SEP in urban areas among both men and women, with fewer signs of convergence across SEP groups in rural areas. Efforts are therefore needed to slow the increasing trend of overweight/obesity among all Indians, as I found evidence suggesting it may no longer be considered a 'diseases of affluence'.

Strengths and Limitations of this study

My use of the most recent nationally representative data available for Indian adults make my results the most up-to-date estimates of the socioeconomic patterning of overweight/obesity, and their trends, in India.

Using a large nationally representative data set also enabled me to generate both precise and nationally generalisable overweight/obesity prevalence trends.

BMI was the only measure used to define overweight/obesity, and prevalence estimates may vary based on the adiposity measure used and the cut-offs used. However, I would not expect the reported socioeconomic patterning of overweight/obesity, and trends, to change considerably between measures.

My results may mask subnational variation in overweight/obesity prevalence and trends, especially given large subnational differences in economic growth, demography and culture between India's states.

5.2. Introduction

Overweight and obesity present considerable challenges to the maintenance of global health improvements due to its association with many NCDs[1]. The WHO's aim to reduce global obesity to 2010 levels by 2025[1], is threatened by the increasing prevalence of overweight and obesity in India[19], where nearly a sixth of the global population lives[37].

In India, economic growth and rising incomes have been accompanied by increases in the proportion of Indians classified as overweight or obese. The proportion of adult women classified as either overweight or more than doubled for adult women from 9% to 21% between 1998 and 2016, while increasing from 11% to 19% among adult men between 2005 and 2016[18–20]. At the same time, undernutrition and infectious diseases continue to threaten population health[91,146,228,229], presenting dilemmas about the appropriate allocation of scarce public finances and policy attention.

In LICs, overweight and obesity is usually more prevalent among higher socioeconomic position (SEP) groups[19,30,32,69,87], whereas the opposite is observed in most HICs, where lower SEP individuals are more likely to be overweight or obese[30,32]. Although considered a LMIC[8], India has experienced considerable economic growth between 1998 and 2015[230], and how this has impacted the proportion classified as overweight or obese in different SEP groups is unknown.

In this study, I aim to estimate recent trends in the proportion of Indians considered overweight or obese by SEP in India. My results are intended to inform health policy decisions by identifying groups currently most at risk of being overweight or obese, and those that have experienced the largest increases in prevalence between 1998 and 2016[231]. I hypothesise that between 1998 and 2016, the proportion classified as overweight or obese has increased in all SEP groups, in both urban and rural areas, however, with greater increases among lower SEP individuals than higher SEP individuals.

5.3. Methods

5.3.1. Study Population

The National Family Health Surveys (NFHS) 2, 3 and 4, collected in 1998-99, 2005-06 and 2015-16, respectively, gathered health and demographic data on 89,199, 124,385 and 699,686 eligible women in surveys 2, 3 and 4, respectively, in addition to 74,369 and 112,122 eligible men in surveys 3 and 4, respectively[18–20]. As NFHS-2 only collected data on ever-married women, I restricted the sample across surveys to this population, to allow comparability over time. Pregnant women were not included in the analysis as their pregnancy may bias their assessment of weight status. From this restricted sample, I further excluded women (1998-99: n=6182 (7.4%); 2005-06: n=3673 (4.2%); 2015-16: 7810 (1.6%)) and men (2005-06: n= 5160 (6.8%); 2015-16: n=3422 (3.1%)) with missing height and weight data. The analytic sample used in my main analysis consisted of 628,795 women aged 15–49 years and 93,618 men aged 15-54 across all three surveys, representing respondents with complete data across all the key variables. In each of the surveys, multi-stage sampling approaches were adopted, and sampling weights were provided in the data sets[18–20]. Between surveys, the number of states or union territories I included in the analysis increased from 26 in 1998-99 in to 36, due to the creation of new states from existing ones, for instance, the creation of Jharkhand from Bihar, and Telangana from Andhra Pradesh.

5.3.2. Outcome

In each survey, the participants' height and weight were measured and used to calculate Body Mass Index (BMI). To make the interpretation of my results more straightforward, I categorised the continuous BMI variable using a meaningful qualitative cut-off that facilitates comparison with other studies and adequately captures excess adiposity. Overweight, as well as obese, adults have been reported to be at higher risk of NCDs and all cause-mortality[232,233], therefore I categorised individuals as either overweight/obese ($BMI \geq 25.0 kg/m^2$), or not overweight/obese ($BMI < 25.0 kg/m^2$), based on the WHO definition[1]. I additionally used cut-off values recommended for use among Asian populations to verify the trends I initially identified[234], whereby individuals with a $BMI \geq 23.0 kg/m^2$ were classified as overweight/obese, and included the results in the Appendix. Lower BMI cut-off values may be more appropriate among Asian populations, given a potentially higher risk of overweight/obesity related diseases at lower BMI levels compared to populations upon which initial classifications were based[234].

5.3.3. Independent Variables

I considered two measures of SEP: an index of standard of living (SoL) and educational attainment. It was not possible to include occupation as an independent variable because it was collected on a limited subsample of respondents in the 2015-16 survey.

I allocated individuals in all the surveys to one of the following four education categories, based on the number of years of schooling: None (0 years); primary (1-5 years); secondary (6-12 years); higher (12+ years). I used Education as a measure of SEP as it may indicate employable skills that expose individuals to more opportunities to earn higher incomes.

The NFHS contains a wealth index, constructed using Principal Components Analysis (PCA) in each survey separately, using information on household asset ownership and household characteristics. As the original wealth index cannot be appropriately compared over time, and as I intended to stratify my analysis by urban and rural areas, I constructed a new index, as an alternative measure of SEP, using PCA from 26 assets and characteristics available in all the surveys[18–20]. Based on my new wealth scores derived from weightings given to each asset or characteristic, households were classified as either ‘lower’, ‘medium’ or ‘higher’ SoL. Asset-based indices are commonly used in cross sectional studies conducted in low and middle-income countries, where income data may be an unreliable indicator of overall SEP, particularly in rural areas[190]. For instance, households may receive income from a variety of sources, which may be difficult to recall, or income may be received in kind[190,191] rather than monetarily. Consequently, a household's stock of assets may provide a more reliable measure of current SEP[190].

I adjusted my final models for the respondent's age (categorised as 15-29; 30-39, and 40-49 (40-54) for women (men)), as it has been reported in previous studies that overweight/obesity prevalence increases with age[235]. Additionally, older adults may have accumulated more assets over a longer lifespan, potentially, confounding the association between SEP and overweight/obesity. Research has found overweight/obesity to be higher among currently married individuals, and therefore could confound the reported association between SEP and overweight/obesity.

5.3.4. Statistical Analysis

I initially calculated the prevalence of overweight/obesity in each SoL index and educational attainment category, by sex and urban/rural residence. I accounted for the complex survey design of the data using sampling weights. Separately for urban and rural areas, I calculated the ratio of the prevalence between the highest and lowest socio-economic status group of my two main SEP variables (eg. higher to lower SoL, and higher to no education) in each of the surveys. Additionally, I calculated the percentage change in the prevalence of overweight/obesity by each category of SoL and educational attainment.

Separately for urban and rural areas, and sex, I fitted multilevel logistic regression models with random intercepts for primary sampling units and states. I chose to include PSU- and state-level random intercepts due to the hierarchical nature of the NFHS data, whereby individuals are nested within PSUs, which are nested within states. Standard errors calculated in my models would have been underestimated if I did not account for this clustering. I modelled the log odds ratio of overweight/obesity in each category of the SEP variable of interest in each of the surveys by fitting a survey specific interaction term. The regression models were adjusted for the covariates mentioned in the independent variables section, in addition to the remaining SEP variable. No evidence of multicollinearity of independent variables with the main exposure of interest was detected when examining changes in the standard error once new variables were added. Finally, I derived and reported the predicted prevalence of overweight/obesity from the model, in addition to their 95% confidence bounds. Adjusted analyses were also carried out using Asian specific BMI cut-offs to observe if the trends identified varied depending on the outcome measure used (see Appendix).

Patient and public involvement

Publicly available survey data was used for the analysis and no patients were involved in the study.

5.4. Results

The study population generally experienced increasing educational attainment and SoL over the period of analysis in both urban and rural areas. Whereas the percentage of respondents with no education declined over the study period, particularly among the rural population, the percentage with secondary education in the 2015-16 survey was generally higher than in 1998-99 and 2005-06. Additionally, in both rural and urban areas, the percentage of individuals from lower SoL households declined, whilst the percentage from higher SoL households increased between 1998 and 2016 (Table 8 and Table 9).

Table 8. Characteristics of rural study participants with recorded BMI information across NFHS surveys (2.d.p)

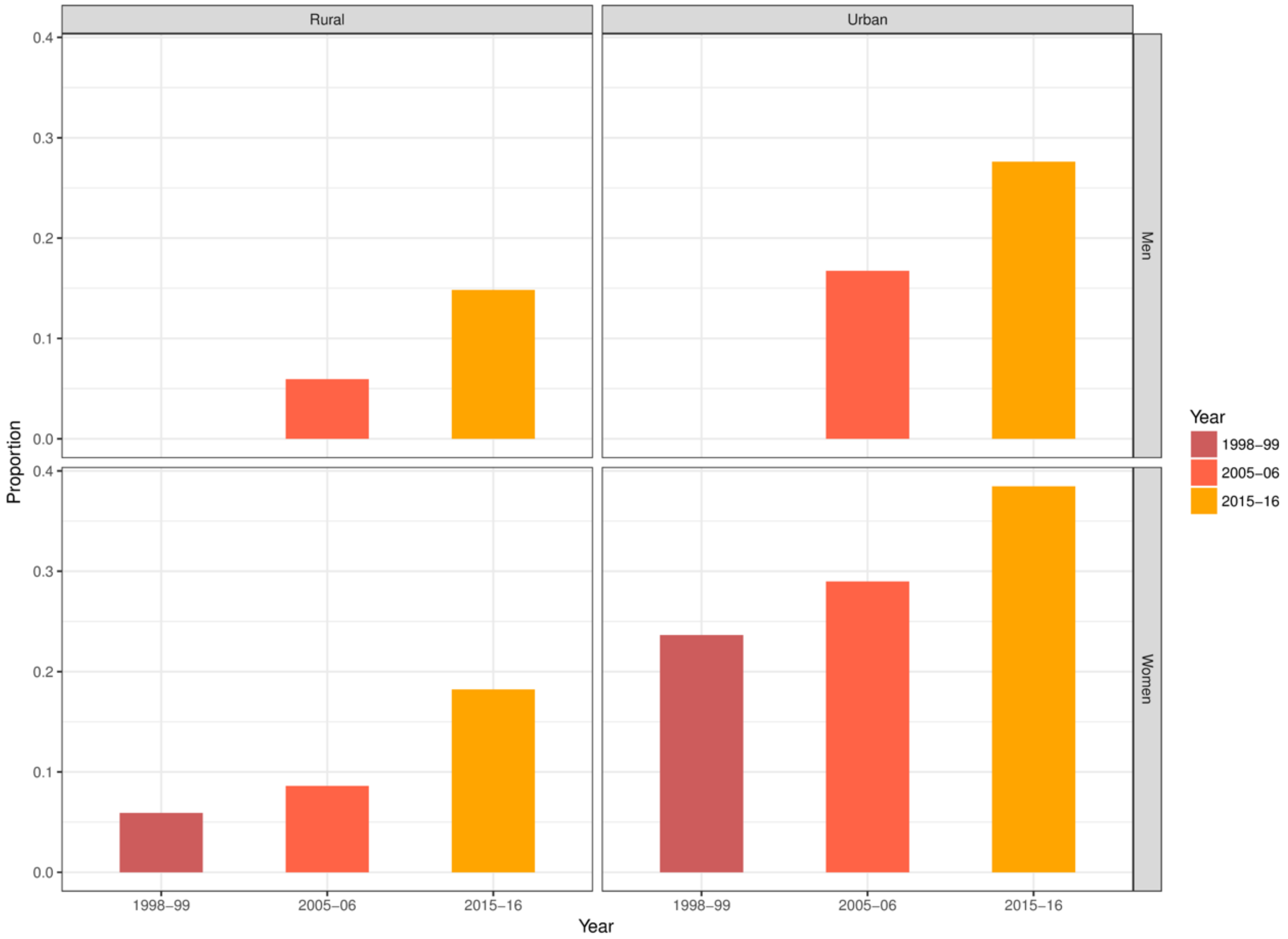
	Women						*Men*			
	NFHS 2		*NFHS 3*		*NFHS 4*		*NFHS 3*		*NFHS 4*	
	Freq	*Proportion*	*Freq*	*Proportion*	*Freq*	*Proportion*	*Freq*	*Proportion*	*Freq*	*Proportion*
Not overweight/obese	49596	0.93	42979	0.90	289482	0.83	32304	0.93	64133	0.86
Overweight/obese	3496	0.07	4912	0.10	61124	0.17	2255	0.07	10550	0.14
Age 15-29	23888	0.45	19279	0.40	126796	0.36	16537	0.48	34589	0.46
Age 30-39	17488	0.33	16892	0.35	122520	0.35	8951	0.26	18965	0.25
Age 40-49(54 males)	11716	0.22	11720	0.24	101290	0.29	9071	0.26	21129	0.28
No Education	31724	0.60	24314	0.51	146302	0.42	6904	0.20	11709	0.16
Primary	9469	0.18	8417	0.18	55652	0.16	6620	0.19	10545	0.14
Secondary	9971	0.19	13872	0.29	131722	0.38	18199	0.53	43737	0.59
Higher	1916	0.04	1285	0.03	16930	0.05	2824	0.08	8692	0.12
Low SoL	28408	0.54	21262	0.44	64998	0.19	14615	0.42	11842	0.17
Middle SoL	18616	0.35	15929	0.33	120050	0.36	12508	0.36	25338	0.35
High SoL	5869	0.11	10645	0.22	149191	0.45	7409	0.21	34202	0.48
Married	49674	0.94	44763	0.93	331883	0.95	22352	0.65	47948	0.64
Not married (No longer married – women)	3418	0.06	3128	0.07	18723	0.05	12207	0.35	26735	0.36

Table 9. Characteristics of urban study participants with recorded BMI information across NFHS surveys (2.d.p)

	Women						*Men*			
	NFHS 2		*NFHS 3*		*NFHS 4*		*NFHS 3*		*NFHS 4*	
	Freq	*Proportion*	*Freq*	*Proportion*	*Freq*	*Proportion*	*Freq*	*Proportion*	*Freq*	*Proportion*
Not overweight/obese	18473	0.75	25454	0.70	87695	0.64	28669	0.83	25285	0.74
Overweight/obese	6048	0.25	10808	0.30	49443	0.36	5981	0.17	8732	0.26
Age 15-29	8950	0.36	12401	0.34	41893	0.31	17434	0.50	15581	0.46
Age 30-39	9253	0.38	13954	0.38	52032	0.38	8652	0.25	8742	0.26
Age 40-49(54 males)	6318	0.26	9907	0.27	43213	0.32	8564	0.25	9694	0.28
No Education	6493	0.26	9048	0.25	28878	0.21	3016	0.09	2884	0.08
Primary	4025	0.16	4959	0.14	16818	0.12	4143	0.12	3407	0.10
Secondary	8814	0.36	16655	0.46	67583	0.49	19902	0.57	19563	0.58
Higher	5181	0.21	5596	0.15	23859	0.17	7574	0.22	8163	0.24
Low SoL	16444	0.67	17263	0.48	33609	0.25	17329	0.50	8773	0.27
Middle SoL	5682	0.23	10147	0.28	50027	0.38	9613	0.28	11925	0.36
High SoL	2310	0.09	8832	0.24	49540	0.37	7694	0.22	12389	0.37
Married	22931	0.94	33845	0.93	128279	0.94	19656	0.57	20375	0.60
Not married (No longer married – women)	1590	0.06	2417	0.07	8859	0.06	14994	0.43	13642	0.40

The prevalence of overweight/obesity increased in each successive survey for both of my samples of men and women. In rural India, the prevalence among men almost tripled from 0.059 to 0.148 between 2005 and 2016, and among women, the prevalence increased from 0.059 to 0.182 between 1998 and 2016. In urban India, the prevalence among women increased to 0.385 in 2015-16, from 0.236 in 1998-99, whereas the prevalence among urban men increased from 0.167 to 0.276 between 2005 and 2016 (Figure 7).

Figure 7. Proportion (weighted) of overweight/obesity in urban and rural India, among men and women



In all surveys, and for men and women in both urban and rural areas, the prevalence of overweight/obesity was highest among participants with higher education and from a higher SoL, whereas the lowest prevalence of overweight/obesity was found among participants with no education and from a lower SoL.

However, over the study periods for both men and women, the greatest percentage increase in overweight/obesity prevalence was observed among participants from the lowest SoL category and participants with no education. Consequently, the ratio of the prevalence of overweight/obesity in all of the highest, compared to the lowest, SEP groups, reduced over time (Table 10 and Table 11).

After adjusting for marital status and age, in urban areas, the predicted prevalence of overweight/obesity among lower SEP women increased over the study period for both men and women, whereas no notable changes were observed among higher SEP women. Among urban men, I observed some increase in the prevalence of overweight/obesity among high SEP respondents, however, the increase among low SEP men was greater. Among both rural men and women, more similar increases were observed among individuals from all SEP groups over the study period (Figure 8 and Figure 9). Equivalent trends were found when using the BMI cut-offs recommended for Asian populations (Figure 27 and Figure 28).

Table 10. Percentage of respondents classified as overweight/obese, by Education level** (1998-2016)

	Women				***Men***		
	1998-99 ***%***	***2005-06*** ***%***	***2015-16*** ***%***	***% change*** ***1998-2016***	***2005-06*** ***%***	***2015-16*** ***%***	***% change*** ***2005-2016***
Rural							
No Education	3.4 (2.5-4.5)	5.3 (3.9-7.0)	13.9 (13.6-14.2)	311.5	3.0 (2.1-4.3)	10.8 (9.9-11.7)	253.8
Primary	7.9 (5.7-10.9)	10 (7.5-13.2)	18.5 (17.9-19.0)	132.7	4.2 (2.7-6.5)	14.1 (13.1-15.1)	233.2
Secondary	10.8 (7.7-14.9)	14.2 (10.7-18.5)	21.8 (21.4-22.2)	102.0	6.6 (4.9-8.8)	14.6 (14.0-15.1)	121.6
Higher	15.9 (12.5-19.9)	22.8 (16.5-30.5)	26.7 (25.8-27.7)	68.6	15.3 (12.9-18.1)	22.3 (21.0-23.7)	45.7
Ratio*	4.7	4.3	1.9	-	5.0	2.1	-
Urban							
No Education	13.5 (11.2-16.2)	18.5 (16.3-20.8)	32.2 (31.2-33.2)	137.8	7.7 (5.6-10.6)	18.3 (16.1-20.6)	136.5
Primary	19.5 (17.1-22.1)	24.5 (22.1-26.9)	37.2 (35.8-38.6)	91.3	10.9 (8.7-13.6)	23.9 (21.4-26.5)	118.9
Secondary	27.2 (24.6-29.9)	33.0 (30.2-36.0)	40.2 (39.4-40.9)	47.7	15.2 (13.4-17.3)	26.3 (25.1-27.6)	72.8
Higher	35.4 (32.3-38.6)	41.8 (38.0-45.6)	41.6 (40.3-42.9)	17.6	28.4 (25.7-31.2)	34.9 (32.5-37.4)	22.8
Ratio*	2.6	2.3	1.3	-	3.7	1.9	-

*Ratio of the percentage among individuals with Higher education and No education

** Chi^2 test p-value of each strata's association with overweight/obesity *p<0.001*

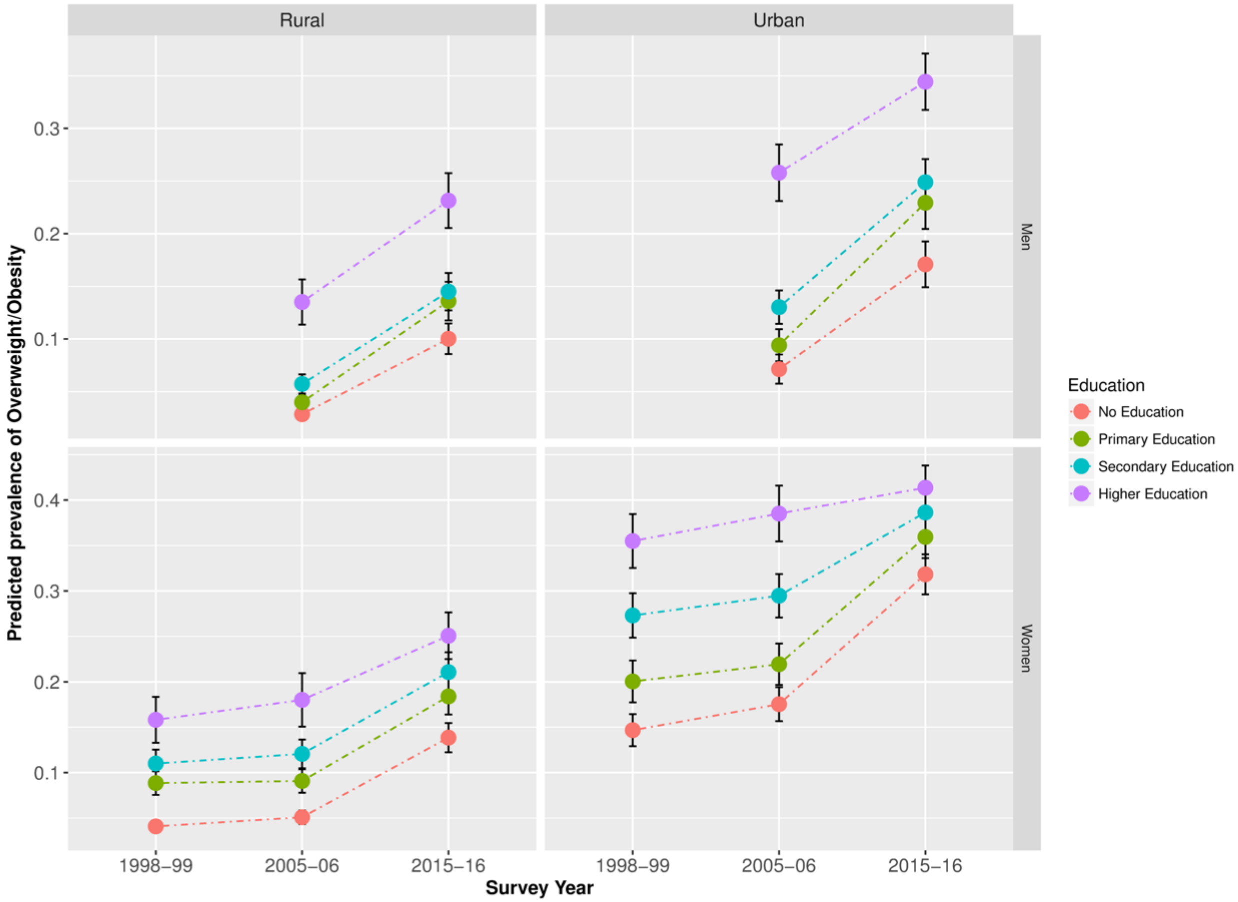
Table 11. Percentage of respondents classified as overweight/obese, by Standard of Living** (1998-2016)

	Women				***Men***		
	1998-99 ***%***	***2005-06*** ***%***	***2015-16*** ***%***	***% change*** ***1998-2016***	***2005-06*** ***%***	***2015-16*** ***%***	***% change*** ***2005-2016***
Rural							
Lower SoL	2.4 (1.9-3.0)	3.0 (2.3-3.9)	6.7 (6.4-6.9)	183.0	1.8 (1.4-2.3)	5.0 (4.5-5.5)	177.1
Middle SoL	8.2 (6.2-10.9)	8.9 (7.5-10.5)	12.9 (12.6-13.3)	57.4	5.7 (4.5-7.2)	9.5 (8.9-10.1)	67.3
Higher SoL	22.9 (18.4-28.2)	25.2 (20.7-30.1)	27.7 (27.3-28.2)	21.0	17.5 (14.5-20.9)	22.3 (21.6-23.0)	27.5
Ratio*	9.8	8.4	4.2	-	9.8	4.5	-
Urban							
Lower SoL	16.3 (14.4-18.4)	17.4 (15.3-19.7)	24.9 (23.9-25.9)	52.6	8.9 (7.3-10.9)	16.0 (14.5-17.7)	79.5
Middle SoL	39.1 (36.4-41.9)	35.0 (31.1-39.1)	38.8 (37.9-39.7)	-0.7	20.6 (18.4-23.0)	26.9 (25.2-28.6)	30.5
Higher SoL	46.9 (43.6-50.3)	48.4 (44.4-52.4)	46.9 (45.9-47.8)	-0.1	30.6 (27.9-33.4)	35.8 (34.0-37.5)	16.9
Ratio*	2.9	2.8	1.9	-	3.43	2.23	-

*Ratio of the percentage in the highest and lowest socio-economic group

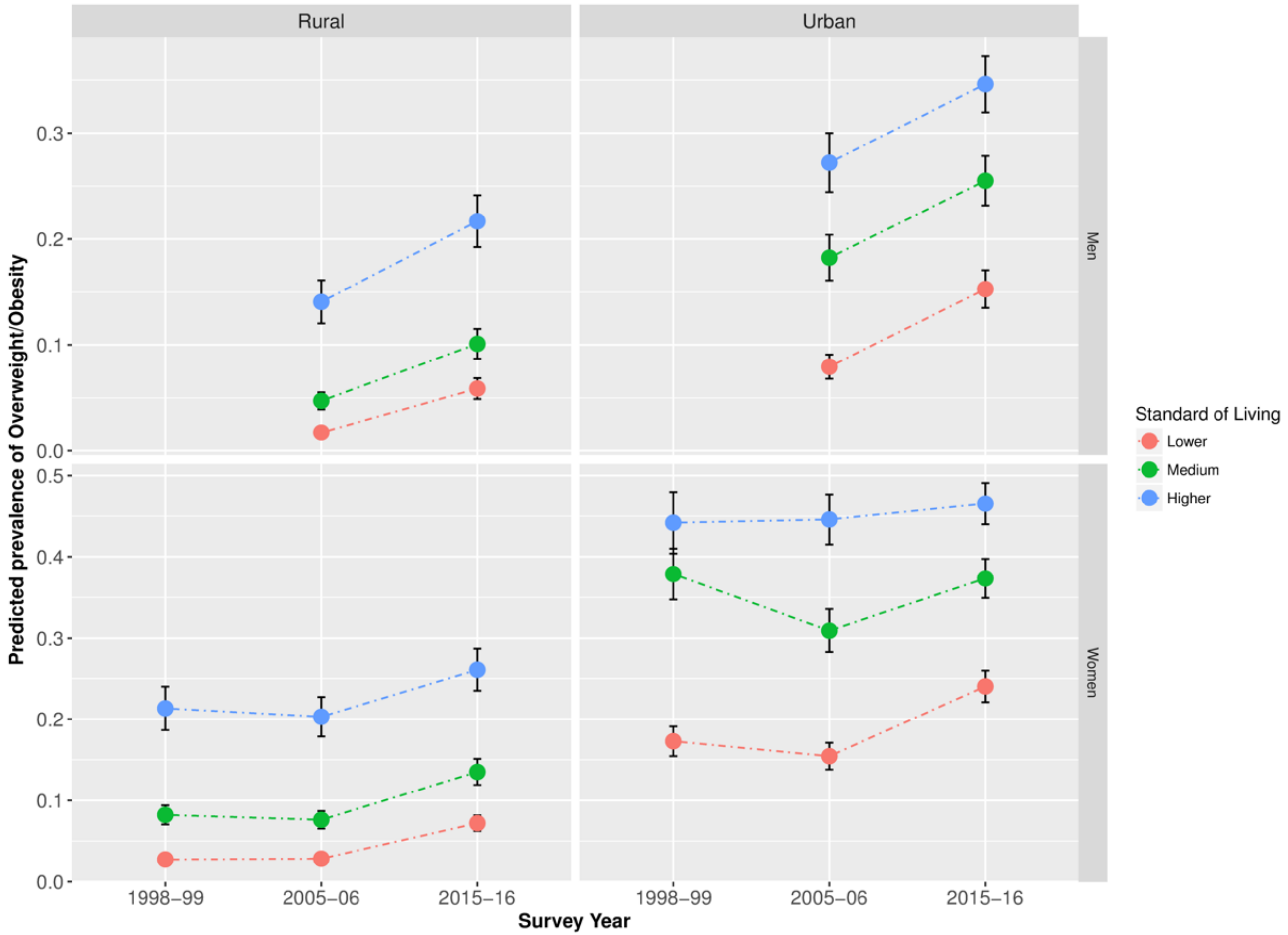
** Chi^2 test p-value of each strata's association with overweight/obesity $p<0.001$

Figure 8. Predicted prevalence of overweight/obesity in India, by Education level (1998-2016)



* Predicted prevalence and confidence intervals are based on multivariate regressions, and the models adjust for the respondent's age, current marital status and the socio-economic variable not considered as the main exposure.

Figure 9. Predicted prevalence of overweight/obesity in India, by Standard of Living (1998-2016)



* Predicted prevalence and confidence intervals are based on multivariate regressions, and the models adjust for the respondent's age, current marital status and the socio-economic variable not considered as the main exposure.

5.5. Discussion

I found that, although overweight/obesity prevalence increased with SEP, in urban areas no notable change in the prevalence of overweight/obesity was observed among higher SEP women, whereas the prevalence among lower SEP women increased considerably between 1998-2016. The prevalence increase of overweight/obesity was greater among lower SEP urban men compared with higher SEP counterparts between 2005 and 2016. Consequently, some convergence of overweight/obesity across SEP was observed in urban areas among both men and women. In rural areas however, overweight/obesity prevalence increased similarly among individuals in all SEP groups, with fewer signs of convergence across SEP groups yet.

The main strength of my study is my use of the most recent nationally representative data available for India, making my results the most up-to-date estimates of overweight/obesity trends by SEP.

My study however has some limitations. Firstly, I derive my only measure of overweight/obesity from BMI, rather than complement my results with alternative measures of overweight/obesity, such as WC[236,237] and body fat percentage. Consequently, the prevalence estimates I report may vary depending on the adiposity measure and the exact definitions/cut-offs used. However, given the high correlation between BMI and measures including WC among Indians[238], I would not expect the reported associations between overweight/obesity and SEP, and trends, to change considerably between measures.

Secondly, to ensure the population of sampled women was comparable over time, I limited my analysis to ever-married women, as this was the selection criteria in the NFHS-2 survey. Prevalence of overweight/obesity is generally lower among never-married women[239], for instance in the NFHS-4 survey data, the prevalence of overweight/obesity was 6.6% among never-married women, compared to 25.0% among currently married women. This may have led me to overestimate overweight/obesity prevalence among women, as the weighted percentage of never-married women were 19.8% and 22.5% in the 2005-06 and 2015-16 samples, respectively. However, although individual point estimates may be affected, I do not expect the trends in the association between overweight/obesity and SEP I identified to be overestimated.

My SoL index may also imperfectly capture household wealth. For instance, no indication about the quality of assets used in the measure were included, potentially misclassifying certain households[190,194]. However, as three broad SoL groups across a large data set were defined, I do not expect any misclassification to substantially bias my results. Additionally, the association between the true SEP and certain assets included in the SoL index may differ between urban and rural areas. I attempted to account for differences in the value of certain assets by calculating separate indices for urban and rural areas, however, differences in the value of some assets may still exist within broad geographical areas, for instance between states.

Finally, my results may mask variation in subnational prevalence and trends, especially given subnational differences between states in economic growth, demography and culture. For instance, research in India has found that in states with a higher prevalence of overweight, lower and higher SEP group may show a converging risk of overweight/obesity, whereas divergent trends have been identified in states with the highest proportion of underweight individuals[90].

The only other India-specific national study I found on this topic did not identify any change in the overweight/obesity-SEP association between 1998-99 and 2005-06 in urban or rural India; with a persisting higher prevalence among high SEP groups[240]. Beyond 2005-06, the authors predicted that future overweight/obesity prevalence would show a similar social patterning as they expected future economic gains to almost solely benefit higher SEP individuals. By contrast, the converging socio-economic patterning of overweight/obesity I have identified in urban areas indicates that economic growth in the past decade may either have been more egalitarian than previously expected, the cost of high calorie food may have become less expensive, or even the pool of susceptible higher SEP individuals may be becoming saturated.

Converging overweight/obesity prevalence between higher and lower SEP groups has been identified sub-nationally in India, when restricted to states defined by a high overall prevalence of overweight[90], mirroring my finding in urban areas. This may suggest that convergence is restricted to areas that have moved beyond the earliest stages of the epidemiological transition.

Though not reported in previous nationally representative studies in India, a converging socioeconomic patterning of overweight/obesity has been noted in some other LICs and MICs, where the highest increases in overweight prevalence have been found among women working in manual labour[54], among the lowest wealth and income groups[55,56,241] and among rural residents[242].

In rural areas I identified similar increases in prevalence among individuals from all SEP groups. Some studies suggest that in low-income settings, increases in overweight and obesity are restricted to higher SEP individuals, which may be due to changing dietary patterns towards fatty and sugary convenience foods[30,32,69,87,91,243], however, the rising prevalence among lower SEP individuals indicates that they may also be increasingly exposed to high calorie foods. Some researchers have also suggested that this mechanism is stronger in low-income or rural settings due to more favourable perceptions of large body sizes across SEP[30,70,244,245].

In urban India, the greater increase in overweight/obesity prevalence among lower SEP individuals mirrors similar findings from places at relatively later stages of economic development, where some researchers have suggested that lower SEP individuals may be priced out of affording relatively expensive low-calorie healthy diets[30,77,81,246]. Additionally, lower SEP individuals in urban areas may be more exposed to sedentary lifestyles driven by technological advances replacing manual energy-exerting labour, and improved transport links[247,248]. Increased health consciousness, in combination with the ability to afford low calorie diets, may explain why no notable change in overweight/obesity prevalence among the higher SEP urban population was found[30,249,250] in addition to the potential saturation of individuals susceptible to becoming overweight or obese.

Some studies argue that in India NCD risk factors are almost exclusively an issue for higher SEP individuals[251]. However, my finding that overweight/obesity prevalence has increased among lower SEP individuals in both urban and rural areas implies that to consider overweight/obesity as 'diseases of affluence'[252] may not be appropriate in India's current context. Efforts to tackle the overall increasing overweight/obesity trend must be inclusive of both the urban and rural poor. This may be especially urgent due to the compounding effect of overweight/obesity and associated NCDs on infectious diseases, which are still highly prevalent among the poor.

Recent initiatives to raise population health include the launch of an integrated National Health Mission[253] which aims to address deficiencies in healthcare delivery across the socioeconomic spectrum in urban and rural areas. Such initiatives may benefit from information about the increasing prevalence among low SEP Indians, as future action aimed at preventing overweight and obesity can be targeted accordingly. Due to the positive association of overweight and obesity with NCDs such as stroke and diabetes[254,255] urgency is required in addressing this modifiable risk factor especially as it could compound existing health complications among poorer Indians, where communicable disease and under-nutrition related diseases already tend to be more prevalent.

Although India is still considered a LMIC, I have identified some convergence of overweight/obesity prevalence across SEP in urban areas among both men and women, with fewer signs of convergence across SEP groups in rural areas. My findings suggest that an urgent response is needed to slow the increasing trend among poorer Indians, particularly as increasing exposure to overweight and obesity related diseases may compound an already high exposure to infectious diseases.

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First Name(s)	Shammi		
Surname/Family Name	Luhar		
Thesis Title	Trends in the socioeconomic patterning of overweight and obesity and predictions of the future prevalence of diabetes in India		
Primary Supervisor	Lynda Clarke		

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Chapter Six. Do trends in the prevalence of overweight/obesity by socio-economic position differ between India's most and least economically developed states?

6.1. Abstract

Background: India's economic development and urbanisation in recent decades has varied considerably between states. Attempts to assess how overweight/obesity varies by socioeconomic position (SEP) at the national level may mask considerable sub-national heterogeneity. I examined the socioeconomic patterning of overweight/obesity among adults in India's most and least economically developed states between 1998 and 2016.

Methods: I used state-representative data from the National Family Health Surveys from 1998-99, 2005-06 and 2015-16. I estimated the prevalence of overweight/obesity by SEP in men (15-54 years) and women (15-49 years) from India's most and least economically developed states using multilevel logistic regressions.

Results: I observed an increasing trend of overweight/obesity prevalence among low SEP women. Amongst high SEP women, overweight/obesity prevalence either increased to a smaller extent, remained the same or even declined between 1998 and 2016. This was particularly the case in urban areas of the most developed states, where in the main analysis, the prevalence of overweight/obesity increased from 19% to 33% among women from the lowest socioeconomic group between 1998 and 2016 compared to no change among women from the highest socioeconomic group. Between 2005 and 2016, the prevalence of overweight/obesity increased to similar extents among high and low SEP men, irrespective of residence.

Conclusions: The converging prevalence of overweight/obesity by SEP in India's most developed states, particularly amongst urban women, implies that this subpopulation may be the first to exhibit a negative association between SEP and overweight/obesity in India. Programs aiming to reduce the increasing overweight/obesity trends may wish to focus on poorer women in India's most

developed states, amongst whom the increasing trend in prevalence has been considerable.

6.2. Background

The considerable rise in the prevalence of overweight (including obesity) in India, where over a billion people reside[18–20,37], presents a serious public health concern given the association of overweight with increased NCD risk[1].

In the early stages of economic development and urbanisation, overweight and obesity prevalence tends to be higher among individuals of a higher socioeconomic position (SEP), arguably due to an increased financial capability to meet and exceed nutritional requirement[29,30,32,39]. As societies develop economically, the prevalence of overweight and obesity increases among the poor and rural population[29,30,32,39,69,91,146,237,256].

Since India's economic liberalisation in the early 1990[88], economic growth has not been uniformly distributed across the country. In addition to considerable heterogeneity in culture, customs and diet, the current levels of economic development between India's states varies substantially. For example, the GDP of Delhi is eight times greater than that of the state of Bihar[257]. Consequently, the prevalence of overweight/obesity, and the extent of the increase in its prevalence in recent decades, varies considerably sub-nationally[18–20]. For instance, in Bihar, the prevalence of overweight/obesity among women increased from 3.7% to 11.7% (an absolute increase of 8%) between 1998 and 2016, whereas in Delhi, the prevalence increased from 12% to 33.5% over the same period (an absolute increase of 21.5%)[19,20]. However, little is known about variation in the sub-national socioeconomic patterning of overweight/obesity.

In this paper, I aimed to understand how recent trends in the association between overweight/obesity and SEP differ between India's most and least economically developed states between 1998 and 2016, a period in which India's GDP per capita quadrupled from US$432 to US$1750[230]. The main rationale for this study was to unmask subnational heterogeneity in trends in the association of overweight/obesity and SEP in India not observed when analysing national trends. Demonstrating this would imply that national-level trends may not be generalisable at a subnational level[258]. A study of this nature is of importance as health policy is dictated at the state level; therefore, estimating the prevalence by state development and urban and rural areas may highlight different immediate health policy priorities between less and more developed states.

I conducted secondary analysis, using repeated cross-sections from state-representative data from 1998 to 2016 to estimate the prevalence of overweight/obesity in India by SEP in the five most and least economically developed states in India. In more economically developed societies, there is usually higher prevalence of overweight/obesity among poorer individuals where, for instance, there is a higher exposure to relatively cheaper fatty foods[30,32,259]. This is more likely to be the case in urban areas, where risk factors for overweight/obesity are usually much greater. I therefore hypothesise that in India's most developed states, I will observe a considerable increase in the prevalence of overweight/obesity among lower SEP individuals and relatively smaller increases among higher SEP individuals. On the other hand, in India's least developed states, I expected to find larger increases among higher SEP individuals, compared to lower SEP individuals. This is supported by the fact that poorer individuals in societies with lower levels of economic development are more likely to be unable to afford to meet nutritional requirements, whereas the relatively rich may be more exposed to overweight/obesity due to a greater access to excess food[30,32].

6.3. Data

I used the National Family Health Survey (NFHS) Surveys 2 (1998-99), 3 (2005-06) and 4 (2015-16). All three surveys collected health and demographic data on women aged 15-49 years, whereas surveys 3 and 4 collected data on men aged 15-54 years. The sampling method was designed to include a nationally-representative sample of individuals within a nationally-representative sample of households. Additionally, in India, the NFHS surveys are also representative at the level of the state.

The NFHS surveys select rural and urban samples separately. Specifically, in rural areas in all three waves analysed, rural samples were selected using two-stage sampling, whereby the first stage involved selecting primary sampling units (PSUs), or villages, with a probability proportional to size (PPS), and the second stage involved selecting random households from each village. In urban areas, NFHS 2 and 3 used a slightly different sampling procedure to the one in NFHS 4. In NFHS 2 and 3, three-stage sampling was adopted whereby in the first stage wards were selected with a PPS, in the second random census enumeration blocks (CEB) were chosen in each ward and, in the third, random households were chosen from each CEB[18,20]. On the other hand, NFHS-4 adopted a two-stage approach in urban areas, whereby CEBs served as the PSU, selected using a PPS, and households from each PSU randomly selected. Were a PSU to contain fewer than 40 households, the PSU was joined to the nearest PSU. The 2011 census helped determine the sampling frame in NFHS-4[19].

In all three surveys Interviews used a uniform questionnaire and were conducted by survey teams. A woman's eligibility for the survey was determined by whether they were between ages 15-49 years and, for the NFHS-3 and 4, whether they spent the previous night in the selected households. Men aged 15-54 years in the households were eligible for the Men's survey in NFHS-3. Of the selected households in NFHS-4, a random sample of households were selected to determine eligibility for the men's survey[19].

In India there are currently 36 States/Union Territories. I restricted my analysis to states that have been in existence since the collection of the NFHS 2 survey. States created between the surveys were not considered in the analysis. I selected five states to indicate the most and least developed states as the study aimed to demonstrate a divergence in the trends in their socioeconomic patterning. My primary objective was to highlight variation in trends in the socioeconomic patterning of overweight/obesity within India. I therefore chose not to include all the states in India as this would lead to the inclusion of states that are closer to the average level of per capita net state domestic product (PCNSDP) for India. As a result, I would risk placing states at similar levels of economic development in the Most and Least developed states categories, consequently underestimating the extent of the variation in trends.

My classification of states was based on the PCNSDP in 2014-15 using the base year 2011-12. The most economically developed states were Goa, Maharashtra, Sikkim, Haryana and Kerala with a PCNSDP ranging from ₹112,444 to ₹241,081, compared to an all India average of ₹72,805. The least economically developed states included Bihar, Assam, Uttar Pradesh, Manipur, and Madhya Pradesh with NSDPPC ranging from ₹23,223 to ₹44,809[28]. I limited my sample to non-pregnant women, whose inclusion could bias the associations I sought to identify. This left a total of 96,365 women and 18,729 men in the most developed states category, and 289,200 women and 54,669 men, respectively, in the least developed states category.

As NFHS-2 only sampled ever-married women, I restricted my samples in 2005-06 and 2015-16 to this population to allow the comparability of the study population across surveys. Additionally, respondents with missing height and weight data were also omitted from the sample, leaving 76,050 women (12,168 in 1998-99; 14,000 in 2005-06; 49,882 in 2015-16) and 18,729 men (8,518 in 2005-06 and 10,211 in 2015-16) as the study population in the most economically developed states, and 213,195 women (22,266 in 1998-99; 20,459 in 2005-06; and 170,470 in 2015-16) and 54,669 men (19,377 in 1998-99; and 35,292 in 2015-16) in the least economically developed states. As multi-stage sampling approaches were adopted in the collection of the NFHS, I included the sampling weights included in the data set to account for unequal selection probabilities.

6.3.1. Outcome

I used the BMI variable included in the surveys (measured as the respondent's weight divided by the square of their height) to separate individuals into two groups: overweight/obesity (BMI≥25.0kg/m^2), and not overweight/obesity (BMI<25.0kg/m^2 or under). This categorisation is based on the WHO's recommended cut-offs for BMI classification[1]. Rather than split the continuous BMI measure into multiple subcategories of overweight/obesity, I used this classification as the main aim of the paper was to analyse trends in excess adiposity, and research has found an elevated risk of NCDs and mortality beyond a BMI of 24.99kg/m^2 [232,233]. I did not use a continuous measure of nutritional status, as observed population-level increases in BMI I would expect to observe over the study period could be driven by a both individuals moving into overweight categories, and individuals moving from underweight to normal weight; the latter of which does not capture increases in excess adiposity.

Height and weight information on women aged 15-49 in NFHS-2, 3 and 4, and men aged 15-54 in NFHS-3 and 4, were collected by specially trained investigators. A solar-powered SECA digital scale was used to measure the weight of respondents, with the NFHS-2 report claiming an accuracy of ±100 grams. The height of respondents in NFHS-2 and 3 was measured using a measuring board designed for use in survey data collection. In NFHS-4, the Seca 213 stadiometer was used to collect respondent's height information[18–20].

6.3.2. Independent Variables

Exposure of interest

I used a measure of educational attainment as my primary indicator of SEP. This was based on the answer to a question regarding the number of completed years of schooling, and respondents were assigned to one of the following education categories: No Education (0 years); Primary Education (1-5 years); Secondary Education (6-12 years); and Higher Education (12+ years). Higher levels of education can increase earning capability, along with the accumulation of employable skills, both of which make it a suitable proxy for SEP.

For sensitivity analysis I verified my results using a SoL asset-based index as an alternative measure of SEP. In surveys, measures of SEP are seldom examined in isolation, as one measure cannot adequately describe all socioeconomic differences in a health outcome[260]. As education and SoL capture different aspects of SEP, the pathways through which it is associated with overweight/obesity may also differ. For example, those with high education may work in more sedentary jobs[29,30,32,39], increasing their risk of overweight/obesity, whereas SoL may be positively associated with overweight/obesity through determining the ability to afford excess food[29,30,32,39]. Some suggest that in low/middle income settings, where there is a substantial informal employment sector and earnings not in the form of monetary enumeration, household income may not be an appropriate measure of SEP. Rather, the stock of assets may be more reliable[190]. Data on household income to proxy SEP is likely to be very sensitive to seasonal fluctuations in repeated cross-sections and may not capture the true level of wealth of the household. Additionally, in transitioning societies, it may be more common to receive income 'in-kind' rather than monetary enumeration[191], and households may draw money from multiple sources[190], limiting the ability for respondents to adequately recall all income in a questionnaire.

I created my own SoL index using principal components analysis (PCA) after pooling the household surveys over time. The inputs I used into the PCA included information on the household's stock of assets, their access to services, and other household characteristics. I completed this process for urban and rural areas separately due to differences in the importance of different assets between urban and rural residents. I then ranked households based on this new index and assigned the first, second and last third of the weighted sample a SoL classification of 'Higher', 'Medium' or 'Lower' SoL.

I examined the validity of the SoL index I created by comparing the ranking of households using the index from the pooled data, within one survey, and the survey-specific wealth index already included in the data. The correlation coefficient in each of the three surveys used was greater than 0.95, suggesting a very strong agreement with my measure and the household rankings determined the survey-specific index.

Covariates

My final models were adjusted for the respondent's age (15-29; 30-39; and 40-49 (40-54 for men)) and marital status. Marital status was categorised as either 'currently married' or 'no longer married' among women, and 'currently married' or 'not married' among men. This was included as married individuals have been found to be at higher risk of being overweight or obese[239]. I would have also preferred to control for the respondent's occupation. Higher prevalence of overweight/obesity may be expected to be observed among individuals in more sedentary jobs[29,30,32,39], and sedentary labour may be expected to be more prevalent among higher SEP individuals. However, it was not possible to control for occupation in my research due to the fact that it was collected on a very limited subsample of the respondents in NFHS-4 (approximately 5% of women in the NFHS-4 national sample).

6.4. Methods

In my preliminary analysis, I calculated the weighted prevalence of overweight/obesity in each strata of the education SEP variable, separately for India's most and least developed states, by sex and urban/rural residence. I then calculated the ratio of the prevalence in the highest educational category to the lowest in each survey.

In order to account for the hierarchical nature of the data, in my main analysis I fitted multilevel logistic regressions with PSU-level random intercepts, for each sex, and urban/rural residence, separately. Failure to account for this deliberate clustering at the sampling stage of the data collection process would have caused me to underestimate the standard errors of my results. I used survey-specific interaction terms to estimate the log odds ratio of overweight in each category of my SEP exposure variables, relative to the lowest category of each SEP variable, in each survey. I monitored changes in standard errors of the main SEP exposure variable in order to determine whether there was multicollinearity of the main exposure with added covariates. Coefficients from the adjusted models were subsequently converted to a predicted prevalence, with 95% confidence intervals, to make the results easier to interpret.

6.5. Results

The characteristics of respondents in the surveys used are presented in Table 12. In both the most and least developed states, the percentage of women with secondary education and in the Higher SoL category is higher in later surveys, compared to earlier ones. On the other hand, the percentage of women with no education and in the Lower SoL category decreases over the surveys. For example, in the most developed states, the percentage of women in the Higher SoL category increases from 16% to 65% between NFHS 2 and 4, whereas the percentage in the Lower SoL category decreases from 44% to 9%. The percentage of respondents classified as overweight/obese increases in each successive survey. The largest increase was observed among women in the least developed states, where the percentage of overweight/obese respondents increased from 6% to 19% between NFHS 2 and 4. Similar trends are found even when I do not limit my sample to non-pregnant and ever-married women (Table 28).

In my preliminary analysis I found a consistent trend of increasing prevalence of overweight/obesity in both India's most and least developed states. This trend was found amongst both men and women in urban and rural areas (Figure 10). As expected, the most developed states generally had a higher overall level of overweight/obesity prevalence compared to the least developed states, and especially in urban areas and among women.

The overall level of overweight/obesity was consistently higher in India's most developed states compared to the least developed states. For instance, in 2015-16 in India's most developed states, the prevalence of overweight/obesity among women was 39% and 23% in urban and rural areas, respectively, whereas the prevalence among men was 31% and 20%. On the other hand, the prevalence of overweight/obesity among women in India's least developed states in 2015-16 was 34% and 14% in urban and rural areas, respectively, whilst the prevalence among men was 21% and 10%.

I found a higher relative increase in overweight/obesity prevalence in India's least developed states. Whereas the prevalence among urban women doubled from 17% to 34% in the least developed states between 1998 and 2016, the prevalence increased from 24% to 39% among urban women in the most developed states. Similarly, in among rural women, overweight/obesity increased nearly five-fold, from 3% to 14%, in the least developed states, compared to an increase from 10% to 23% in the most developed states.

Table 12. Percentage and number of study participants by key variables in each of the surveys

	Most developed states									
	Women						Men			
	NFHS-2		NFHS-3		NFHS-4		NFHS-3		NFHS-4	
	%	Freq	%	Freq	%	Freq	%	Freq	%	Freq
Overweight/Obesity	18.2	2220	24.1	3377	27.3	13598	14.2	1658	24.2	3323
Age 15-29	38.4	4677	33.8	4737	33.1	16518	48.7	6041	44.8	7056
Age 30-39	36.0	4386	38.9	5446	36.1	18033	25.6	3145	25.8	4054
Age 40-49 (54 males)	25.5	3105	27.3	3817	30.7	15331	25.7	3088	29.5	4454
Urban	40.4	4910	49.4	6916	35.4	17656	59.3	7294	37.3	5788
Rural	59.7	7258	50.6	7084	64.6	32226	40.7	4980	62.7	9776
No Education	32.1	3905	23.6	3309	19.3	9626	7.0	1010	6.2	1292
Primary	18.9	2294	15.4	2160	13.6	6771	13.9	1741	10.2	1856
Secondary	35.9	4371	50.2	7030	54.5	27178	63.3	7624	64.5	9784
Higher	13.1	1597	10.7	1501	12.6	6307	15.9	1895	19.2	2632
Lower SoL	44.3	5373	30.4	4250	9.0	4447	36.4	4524	8.7	1693
Middle SoL	39.7	4822	34.8	4862	26.2	12985	34.5	4335	25.0	4418
Higher SoL	16.0	1940	34.8	4873	64.9	32161	29.1	3406	66.3	9351
Married	93.4	11366	93.2	13053	94.2	46971	59.0	7339	62.1	9961
Not Married (No longer married – women)	6.6	802	6.8	947	5.8	2911	41.0	4935	37.9	5603

Table 12 continued…

	Least developed states									
	Women						***Men***			
	NFHS-2		***NFHS-3***		***NFHS-4***		***NFHS-3***		***NFHS-4***	
	%	***Freq***	***%***	***Freq***	***%***	***Freq***	***%***	***Freq***	***%***	***Freq***
Overweight/Obesity	6.0	1336	14.7	3002	18.5	31546	9.6	1853	12.9	4544
Age 15-29	46.5	10352	39.3	8044	36.9	62868	51.0	9882	49.0	17300
Age 30-39	32.2	7168	35.9	7353	34.7	59173	24.9	4819	24.2	8527
Age 40-49 (54 males)	21.3	4746	24.7	5062	28.4	48429	24.1	4676	26.8	9465
Urban	20.5	4564	40.8	8338	23.0	39174	46.6	9034	27.6	9724
Rural	79.5	17702	59.3	12121	77.0	131296	53.4	10343	72.5	25568
No Education	62.7	13951	48.9	9999	44.4	75735	16.1	3122	16.5	5820
Primary	14.2	3166	13.5	2766	14.3	24364	13.8	2667	14.1	4990
Secondary	16.1	3594	28.9	5921	33.9	57798	53.8	10416	55.4	19535
Higher	7.0	1550	8.7	1771	7.4	12573	16.3	3164	14.0	4947
Lower SoL	69.2	15333	55.3	11301	30.0	47214	51.8	10032	28.2	9164
Middle SoL	25.0	5534	27.1	5546	38.5	60571	28.5	5525	39.0	12667
Higher SoL	5.8	1288	17.6	3594	31.5	49457	19.7	3806	32.8	10654
Married	94.2	20984	94.6	19356	95.4	162655	60.8	11788	62.4	22006
Not Married (No longer married- women)	5.8	1282	5.4	1103	4.6	7815	39.2	7589	37.7	13286

*All percentages are based on unweighted proportions

Figure 10. Proportion (weighted) of overweight/obesity in 1998–99, 2005–06 and 2015–16 in urban and rural India

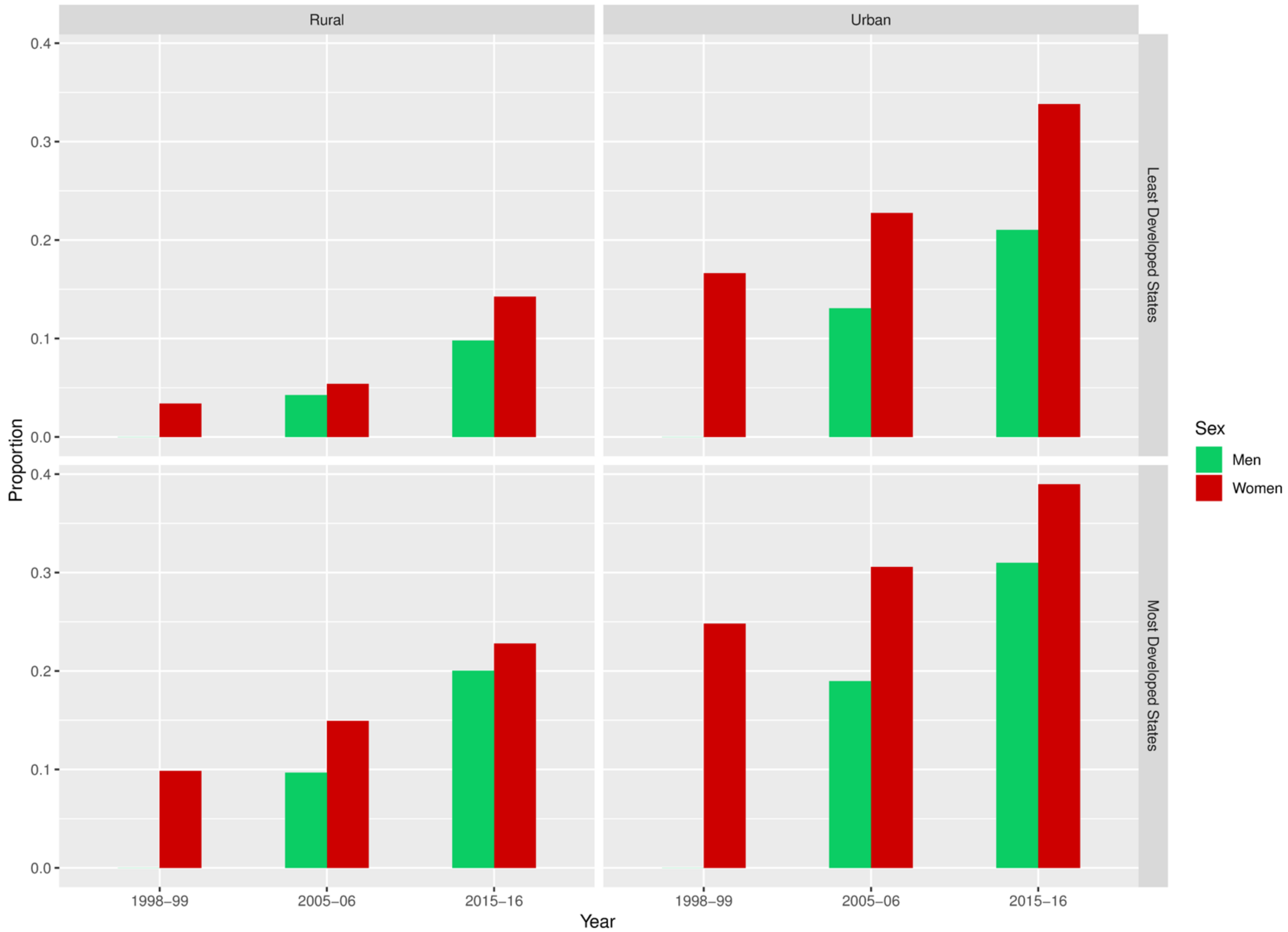


Table 13. Percentage* of respondents classified as overweight/obese by education level (Most Developed States)

	Most developed states				
			Women		*Men*
	NFHS-2	*NFHS-3*	*NFHS-4*	*NFHS-3*	*NFHS-4*
Rural					
No Education	4.1 (0.9-17.1)	7.9 (3.1-18.6)	16.5 (9.7-26.7)	4.3 (2.9-7.5)	13.9 (8.3-19.1)
Primary Education	10.1 (3.4-24.6)	15.5 (6.1-34.2)	20.7 (13.5-30.5)	8.1 (6.1-10.1)	19.8 (18.3-22.3)
Secondary Education	13.7 (4.4-34.3)	18.4 (5.7-45.7)	24.5 (11.9-43.7)	9.4 (8.9-9.9)	19.3 (16.4-22.2)
Higher Education	21.0 (12.3-31.8)	28.2 (9.9-58.5)	29.5 (19.4-42.0)	19.3 (16.2-22.4)	25.5 (19.5-31.5)
Ratio (Higher: No education)	**5.1**	**3.6**	**1.8**	**4.5**	**1.8**
Urban					
No Education	16.6 (15.2-18.0)	21.3 (18.1-24.8)	34.8 (23.4-48.2)	11.7 (8.2-15.2)	15.9 (14.2-17.5)
Primary Education	21.1 (15.2-27.0)	25.6 (19.5-32.8)	37.1 (33.7-40.5)	13.6 (10.1-18.6)	29.5 (18.6-38.8)
Secondary Education	25.4 (21.4-27.9)	32.5 (23.1-43.7)	39.8 (36.0-43.7)	17.7 (16.0-19.4)	28.4 (23.6-32.2)
Higher Education	35.2 (27.9-42.5)	37.7 (34.5-41.0)	40.2 (33.9-46.9)	27.5 (16.7-38.3)	40.8 (28.7-55.2)
Ratio	**2.1**	**1.8**	**1.2**	**2.4**	**2.56**

Table 14. Percentage* of respondents classified as overweight/obese by education level (Least Developed States)

	Least developed states				
			Women		*Men*
	NFHS -2	*NFHS-3*	*NFHS-4*	*NFHS-3*	*NFHS-4*
Rural					
No Education	2.4 (1.7-3.5)	3.7 (1.6-8.2)	11.7 (5.5-17.9)	2.2 (1.4-3.5)	6.3 (4.8-8.2)
Primary Education	4.4 (2.8-6.3)	6.2 (2.3-16.0)	14.3 (9.2-19.4)	1.6 (0.7-3.8)	7.4 (6.8-8.1)
Secondary Education	6.3 (5.3-7.4)	9.9 (8.0-12.0)	17.5 (13.3-21.7)	4.5 (2.9-6.8)	9.9 (8.0-12.1)
Higher Education	11.0 (7.7-16.1)	16.4 (12.5-21.3)	22.4 (20.9-23.9)	15.4 (9.6-23.8)	18.6 (12.9-26.0)
Ratio (Higher: No education)	**4.5**	**4.5**	**1.9**	**6.9**	**3.0**
Urban					
No Education	9.0 (5.6-13.8)	14.4 (10.2-19.8)	28.7 (20.7-38.4)	4.6 (1.8-11.2)	14.6 (11.7-18.1)
Primary Education	13.1 (8.8-18.9)	19.9 (15.1-25.8)	29.7 (23.1-37.2)	7.0 (3.5-13.4)	15.3 (13.2-17.6)
Secondary Education	18.9 (12.9-26.3)	27.7 (22.4-33.8)	34.8 (29.9-40.0)	11.2 (6.3-19.3)	19.4 (15.3-24.2)
Higher Education	29.3 (23.1-36.0)	37.8 (31.6-44.3)	42.1 (38.2-46.1)	26.4 (18.8-35.7)	30.6 (26.1-35.4)
Ratio	**3.3**	**2.6**	**1.5**	**5.7**	**2.1**

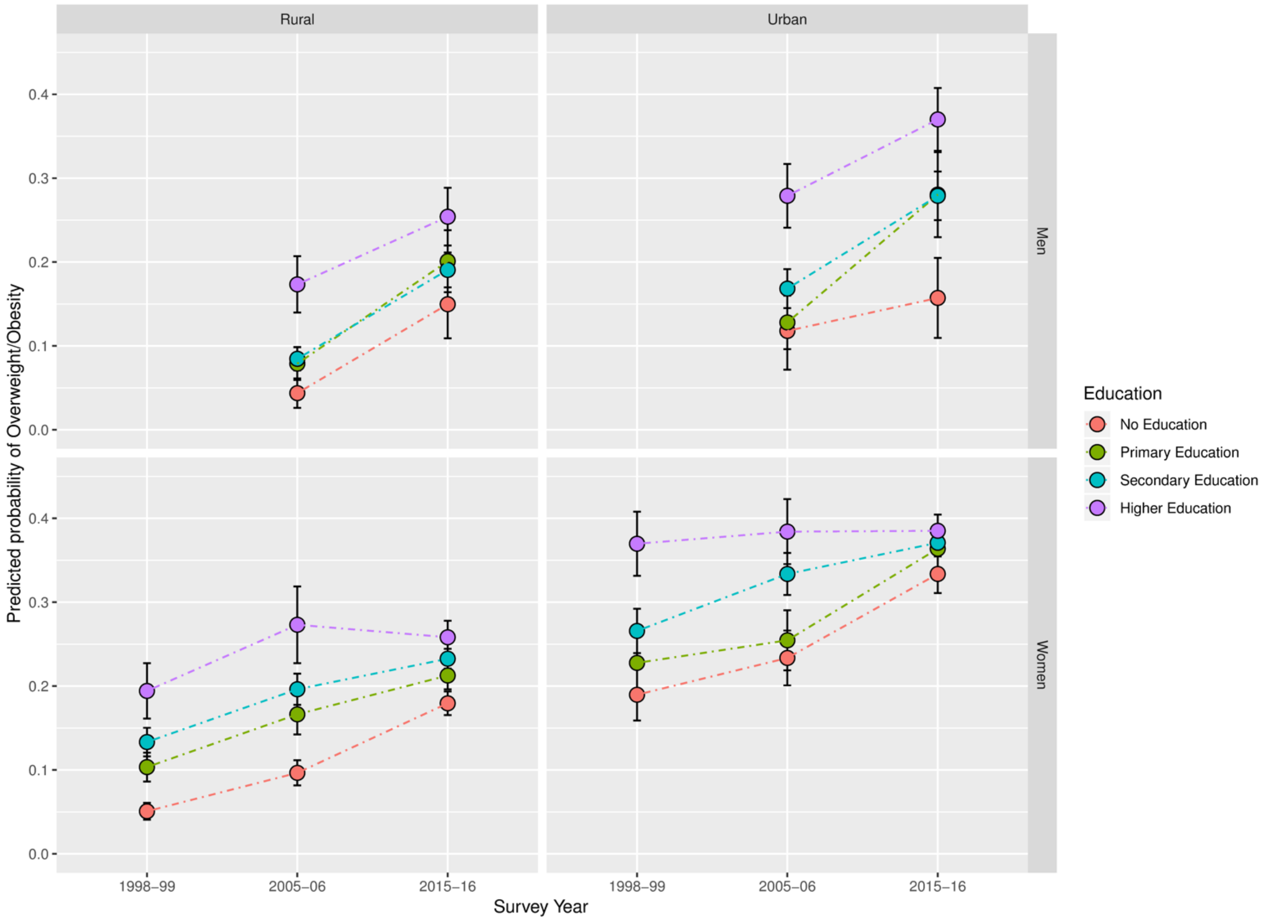
*All percentages were calculated using sampling weights;

**Chi-squared test p value of the variable's association with overweight/obesity: p<0.001.

Although the prevalence of overweight/obesity increased among individuals of all educational attainments, the extent of the increase in prevalence over the study period was consistently highest among those with lower levels of education (Table 13). This was reflected in a declining the ratio of prevalence among those with higher education compared to those with no education. For example, in urban areas of India's most developed states, the prevalence of overweight/obesity was 5.14 times higher among highly educated women than women with no education in 1998-99 compared to 1.79 times higher in 2015-16.

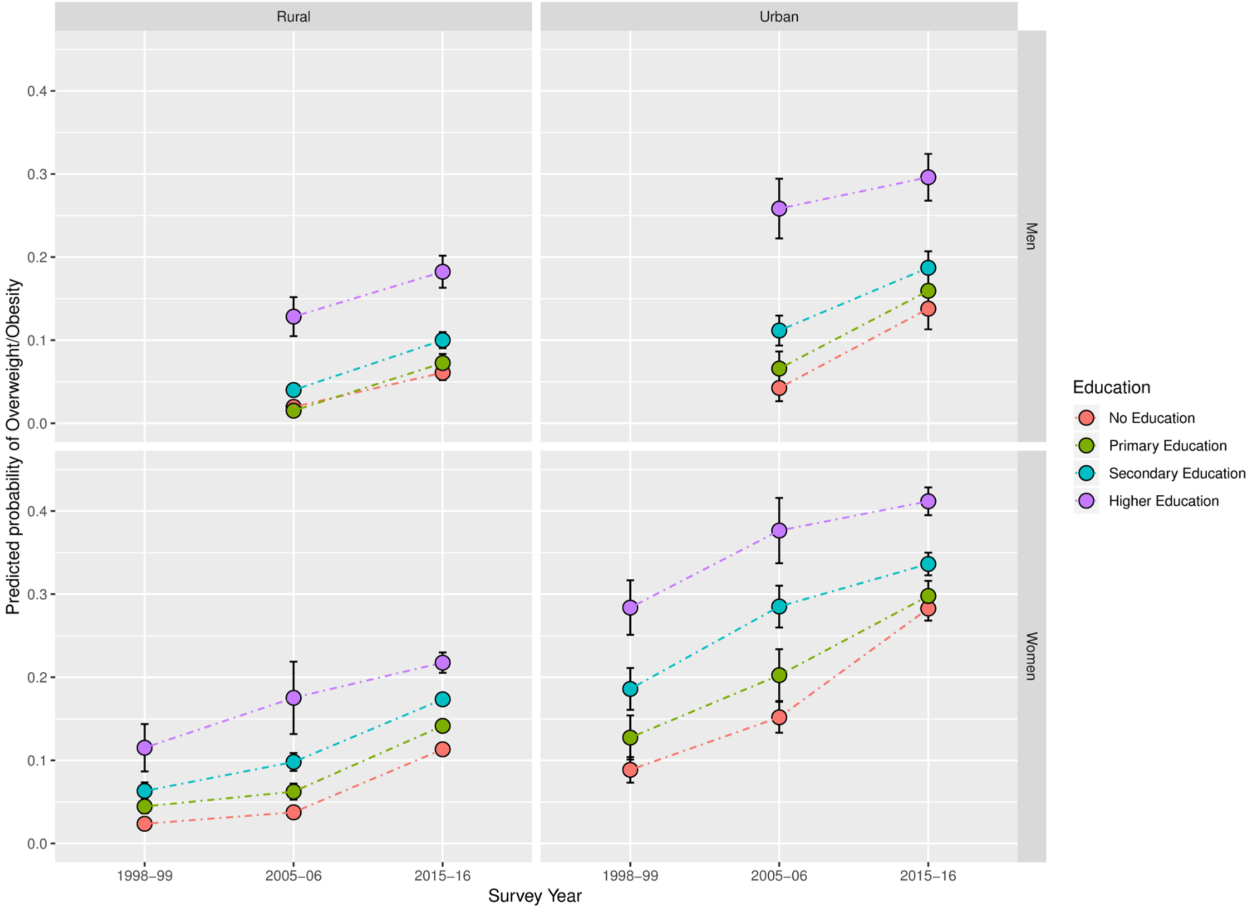
Notably, the smallest ratio was reported among women in 2015-16 in urban areas of the most developed states, whereas the highest ratio among women was found in rural areas of the least developed states. Among men, the lowest ratio was found among rural residents in the most developed states, whereas the highest was found in rural areas of India's least developed states.

Figure 11. Predicted probability of overweight/obesity by Education between 1998-99 and 2015–16 in India's most developed states



Predicted probability and confidence intervals are based on multivariate regressions, and the models adjust for the respondent's age, current marital status and the socio-economic variable not considered as the main exposure.

Figure 12. Predicted probability of overweight/obesity by Education between 1998 -99 and 2015–16 in India's least developed states



Predicted probability and confidence intervals are based on multivariate regressions, and the models adjust for the respondent's age, current marital status and the socio-economic variable not considered as the main exposure.

In my adjusted analysis I found that the difference in prevalence between the highest and lowest SEP category generally declined among women between 1998-99 and 2005-06 (Figure 11 and
Figure 12). The largest decline in this difference was among women in the most developed states, where I observed substantial increases among women with low educational attainment between 1998 and 2016, and no notable increase among women with higher education. In the least developed states, I observed increases in overweight/obesity prevalence among women of all educational attainments, however, the increases were to a greater extent among women with little or no education.

Although the overall prevalence of overweight/obesity is consistently higher among urban women than rural women, I found no notable differences between them in their socioeconomic patterning trends. I identified very limited evidence of a smaller difference of overweight/obesity prevalence between men with higher education and no education in 2015-16 compared to 2005-06.

Table 15. Percentage* of respondents classified as overweight/obese by Standard of Living

	Most developed states				
	Women			***Men***	
	1998-99	***2005-06***	***2015-16***	***2005-06***	***2015-16***
Rural					
Lower SoL	3.1 (0.7-12.7)	4.3 (1.7-10.3)	7.6 (6.7-8.7)	2.8 (1.2-4.4)	7.9 (6.1-8.7)
Middle SoL	9.7 (2.8-27.8)	11.0 (5.2-21.6)	13.0 (10.0-16.6)	6.4 (3.0-7.6)	9.6 (8.6-10.6)
Higher SoL	24.8 (13.5-40.7)	27.4 (12.5-49.9)	27.3 (16.4-41.8)	18.1 (14.9-21.3)	24.0 (20.8-27.2)
Ratio (Higher: Lower SoL)	**7.9**	**6.4**	**3.6**	**6.6**	**3**
Urban					
Lower SoL	16.6 (14.4-18.8)	19.6 (13.2-28.1)	26.5 (21.6-32.1)	11.0 (8.9-11.8)	19.9 (14.6-25.2)
Middle SoL	39.1 (37.6-40.6)	32.6 (25.5-40.7)	38.5 (34.3-42.9)	23.4 (21.4-25.4)	27.5 (22.8-32.2)
Higher SoL	49.6 (44.3-54.9)	46.5 (36.6-56.7)	44.5 (38.5-50.6)	29.0 (26.1-31.9)	38.8 (27.8-50.1)
Ratio	**3.0**	**2.4**	**1.7**	**2.6**	**2**

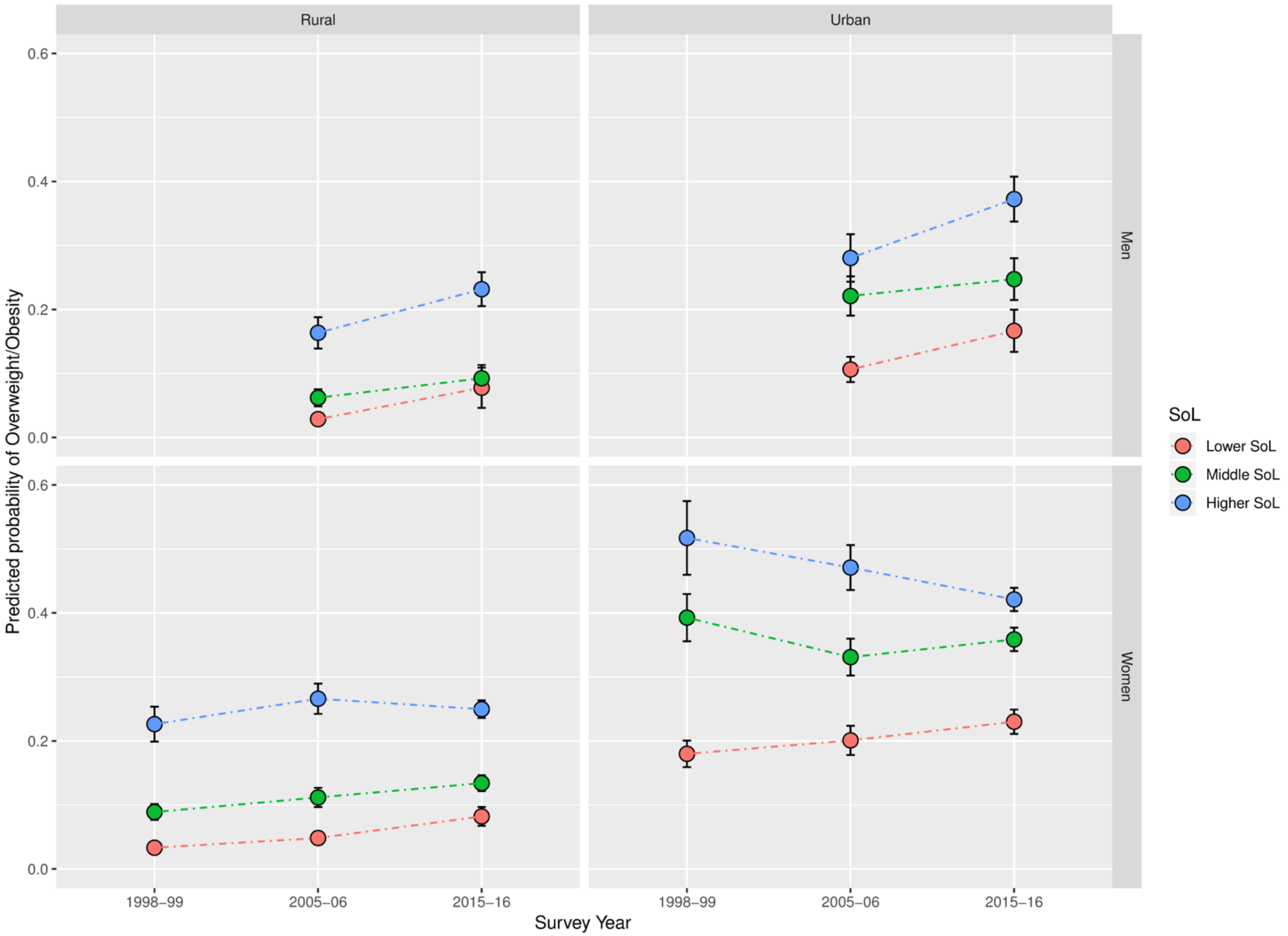
Table 15 continued…

	Least developed states				
	Women			*Men*	
	1998-99	*2005-06*	*2015-16*	*2005-06*	*2015-16*
Rural					
Lower SoL	1.9 (13.5-27.7)	2.4 (1.0-5.5)	7.1 (3.8-10.4)	1.7 (1.2-2.3)	4.7 (3.0-7.4)
Middle SoL	5.0 (3.6-6.7)	6.9 (4.3-11.1)	12.3 (8.3-16.3)	4.8 (2.7-8.4)	7.8 (5.1-11.6)
Higher SoL	16.0 (11.9-20.1)	20.0 (15.0-26.0)	25.2 (23.1-27.3)	16.5 (9.5-27.2)	17.7 (14.5-21.4)
Ratio (Higher: Lower SoL)	**8.5**	**8.41**	**3.5**	**9.7**	**3.8**
Urban					
Lower SoL	11.5 (7.8-16.4)	13.6 (11.0-16.6)	20.4 (17.0-24.2)	5.6 (3.0-10.2)	11.2 (8.7-14.2)
Middle SoL	33.1 (22.7-45.0)	29.3 (25.1-33.8)	34.7 (28.6-41.4)	17.2 (10.6-26.6)	21.7 (17.5-26.5)
Higher SoL	38.3 (27.8-50.1)	43.8 (39.5-48.1)	44.8 (40.4-49.3)	31.1 (23.1-40.4)	30.7 (27.5-34.1)
Ratio	**3.3**	**3.2**	**2.2**	**5.6**	**2.8**

*All percentages were calculated using sampling weights;

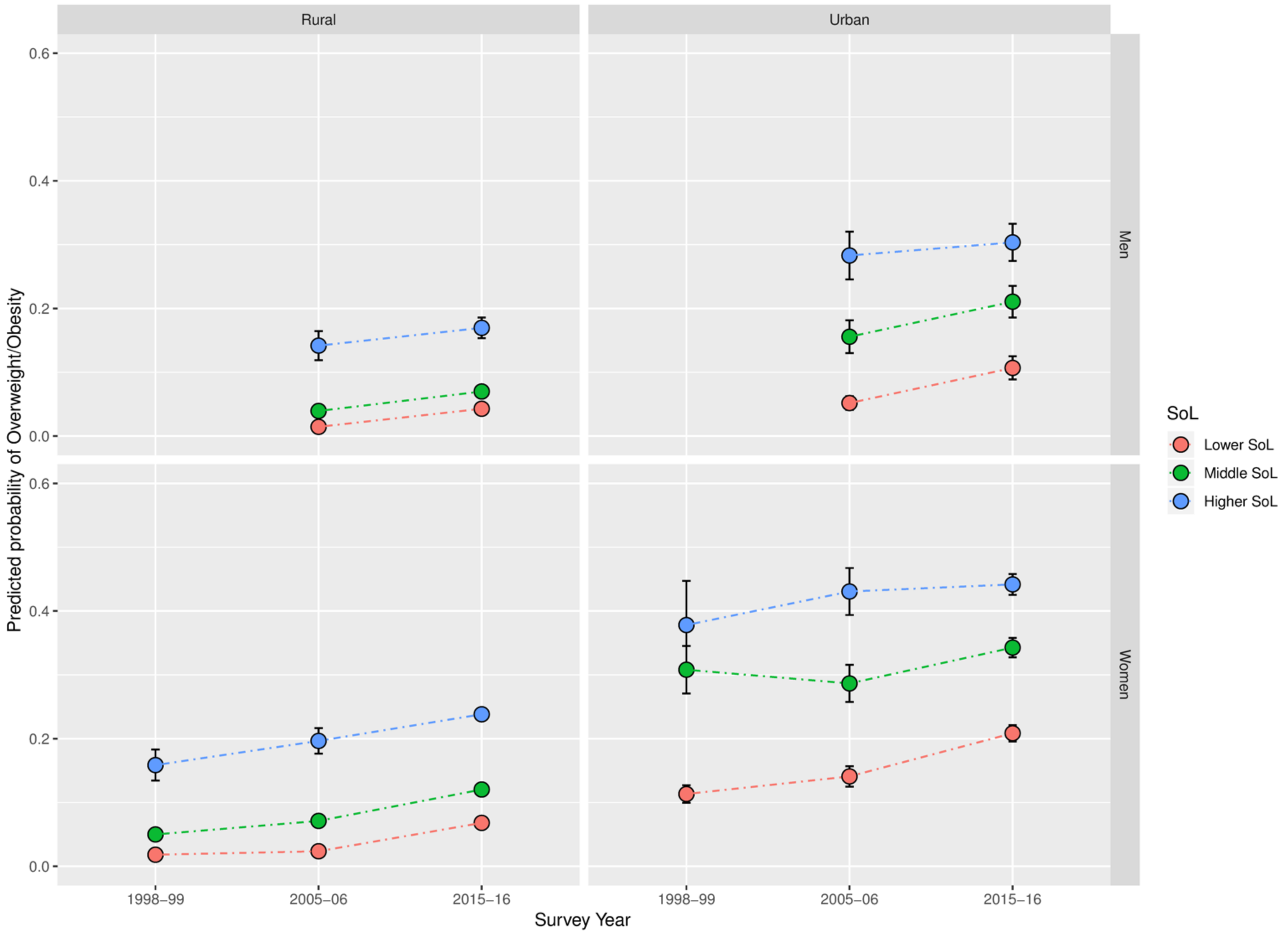
**Chi-squared test p value of the variable's association with overweight: p<0.001.

Figure 13. Predicted probability of overweight/obesity by SoL between 1998 -99 and 2015–16 in India's most developed states



Predicted probability and confidence intervals are based on multivariate regressions, and the models adjust for the respondent's age, current marital status and the socio-economic variable not considered as the main exposure.

Figure 14. Predicted probability of overweight/obesity by SoL between 1998 -99 and 2015–16 in India's least developed states



Predicted probability and confidence intervals are based on multivariate regressions, and the models adjust for the respondent's age, current marital status and the socio-economic variable not considered as the main exposure.

Results of my sensitivity analysis are presented in Table 15, and in Figure 13 and Figure 14. Using the SoL index as the main exposure, shows a similar trend of a notable convergence of overweight/obesity prevalence across SEP among women, particularly in urban areas of India's most developed states. Additionally, it supports the considerably more mixed trend of overweight/obesity patterning among men I identified when using education as the exposure of interest.

6.5. Discussion

This study has found that the trends in the socioeconomic patterning of overweight/obesity in India varied between India's most and least developed states between 1998 and 2016. When examining the difference between overweight/obesity prevalence in the highest and lowest SEP groups, I found a converging trend of overweight/obesity prevalence across SEP among women between 1998 and 2016. As expected, this trend amongst women was more pronounced in India's most developed states, particularly in urban areas, however, similar trends were observed in the least developed states and in rural areas. The converging trend amongst women appears to be driven by relatively smaller increases, and in some cases a decline, in the prevalence of overweight/obesity in higher SEP groups compared to lower SEP groups. This convergence appears to be limited to women, as amongst men, I did not identify any notable convergence in the socioeconomic patterning of overweight/obesity between 2005 and 2016. Using SoL as the main exposure of interest, I found similar, albeit a more attenuated convergence in the socioeconomic patterning of overweight/obesity.

Few studies have examined sub-national variation in the association of SEP and overweight/obesity in countries that have undergone rapid economic development. The only similar study I identified in India used a SoL index as the primary exposure and reported a similar converging trend in the prevalence of both overweight and obesity across SEP in states with a high overall prevalence of overweight/obesity. On the other hand, they identified a diverging trend in SoL in states with a high prevalence of underweight amongst women between 1998 and 2006[90]. The more up-to-date examination of sub-national trends in additional subpopulations suggests a more nuanced picture of the socioeconomic patterning. Notably I find no evidence of a diverging trend of overweight/obesity across SEP in any of the subpopulations, and that there are notable differences in the trends between the sexes and urban and rural areas.

Although there still remains a positive association between SEP and overweight/obesity across all the subpopulations I analysed in India, studies in other countries have identified a negative association between SEP and excess weight in more economically areas of countries that have undergone rapid economic development. One study in Brazil found a positive association between obesity and per capita household income in both more and less economically developed regions of Brazil in 1974/75. By 1996/97 the association was negative in the more economically developed regions, whereas the positive association in the less developed regions persisted[261]. This suggests that Brazil's more developed regions in 1996/97 may have been at a more advanced stage of the epidemiological transition than India's most developed states currently. Other studies using measures of household income and educational attainment as the primary exposures and focusing on women in China's most economically prosperous regions have also found a negative association between SEP and prevalence of overweight[59,60].

I also identified a particularly notable convergence in the prevalence of overweight/obesity by SEP among women when compared to men. Other studies have identified similar differences by sex. One study in China found high-income men and women with low education to be at highest risk of obesity in an economically prosperous province[59]. Another study in China found that higher education was associated with lower odds of high adiposity among women and higher odds of high adiposity among men[60]. In South Korea, a country that experienced a remarkable pace of economic growth in previous decades[262], one study still found a positive association of income with obesity among men, whereas they found a negative association among women[263].

The increased capacity of higher SEP individuals to afford to consume excess food[29,30,32,39] is a commonly suggested reason as to why the association between overweight and obesity and SEP is positive in low- or low-middle-income countries like India. However, the smaller difference in overweight/obesity prevalence between lower and higher SEP women in India's most developed states, particularly in the most recent period, may be due to an increased ability to afford expensive healthy foods and an increased level of health consciousness among higher SEP individuals[30,249,250]. On the other hand, particularly in India's most developed states, lower SEP individuals may be increasingly able to afford cheap high calorie fatty foods[30,77].

My study has some limitations. Firstly, I would have ideally liked to have used additional indicators of excess adiposity to complement my findings. BMI may be limited in that it cannot distinguish between lean mass and body fat, nor does it have information on the distribution of body fat, potentially making it an inaccurate measure of central adiposity[264]. However, other studies have shown a strong correlation of BMI with measures of central adiposity among Indians, such as WC[238]. Consequently, I would not expect the trends I report to vary considerably between adiposity measures. Another possible limitation associated with my use of the BMI variable to inform my main outcome of interest is the potential difference in the body fat percentage at any given BMI between higher and lower SEP groups. Research amongst children from HICs have shown that lower SEP groups may have a higher percentage of body fat at any given BMI compared to higher SEP groups[237,265]. Although this may be limited to high income societies, I am unable to verify the association of body fat and BMI in my data as the NFHS does not collect body fat information. Were a similar phenomenon observed in India, this would imply a more rapid convergence in the socioeconomic patterning of overweight/obesity in India than I have reported.

I limited my study population of women in 2005-06 and 2015-16 to ever-married women, as this was the sampled population in 1998-99. However, a slightly higher proportion of the sample was never-married in 2015-16 (22.5 percent) than in 2005-06 (19.5 percent). Additionally, the prevalence of overweight/obesity is lower among never-married than in currently married women (prevalence of overweight/obesity was 6.6 percent and 25 percent among never married and currently married women, respectively, in 2015-16). This may have led me to potentially overestimate the prevalence I reported for 2015-16 and therefore underestimate the extent of convergence of overweight/obesity prevalence across SEP.

There are some slight differences in the rankings of states by PCNSDP in 2005-06 and 1998-99 compared to in 2014-15. For example, in 2005-06, the state of Odisha had a slightly lower PCNSDP than Manipur. Additionally, Gujarat's economy is 19% larger than Sikkim's in 2005-06, however, Sikkim's economy almost tripled within a decade[28]. These discrepancies are however unlikely to change the overall message of the study, and instead inclusion of these states is expected make results relatively conservative.

Another limitation of my study involves my use of the SoL index based in part on the ownership of assets. Common criticisms of an asset-based index like the one I used, includes the fact that it makes little accommodation for the quality of assets[190,194], potentially leading to misclassification of households. For instance, televisions in poorer households may only receive terrestrial transmission, whereas in higher SEP households may receive digital transmission. Despite this, the simple collection of asset ownership information is not expected to affect the variable substantially[194]. Additionally, as I used three broad SoL categories across a large data set, any misclassification is not expected to be substantial. Another criticism of an asset index is that certain assets are likely to have different importance between broad geographical areas. Although I attempted to remedy this to an extent by calculating separate SoL indices in urban and rural areas, the importance of some assets may still differ between other geographical levels of aggregation[258]. Despite these issues, asset-based indices offer an affordable and stable long-term measure of household wealth for large surveys in low-income settings[190]. Furthermore, my use of two different measures of SEP in this study ensures that I have captured a large portion of the avenues through which SEP and overweight/obesity are associated.

Finally, the cross-sectional nature of the data I used did not enable me to draw conclusions about the causal relationship between overweight/obesity and SEP. Although this was not an explicit study aim, such information may have enriched my understanding of the reasons as to why overweight/obesity is more prevalent among particular socioeconomic groups in India.

Despite these limitations, I use the most recent state representative data, making my findings both generalisable and the most current estimates of these trends.

Some have suggested that overweight/obesity is a 'disease of affluence' in low and low-middle income countries[266,267]. I find evidence of a much more nuanced picture of the socioeconomic patterning of overweight/obesity, when I examine sub-national trends. Whereas it may be an appropriate description of the positive associations between SEP and overweight/obesity I identified, were the identified trends to continue especially among women in India's more economically developed states, there may be a negative association in the coming years. I find no evidence that were past trends to continue, there would be any change to the socioeconomic pattering among men.

The markedly higher increase in overweight/obesity among lower SEP Indians will be an important consideration in the near future as state governments are already tasked with tackling the burden of infectious diseases within this demographic. A state-specific approach will be needed to face the challenge of raising general access to staple foods whilst simultaneously trying to lower demand for unhealthy foods[90,243,267,268]. Additionally, attempts to close the difference in the association of overweight/obesity with SEP between men and women may wish to focus on improving health-related behaviours among men.

6.6. Conclusion

Although the association between SEP and overweight/obesity is still positive, a continuation of past trends suggests that urban areas of the most developed states in India may be the first to show a negative association commonly seen in HICs. The success of policies to slow the increasing prevalence of overweight/obesity may depend on understanding how trends in socioeconomic patterning of overweight/obesity have developed and may continue to develop in the future.

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Student ID Number	1300428	**Title**	Mr
First Name(s)	Shammi		
Surname/Family Name	Luhar		
Thesis Title	Trends in the socioeconomic patterning of overweight and obesity and predictions of the future prevalence of diabetes in India		
Primary Supervisor	Lynda Clarke		

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

SECTION B – Paper already published

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Stage of publication	**Undergoing revision**

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For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)	Led the research conceptualisation; study design; data analysis; manuscript preparation; and review - Lead Author

SECTION E

Student Signature	[redacted]
Date	23.09.19

Supervisor Signature	
Date	

Chapter Seven. Forecasting the Prevalence of Overweight and Obesity in India to 2040

7.1. Abstract

Background: In India, the prevalence of overweight and obesity has increased rapidly in recent decades. Given the association between overweight and obesity with many NCDs, forecasts of the future prevalence of overweight and obesity can help inform policy in a country where around one sixth of the world's population resides.

Methods: I used a system of multi-state lifetables to forecast overweight and obesity prevalence among Indians aged 20-69 years by age, sex and urban/rural residence to 2040. I estimated the incidence and initial prevalence of overweight and obesity using nationally-representative data from the National Family Health Surveys 3 and 4, and the Study on global AGEing and adult health, waves 0 and 1. I forecasted future mortality, using the Lee-Carter model fitted lifetables reported by the SRS, and adjusted the mortality rates for BMI using relative risks from the literature.

Results: The prevalence of overweight will more than double among Indian adults aged 20-69 years between 2010 and 2040, while the prevalence of obesity will triple. Specifically, the prevalence of overweight and obesity will reach 30.4% (UI: 26.5%-34.6%) and 9.6% (UI: 5.6%-13.6%) among men, and 27.4% (UI: 23.9%-30.9%) and 13.9% (UI: 10.0%-17.5%) among women, respectively, by 2040. The largest increases in the prevalence of overweight and obesity between 2010 and 2040 is expected to be in older ages, and I found a larger relative increase in overweight and obesity in rural areas compared to urban areas. The largest relative increase in overweight and obesity prevalence was forecast to occur at older age groups.

Conclusion: The overall prevalence of overweight and obesity is expected to increase considerably in India by 2040, with substantial increases particularly

among rural residents and older Indians. Detailed predictions of excess weight are crucial in estimating future NCD burdens and their economic impact.

7.2. Background

Approximately 39% of the global adult population were classified as overweight (BMI 25.0 – 29.9 kg/m^2) or obese (BMI > 29.9kg/m^2) in 2014; a doubling since 1975[36]. Whereas the prevalence of obesity was 6.4% among women and 3.2% among men in 1975, it had risen to 14.9% and 10.8%, respectively by 2014[36]. In developing countries like India, the increasing prevalence of overweight and obesity has coincided with the demographic and epidemiological transitions, in which mortality and fertility have declined, and lifestyle-related diseases have become more common[15,21,187].

The prevalence of overweight and obesity in India is increasing faster than the world average. For instance, the prevalence of overweight increased from 8.4% to 15.5% among women between 1998 and 2015, and the prevalence of obesity increased from 2.2% to 5.1% over the same period[18–20]. This fast-paced growth has been accompanied by notable increases in the burden of NCDs. Whereas in 1990 the number of DALYs attributable to communicable, maternal, neonatal and nutritional disorders exceeded that attributable to NCDs in virtually all of India's states, currently the opposite is true[15]. Given the extent of the increase in prevalence of overweight and obesity, and its relationships with NCDs[1], reliably predicting its future prevalence has become increasingly important.

Despite this, few studies have attempted to estimate future trends in overweight and obesity in India. One study that reports on global trends estimated that 27.8% of all Indians would be overweight, and 5.0% obese, by 2030[99]. Another study estimated that around 20% of rural Indian adults will be either overweight or obese by 2030[118]. However, these previous studies have merely extrapolated previous trends in prevalence without accounting for a changing population at risk of becoming overweight or obese which declines as the proportion of the population classified as overweight or obese increases.

Simulation models offer a more sophisticated alternative to the extrapolation of secular trends and may produce more accurate forecasts. For example, as an internally logical system, the population at-risk of becoming overweight or obese is regularly updated at each forecasted time interval. Such models therefore allow the incorporation of the impact on future prevalence of past increases in the incidence of overweight or obesity[98]. Additionally, the logical framework enables the estimation of potential impacts of policy decisions, directed at the incidence of overweight and obesity[98,269], and identification of 'at-risk' subpopulations[98,102,270].

This analysis brings together nationally-representative data from a range of publicly available sources in a dynamic simulation model to forecast the future prevalence of overweight and obesity in India to 2040 among adults aged 20-69 years.

7.3. Data and Methods

7.3.1. Data

National Family and Health Survey (NFHS)

The nationally-representative NFHS collects health and demographic data among women aged 15-49 years and men aged 15-54 years. NFHS 3 (2005-06) interviewed 124,385 and 74,369 adult women and men respectively, and NFHS 4 (2015-16) contains data on 625,000 adult women and 93,065 adult men[18,19].

The Study on global AGEing and adult health (SAGE)

SAGE Waves 0 (2002-04) and 1 (2007-10) contain longitudinal health and demographic data on people aged 50 or more years from six states which are believed to be nationally-representative [271]. Wave 0 collected health information on 2559 adults aged 50 or more years, whereas Wave 1 collected data on approximately 3000 men and 3000 women aged 50 or more years.

Sample Registration System (SRS)

The SRS reports sex- and residence-specific abridged lifetables by five-year age groups for each state for every year between 1997 and 2015[216–221]. The SRS dually records deaths using representative samples from across the country[149].

UN World Population Prospects 2017 and World Urbanization Prospects 2018

The 2017 round of the World Population Prospects includes population projections and estimates by the Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat[37]. The Division uses the cohort-component method for each country and major geographical region to produce population projections under a number of different future fertility scenarios. Separate urban and rural projections that are consistent with the national projections are reported by the UN World Urbanization Prospects 2018[9].

7.3.2. Model inputs

From these data sources, I extracted the following model inputs for the age, sex and residence-specific forecasts of overweight prevalence in India:

Age-specific prevalence of overweight and obesity

I estimated the prevalence of overweight and obesity among individuals aged 20-49 using the BMI variable in NFHS-3 and NFHS-4, whereby individuals with a BMI>24.9kg/m^2 and <30.0kg/m^2 were classified as overweight, and those with a

BMI>29.9kg/m^2 were classified as obese following the WHO recommendations[1]. Pregnant women (5.2% of women in NFHS 3 and 4.4% in NFHS 4) were excluded from my sample as their pregnancy could give misleadingly high BMI scores. I used survey weights to calculate age-specific prevalence accounting for the complex survey design and based the baseline (2010) age-specific prevalence on the mid-point prevalence of the two surveys. Among individuals aged 50-69, I used the BMI variable, and the same cut-offs, in SAGE wave 0 and 1 to estimate the overall age-specific prevalence and applied the overall relative risk of overweight and obesity among urban and rural residents to obtain residence-specific prevalence estimates. The prevalence estimates from the data are included in the Appendix.

Age-specific incidence of overweight and obesity and age-specific rates of urbanization

I used the changing prevalence of overweight and obesity between 2005 and 2015 among the population aged 20-49 years to estimate the age-specific incidence of overweight among the underweight/normal weight population, and incidence of obesity among overweight individuals in the baseline year of 2010. I used the iterative intracohort interpolation procedure[199] whereby the observed changes in overweight status to specific cohorts are translated into age-specific rates for the inter-survey interval (a more detailed explanation is presented in Chapter 4). The age-specific rates were estimated separately by sex, residency (urban and rural) and age (20-24, 25-29, 30-34, 35-39, 40-44, 45-49 years).

Age-specific rates of urbanisation were also calculated by the same method, using the age-specific proportions of the population in urban and rural areas in the two NFHS surveys.

For those aged 50-69, I calculated the incidence of overweight and obesity using longitudinal data from SAGE waves 0 and 1 for men and women separately by dividing the number of incident cases by the person-years of exposure. As information on the exact time an incident case occurred was not available, incident cases were assumed to have occurred at the halfway-point between the two waves. I calculated an overall incidence rate among men and women separately, and indirectly standardised the rates using the age-distribution of obesity incidence from a study in the United States[200] that used data from the Behavioral Risk Factor Surveillance System in order to obtain net rates for the following age groups: 50-54, 55-59, 60-64, and 65-69 years (See Chapter 4 section 4.2).

I fitted a spline to smooth the age-specific incidence rates across the lifespan and used age-specific incidence by the five-year age groups in the final analysis.

Remission

I incorporated the potential for individuals to transition from overweight and obesity to lower BMI groups by modelling gross, rather than net incidence rates at all ages. Remission refers to reverse transitions, whereby the simulated population is able to transition from a state of 'Obese' to 'Overweight', and 'Overweight' to 'Not Overweight/Obese' (*Figure 15*). I used rates of remission that allowed my model with gross rates to closely match the measured age-specific prevalence in 2015 from NFHS-4. To estimate remission in older ages, I applied an odds ratio of remission in older ages (50+ years), relative to younger ages. A prospective study in rural India carried out between 2008 and 2017[95] found an elevated odds of remission from higher to lower BMIs of 1.74 and 2.12 among older aged men and women, relative to younger counterparts.

Current and future age-, sex- and urban/rural residence- specific mortality rates

I converted conditional mortality probabilities reported by the SRS to age-specific mortality rates from 1997 to 2013 using standard demographic procedures[205] and used these rates to forecast future mortality to 2040 using the Lee-Carter method[201,203]. In brief, the Lee-Carter method summarizes a series of sets of age-specific mortality rates for successive periods of time by its average age-schedule, age-specific deviations from the average age-schedule, and the trend in the overall level of mortality over time. The forecast is contingent on the extrapolation of this latter parameter (Chapter 4).

Relative risk of dying for those overweight or obese compared with those who are not

I adjusted the forecasted mortality rates to account for differential mortality between overweight and obese individuals and those who are in lower weight categories. Relative risks of dying, based on BMI group, were adopted from the findings reported in a study that examined the association between BMI and mortality in Mumbai[209]. This study reported relative risks of dying for those who are overweight excluding obesity (OW), relative to normal (N) weight, those who are obese (OB) relative to normal weight, and those who are underweight (UW) relative to normal weight. The authors report risk ratios, along with confidence intervals, for men and women aged 35-59 and 60 or more, separately. As the study did not calculate risk ratios for individuals aged 20-34, I assumed that the relative risk of dying at 35-59 also prevailed at these ages. I obtained separate relative risks of dying for those who are overweight and obese relative to new reference categories of 'not overweight' and 'not obese' using a basic algebraic approach (Chapter 4), and subsequently used these relative risks to calculate BMI specific rates of mortality using the population level mortality rate.

Age-, sex- and urban/rural residence-specific population in 2010

Estimates of the 2010 urban and rural population were taken from the World Urbanization Prospects[9] and disaggregated using the average age-group and sex structure of urban and rural populations separately, which I obtained from the NFHS-3 and NFHS-4[18,19].

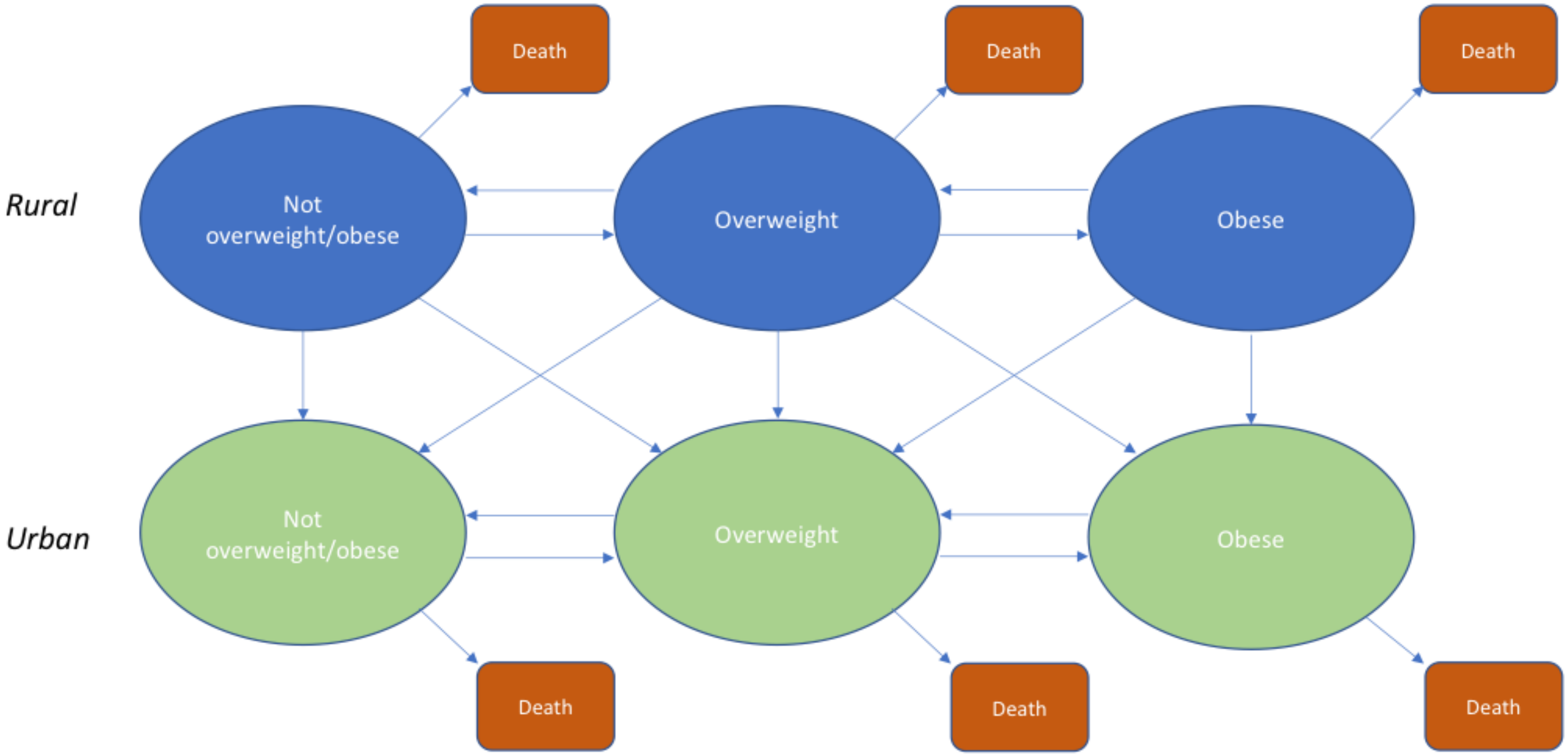
Population aged 20-24 entering the simulation at every interval

The new entrants aged 20-24 that join the urban and rural populations in each time interval were estimated using the projected population aged 20-24 from the medium fertility projection scenario by the UN' World Population Prospects[37] and split into the projected proportions of the population in urban and rural areas from the World Urbanization Prospects[9].

7.3.3. The Model

I estimated the future prevalence of overweight and obesity through 2040 using an age-stratified simulation model based on a system of multi-state lifetables[210], that moved individuals through mutually-exclusive health states depending on my estimated transition rates as they age. The model operated in discrete time, estimating the prevalence of overweight and obesity separately among men and women in urban and rural areas separately, at five-yearly intervals between 2010 and 2040. The system of multi-state lifetables is shown in Figure 15.

Figure 15. Compartmental model to forecast overweight and obesity prevalence in India



Most epidemiological studies apply transition probabilities to the population at risk of a transition at the beginning of a time period to determine the distribution of the population across health states in a succeeding time period, without taking account of a changing population at risk within a time interval. This is due to individuals being able to enter and re-enter a particular BMI group within a time interval. In order to sufficiently account for this, I employed a multi-state lifetable system first developed by Schoen and Nelson (1974) who addressed questions about flows in and out of marriage in the UK and USA. Rather than work with transition probabilities derived from the rates, this approach to forecasting health states uses the rates directly. A detailed description of this method is included in Chapter 4.

Assumptions

Firstly, between 2005 and 2015 the pace of increase in prevalence of overweight and obesity is faster in rural populations than in urban areas. As the prevalence of overweight and obesity among the 20-24 population is not determined within the model, I assumed that the rate of increase in this age group observed from the overweight and obesity prevalence in the NFHS data decreased and converged towards a 0% increase by 2040, so as not to overinflate my estimates. Additionally, my baseline forecasts, assumed that the empirically estimated overweight and obesity incidence for each demographic group for the baseline year (2010) applied throughout the forecasting period. This assumption provides a clear and easily interpretable counterfactual scenario against which to compare other scenarios whereby incidence is allowed to vary over the forecast period. For simplicity, I assumed that there is no migration in and out of India. Finally, it was assumed that the rate of urbanisation measured between 2005 and 2015 prevailed throughout the forecast period.

Uncertainty Analyses

To obtain uncertainty bounds for my estimates I simultaneously selected random prevalence, incidence and mortality rates from the distributions that informed their uncertainty. I repeated the simulation 5000 times and I reported the median estimate as the final point estimate, whilst the range of estimates for each population subgroup informed my uncertainty bounds. The analysis was conducted in R version 3.5.1.

Sensitivity Analyses

The future incidence of overweight and obesity may continue to increase due to economic development creating an increasingly obesogenic environment. To explore the implications of this potential trend, I included additional scenarios. Scenario 1 involved examining the effect on future prevalence the incidence parameter increasing at a constant annual rate of 1%. In Scenario 2, I examined the effect on future overweight and obesity of the urbanisation rate being set at its upper confidence bound throughout the forecast period. Finally, Scenario 3 examined the extent to which the total prevalence of overweight and obesity prevalence would change if no further urbanisation were to take place to 2040. Although unrealistic, this provides an understanding as to the extent to which the future increase in prevalence is driven by future urbanisation.

I also performed additional analysis using the South Asian BMI cut-offs values. Some advocate the use of these BMI cut-offs due to a stronger positive association between BMI and body fat observed in South Asians compared to White Caucasians, and consequently an elevated disease risk at lower BMI levels[185,186]. Under this assumption, a BMI between 23.00 kg/m^2 and 27.49 kg/m^2 was used to define individuals who are overweight, and a BMI greater than 27.50 kg/m^2 was used to define obesity[234].

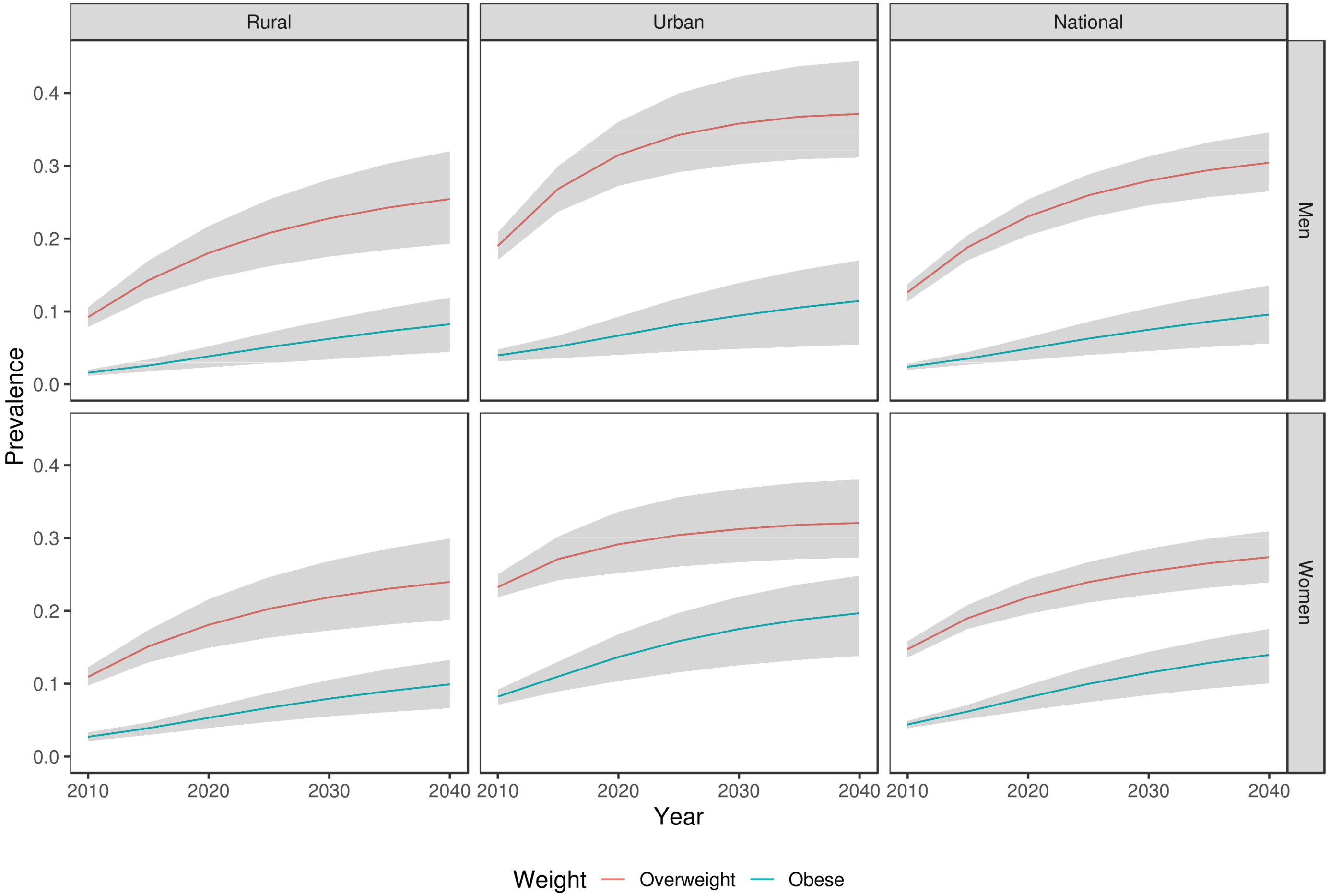
7.4. Results

Nationally, my model estimates that the prevalence of overweight among women will increase from 14.7% (UI: 13.6%-15.8%) to 27.3% (UI: 23.9%-30.9%) between 2010 and 2040, whereas the prevalence of obesity is forecasted to increase from 4.4% (UI: 3.9%-4.9%) to 14.0% (UI: 10.0%-17.5%) over the same period (Figure 16). Among men, the prevalence of overweight and obesity is forecasted to increase from 12.6% (UI: 11.4%-13.8%) and 2.4% (UI: 2.0%-2.9%) in 2010 to 30.4% (UI: 26.5%-34.6%) and 9.6% (UI: 5.6%-13.6%), respectively, by 2040 (Figure 16).

The prevalence of overweight and obesity is forecasted to remain higher in urban areas, compared with rural areas, reaching 32.1% (UI: 27.3%-38.0%) and 19.7% (UI: 13.8%-24.8%), respectively among urban women and 37.1% (UI: 31.1%-44.4%) and 11.4% (UI: 5.4%-17.0%), respectively, among urban men by 2040. However, the relative increase will be larger in rural areas, where the baseline model forecasts that the prevalence of obesity among women will be 4 times higher in 2040 than in 2010 in rural areas, compared to a 2.6 times higher prevalence of obesity in urban areas over the same period.

The model also predicts larger increases in the prevalence of overweight and obesity in older age groups. Using broad age groups, I find that, for example, among men, the prevalence of overweight in urban areas among 55-69-year-olds is predicted to almost quadruple from 10.7% (UI: 8.1%-13.5%) to 38.6% (UI: 30.7%-47.8%) between 2010 and 2040, whereas the prevalence of overweight in rural areas is predicted to increase from 4.7% (UI: 3.4%-6.0%) to 30.2% (UI: 23.0-37.7%) (Table 16 and Table 17). On the other hand, my model predicts that younger age groups in my model will experience the smallest absolute increase in the overweight (Figure 17 and Figure 18; Table 16 and Table 17).

Figure 16. Forecasted prevalence of overweight and obesity at ages (20-69 years) 2010–2040



This forecast represents the scenario in which incidence remains constant over the forecast period.
95% uncertainty bounds in grey

Figure 17. Forecasted age-specific prevalence of overweight and obesity to 2040 (men)

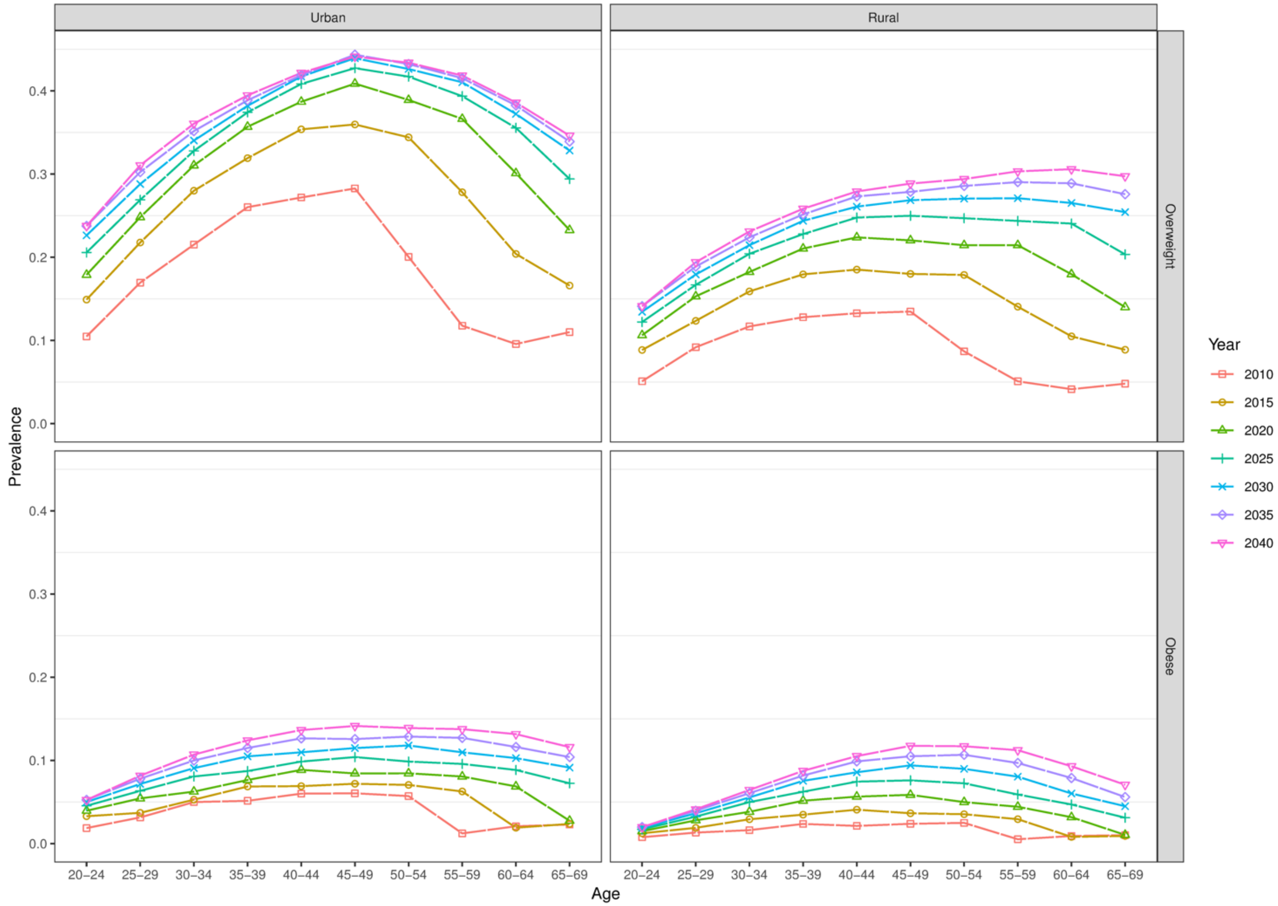
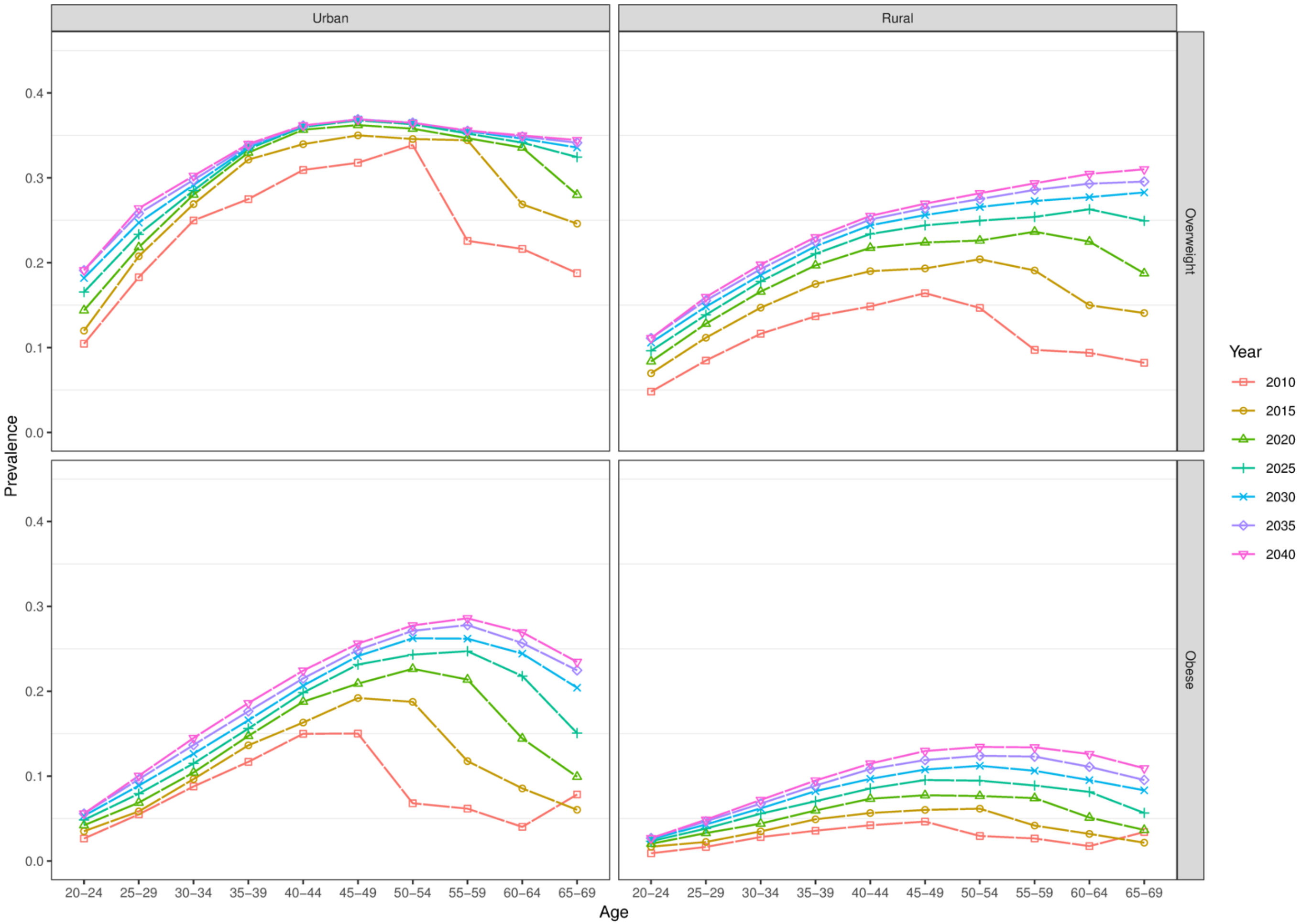


Figure 18. Forecasted age-specific prevalence of overweight and obesity to 2040 (women)



Under the assumption of a 1% annual increase in incidence of overweight and obesity from 2015, I expect the national prevalence of overweight to increase to 29.7% (UI: 26.1%-33.9%) by 2040 among women and to 33.2% (UI: 29.4%-37.6%) over the same period for men (Figure 19). Over the same period, I expect the national prevalence of obesity to increase to 16.9% (UI: 12.2%-21.4%) among women and 12.2% (UI: 7.1%-17.0%) among men. Under the high urbanization scenario, I find that the future national prevalence of overweight between 2010 and 2040 will increase to 31.7% (UI: 27.4%-35.8%) among women, compared to 25.0% (UI: 23.5%-30.9%) under an assumption of no further urbanisation. In contrast, although the high urbanisation scenario for men finds a 1.5% higher prevalence of overiwght among men in 2040, compared to the scenario of no further urbanisation, the prevalence of obesity in 2040 does not vary notably between these scenarios (Figure 19).

Figure 19. Forecasted prevalence of overweight and obesity to 2040 under the four different scenarios tested

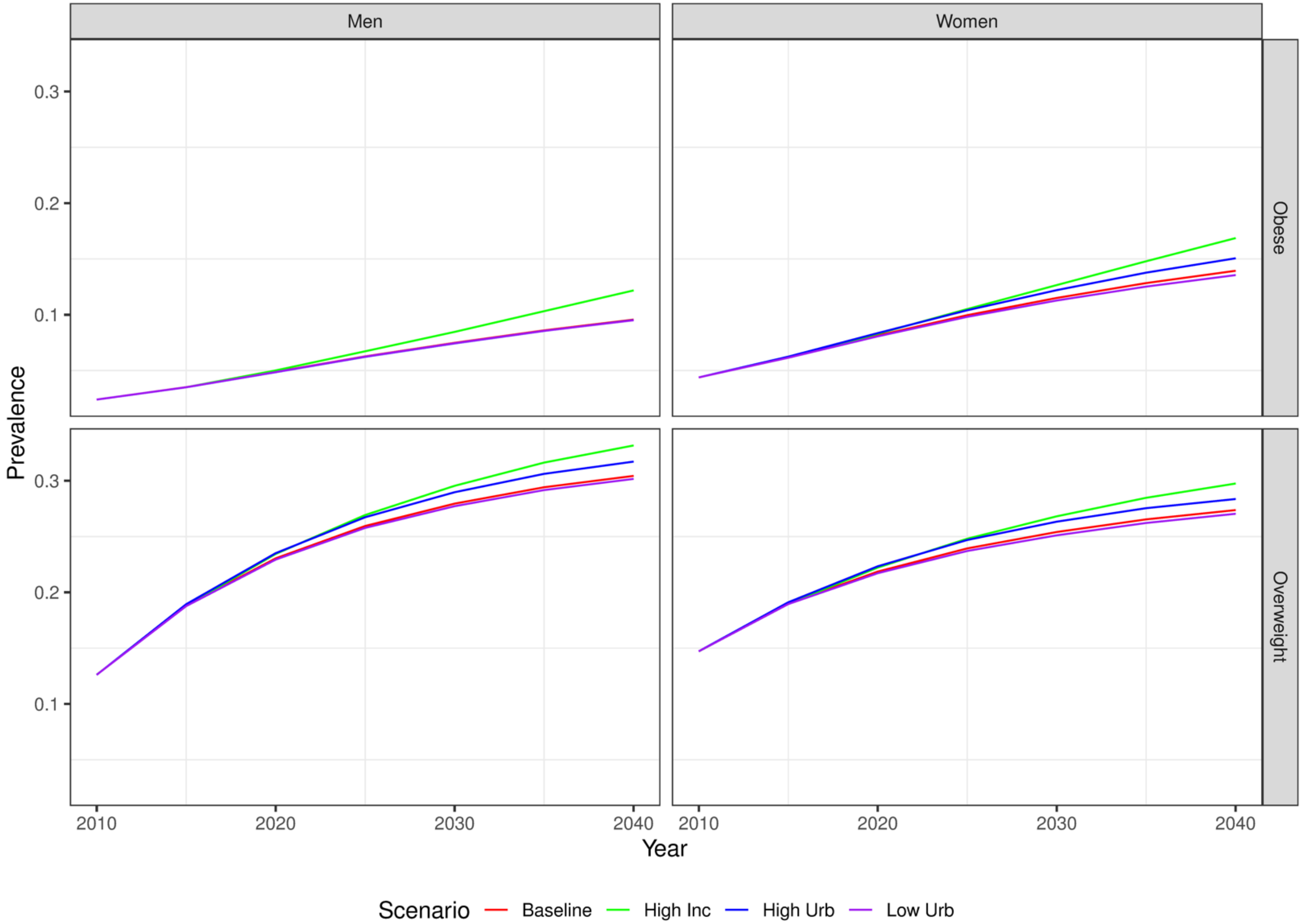


Table 16. Forecasted percentage prevalence of men classified as overweight and obese 2010–2040

Weight	*Residence*	*Year*	*20-34*			*35-54*			*55-69*			*All*		
			Point est.	*Lower*	*Upper*	*Point est.*	*Lower*	*Upper*	*Point est.*	*Lower*	*Upper*	*Point est.*	*Lower*	*Upper*
Overweight	*Rural*	*2010*	8.4	6.6	10.2	12.3	9.9	14.6	4.7	3.4	6.0	9.2	7.9	10.6
		2020	14.5	11.4	18.0	21.7	17.5	26.5	18.3	14.1	22.4	18.0	14.5	21.7
		2030	17.6	13.8	22.1	25.9	19.8	32.3	26.5	20.2	33.0	22.8	17.5	28.2
		2040	19.0	14.9	24.0	27.9	20.8	35.4	30.2	23.0	37.7	25.4	19.3	32.0
Obese	*Rural*	*2010*	1.2	0.7	1.7	2.3	1.6	3.1	0.8	0.2	1.3	1.6	1.1	2.0
		2020	2.6	1.3	3.9	5.4	3.5	7.6	3.1	1.7	4.7	3.8	2.3	5.2
		2030	3.7	1.9	5.6	8.5	4.8	12.3	6.4	3.4	9.9	6.2	3.4	8.9
		2040	4.3	2.1	6.5	10.6	5.9	15.3	9.4	4.7	14.1	8.2	4.4	11.9
Overweight	*Urban*	*2010*	15.9	13.9	17.9	25.8	22.7	28.8	10.9	8.1	13.5	19.0	17.1	20.8
		2020	24.6	21.2	28.5	38.4	33.0	44.0	30.8	25.2	36.4	31.5	27.2	36.0
		2030	28.3	24.3	32.9	41.6	34.6	49.0	37.4	30.3	45.4	35.8	30.2	42.2
		2040	30.2	25.8	35.1	42.2	35.3	50.4	38.6	30.7	47.8	37.1	31.1	44.4
Obese	*Urban*	*2010*	3.2	2.2	4.3	5.7	4.3	6.9	1.7	0.6	2.9	4.0	3.1	4.8
		2020	5.2	3.3	7.2	8.3	4.8	11.8	6.2	2.5	9.6	6.7	4.0	9.3
		2030	7.0	4.4	9.7	11.2	5.5	16.8	10.2	3.3	17.1	9.4	4.9	13.9
		2040	8.0	5.0	11.0	13.5	6.6	20.4	12.9	3.4	21.8	11.4	5.5	17.0

Table 17. Forecasted percentage prevalence of women classified as overweight and obese 2010–2040

Weight	*Residence*	*Year*	*20-34*			*35-54*			*55-69*			*All*		
			Point est.	*Lower*	*Upper*	*Point est.*	*Lower*	*Upper*	*Point est.*	*Lower*	*Upper*	*Point est.*	*Lower*	*Upper*
Overweight	*Rural*	*2010*	8.0	6.5	9.6	14.9	12.8	17.0	9.3	7.7	10.8	10.9	9.7	12.3
		2020	12.6	10.2	15.1	21.5	17.4	25.8	21.9	17.4	26.9	18.1	14.9	21.6
		2030	14.7	11.8	17.6	24.6	19.4	30.2	27.7	21.2	35.9	21.9	17.3	26.8
		2040	15.8	12.7	18.9	25.9	20.4	32.1	30.2	22.5	39.6	24.0	18.8	29.9
Obese	*Rural*	*2010*	1.7	1.2	2.2	3.9	2.8	4.9	2.5	1.5	3.6	2.7	2.1	3.3
		2020	3.3	2.3	4.2	7.1	5.1	9.1	5.6	2.9	8.4	5.3	3.9	6.7
		2030	4.4	3.0	5.7	9.9	7.1	13.0	9.6	5.0	14.4	7.9	5.5	10.5
		2040	5.0	3.4	6.5	11.8	8.4	15.5	12.4	6.4	18.4	9.9	6.6	13.3
Overweight	*Urban*	*2010*	17.4	15.7	19.1	30.6	28.8	32.6	21.3	17.6	25.0	23.2	21.9	25.0
		2020	21.5	19.1	23.8	35.0	30.8	40.1	32.5	25.4	41.2	29.1	25.2	33.6
		2030	23.9	21.2	26.7	35.7	31.1	41.4	34.7	27.0	46.0	31.2	26.7	36.8
		2040	25.2	22.3	28.1	35.9	31.2	41.6	35.0	27.3	46.7	32.1	27.3	38.0
Obese	*Urban*	*2010*	5.4	4.5	6.3	12.3	10.5	13.9	5.9	3.7	8.1	8.2	7.1	9.2
		2020	7.2	5.9	8.5	18.8	14.7	22.6	16.0	8.3	22.8	13.6	10.3	16.8
		2030	8.9	7.2	10.6	21.7	16.6	26.4	24.0	12.8	33.1	17.5	12.5	21.9
		2040	10.0	8.1	11.9	23.5	17.9	28.7	26.5	14.0	36.5	19.7	13.8	24.8

7.5. Discussion

Overall, I predict that the prevalence of overweight will increase approximately double among Indian adults aged 20-69 years between 2010 and 2040, whilst the prevalence of obesity is expected to increase approximately three-fold over the same period. Specifically, amongst men, I predict that the prevalence of overweight and obesity respectively will reach around 30% and 10%, whilst 27% and 14% of women are expected to be overweight and obese, respectively, by 2040. My model additionally predicts an ageing distribution of overweight and obesity, with the largest relative increases in prevalence observed among the 55-69-year age group (in this age group the prevalence of obesity among women is predicted to increase almost 6-fold in rural areas and almost 5-fold in urban areas over the forecast period). Whilst prevalence of overweight and obesity is expected to be higher in urban areas throughout the forecast period, I predict larger relative increases in their prevalence in rural areas.

My forecasting model has a number of limitations. Firstly, I determine the future prevalence of the new cohorts of 20-24-year individuals outside of the model, where I applied a declining rate of increase in prevalence, so as to not grossly inflate future prevalence in this age group to unrealistic levels. Studies have documented increasing overweight prevalence among young adults in India, especially among men and high socioeconomic status individuals[272].

Secondly, I used standard global BMI thresholds over which there is some controversy. Some researchers advocate for using lower BMI thresholds for South Asians[234] due to a higher percentage of body fat among South Asians compared to Caucasians of the same BMI[185,186]. Some research has documented a nearly 10-15% higher prevalence of overweight among individuals with Asian heritage if Asian-specific cut-offs are used[186]. Others have found no higher risk of mortality among obese Asians compared to obese non-Asians, and advocate for global consistency in the definition of overweight and obesity[99,273,274]. I opted to use global cut-offs for this reason and in order to facilitate direct comparison of the predictions with similar forecasting studies in Western countries[106,108,115]. I sought to remedy this limitation by performing sensitivity analysis using South-Asian BMI cut-offs, and identified potential underestimation of my results (Table 43 and Table *44*). For instance, among urban men, I identified a potential underestimation of the 2040 obesity prevalence of nearly 20 percentage points, suggesting that using global cut-offs may underestimate the future overall public health challenge related to excess weight in India.

Thirdly, my assumption of no migration in and out of India may slightly bias my findings if individuals leaving India to elsewhere are more likely to be overweight or obese than individuals who remain or enter. Any bias attributable to my assumption of zero migration in an out of India is however likely to be negligible as the number of annual net migrants (minus 2.5 million in 2017 according to the World Bank[275]) currently represents less than 1% of the total population[37].

Despite these limitations, my study has a number of strengths. Firstly, I have quantified the future prevalence of overweight and obesity in India using the most recent nationally-representative publicly available data. My model is able to reflect the changing demographic profile of India in future estimates of the prevalence of overweight and obesity and, in addition, to incorporate future rates of urbanisation. Additionally, it models the future age- and sex-specific prevalence of overweight as a function of past and current age- and sex-specific incidence and mortality; reflecting the real-life lag between demographic changes, changes in incidence and mortality and their effect on the overall prevalence at various ages in the future. Unlike previous studies predicting future prevalence of overweight and obesity in India[99,118], I forecasted prevalence for age-stratified subgroups as well as generating aggregated forecasts, putting emphasis on demographic groups that are expected to experience particularly high increases in prevalence.

Few studies have attempted to forecast the future prevalence of overweight and obesity in India. One study from 2005 predicted that the prevalence of overweight among Indian adults, assuming a continuation of past trends, will increase to 27.8% by 2030, whist the prevalence of obesity is predicted to reach 5.0%[99]. The overweight estimations closely resemble my predictions for men and are slightly above what I predict for women. However, my model predicts a considerably higher prevalence of obesity by 2030, with 11.5% of women and 7.4% of men predicted to be obese by 2030.

Another study, focusing on rural India estimated that the prevalence of combined overweight and obesity will approach 20% among men and just exceed 20% among women aged 18 and over by 2030[118]. We, on the other hand, expect 28.9% of men and 29.8% of women to be either overweight or obese by 2030. The discrepancy between these two separate findings may indeed be due to the different methodologies adopted but is more likely explained the fact that my study included older age groups among whom overweight and obesity prevalence is expected to increase most substantially by 2030.

The differences between my results and previous forecasts of the prevalence of overweight and obesity in India may also be explained by my attempts to take into account some of the heterogeneity in the incidence of overweight an obesity and mortality sub-nationally, estimating urban and rural outcomes separately for men and women. Also, instead of making a priori assumptions about the future prevalence of overweight and obesity, for instance a linearly increasing prevalence rate, I model future prevalence as a function of a continuously updated 'population at-risk'. Although I expect my baseline results to be relatively conservative, as I fix age-specific incidence rates over the forecast period, I expect them to be more accurate than previous attempts. This is due to my use of the most up-to-date data, and the fundamental differences in modelling approaches.

The ageing age distribution of overweight and obesity prevalence is likely to be driven by a cohort effect. Previous research has reported a peak in the prevalence of overweight in the 40-49 age group in 2005 in India, whereas in more economically developed countries, the prevalence in the same year peaks in the 60-69 age group[99]. My finding of an older age distribution of both overweight and obesity prevalence in 2040, compared with 2010, may be associated with India's increasing resemblance to HICs in terms of overall prevalence of overweight and obesity, and economic development. When I tested my forecasts holding future mortality rates at the 2010 level, future prevalence did not notably differ from the forecasts in which future mortality was allowed to decline. Consequently, previous and continuing increases in longevity are not likely to be an important driver of this ageing age distribution of overweight and obesity.

I confirmed that my model predictions were very similar to the 2015 age-specific prevalence estimates reported by the NFHS. Another way I assessed the ability of my model to accurately predict future excess weight was to compare my output with collected data on overweight and obesity prevalence from a data source that was not used in the parameterization of my model. The National Nutrition Monitoring Bureau (NNMB) reports that in 2017 the prevalence of combined overweight and obesity in urban areas was 34% among men. In my model, the prevalence of overweight and obesity combined among urban men is 35%, and the NNMB estimate falls comfortably within my uncertainty bound of 29.3% - 40.9%. The NNMB also reports a point estimate of 44.0% prevalence among urban women in 2017, falling within my uncertainty bound of 34.3% – 46.8%, although my point estimate is lower, at 40.4%. I would expect the interval around their estimate to considerably overlap with ours, however this interval was unavailable. Although NNMB estimates fall comfortably within my uncertainty bound, differences between point estimates can derive from a number of sources. Firstly, different sampling frames are used in the surveys, whereby the NNMB in urban areas selects a sampling frame from under half (16) of Indian states they believe to accurately reflect national trends[276]. Additionally, the NNMB included individuals aged 70 years or more, the majority of whom are likely to be urban women due to their higher life expectancy[219].

My study has found that the prevalence of obesity in 2040 is expected to be lower than levels that are currently observed in some of the world's most industrialised economies, implying potential for considerable further increases beyond 2040. For instance, a recent survey has found that using the same BMI cut-offs as in my study, 40.4% and 35.0% of women and men in the US, respectively were classified as obese in 2013-14[277], whereas I find that in urban India, a relatively obesogenic environment, 19% of women and 16% of men are likely to be obese by 2040, however, this is one of my most conservative estimates, assuming a constant rate of incidence over the forecast period. Nevertheless, a 1% annual increase in incidence, corresponding to a 35% overall increase in incidence over the forecast period only leads to a 2% higher prevalence in overweight and obesity by 2040, suggesting that much of the future forecasted prevalence will be determined by the changing demographic profile and background BMI trends of India. Attempts to reduce the forecasted prevalence in 2040 may aim to target a reduction in overweight and obesity incidence, starting among children and adolescents yet to pass through the 20-69-year-old population.

The future task of tackling the increasing disease burden associated with the tripling of obesity prevalence will be particularly challenging in India, given its already high burden of infectious diseases[15], and given that it is expected to have the largest population in the world by 2024[37]. Obesity is the main risk factor for a range of NCDs, including diabetes. A meta-analysis of prospective cohort studies found a 7.19 times higher risk of diabetes among obese individuals compared to normal weight individuals[222]. Given that people with diabetes are at a high risk of diabetes related complications, including long-term vascular complications affecting the kidneys, heart, and nerves[278], addressing the growing obesity prevalence and ageing pattern of prevalence, is of great urgency. The demand for medical services to tackle the increasing burden of overweight/obesity related diseases is also likely to increase substantially into the near future. Potential interventions include preventative measures such as screening for diabetes among high risk overweight/obese individuals to increase the proportion of people with diabetes that are diagnosed[279]. Further efforts may also wish to improve the provision of already established initiatives, particularly the NPCDCS, that in-part aims to reduce out of pocket expenditure on diabetes healthcare and promote behavioural and lifestyle improvements that reduce the risk of such diseases[179].

Although the overall prevalence of overweight is expected to be higher in urban areas, my baseline scenario suggests that in urban India future overweight prevalence may begin to plateau during the forecasting period if incidence remains at 2010 levels over the forecast period, while rural areas will continue to experience an increasing prevalence. On the other hand, my model has predicted an almost linear growth in the prevalence of obesity in both urban and rural areas. Irrespective of future incidence or urbanisation rate however, my results suggest that a considerably larger proportion of the population in both urban and rural areas will be either overweight or obese by 2040 compared to 2010, driven by the ageing of overweight and obese younger people and increasing prevalence of overweight and obesity in younger ages.

Close monitoring of these populations may be warranted, and interventions to reduce the overall growth in prevalence way wish to target these populations, particularly among populations susceptible to becoming obese for whom the risk of NCDs is substantially higher[280]. Additionally, health policy planners may wish to pay particular attention to individuals at younger ages to avoid early onset of overweight and obesity and the accumulation of overweight and obesity prevalence in older age groups.

Given the considerable heterogeneity in customs, diet and economic development between India's states, these forecasts are likely to mask subnational variation. In future work, an examination of how these forecasts may differ at the state level may be particularly useful for health policy planning as the constitution of India devolves the deliverance of health and nutrition policy to the state level[281].

My model is simple enough to apply to other developing countries with similarly limited data, and its flexibility can be demonstrated by appropriately adjusting the transition rates[117]. My predictions can also provide the basis of future modelling studies aiming to quantify both monetary costs and future disease burden associated with excess weight in India[128,130–132,282].

7.6. Conclusion

My model predicts a considerable increase and an ageing cohort pattern in overweight and obesity across India to 2040, which could have serious implications for future levels of obesity-related diseases, such as diabetes.

Initiatives, such as the integrated National Health Mission[253], which aims to raise overall population health, may wish to use these forecasts to target sub-populations in which the prevalence of excess weight is likely to be highest in the future. My findings can be extended to quantify the impact of reductions in the incidence of overweight and obesity among certain subgroups and ages. This information may be crucial in estimating the future burden of NCDs, as well as their economic impact.

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SECTION A – Student Details

Student ID Number	1300428	**Title**	Mr
First Name(s)	Shammi		
Surname/Family Name	Luhar		
Thesis Title	Trends in the socioeconomic patterning of overweight and obesity and predictions of the future prevalence of diabetes in India		
Primary Supervisor	Lynda Clarke		

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

SECTION B – Paper already published

Where was the work published?			
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SECTION C – Prepared for publication, but not yet published

Where is the work intended to be published?	Population Health Metrics
Please list the paper's authors in the intended authorship order:	Luhar, S., Jones, R., Kondal, D., Mohan, A., Patel, S.A., Kinra, S., Clarke, L., Ali, M.K., Prabhakaran, D., Kadir, M., Tandon, N., Mohan, V., Narayan, V
Stage of publication	**Not yet submitted**

SECTION D – Multi-authored work

For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)	Led the research conceptualisation; study design; data analysis; manuscript preparation; and revisions based on author's comments - Lead Author

SECTION E

Student Signature	[redacted]
Date	23.09.19

Supervisor Signature	
Date	

Chapter Eight. Forecasting future diabetes in India to 2040 based on overweight and obesity forecasts

8.1. Abstract

Background: Previous forecasts of the future diabetes prevalence in India suffer from over-simplistic assumptions, such as the continuation of past prevalence trends. I forecasted the future prevalence of diabetes in urban India by incorporating future incidence, mortality, overweight and obesity, and demographic change in a coherent and flexible model.

Data & Methods: I used a dynamic simulation model inspired by the MEDCHAMPS IMPACT model, to estimate the prevalence of diabetes in urban India to 2040. I used prevalence, incidence and mortality estimates from a nationwide and community/cohort studies to generate transition probabilities for my model, and modified transition probabilities based on relative risks reported in the literature. I tested different scenarios, for instance, the future prevalence if there were no further increases in overweight and obesity prevalence, and if the incidence of diabetes increased annually throughout the forecast period.

Results: I predict that the prevalence of diabetes among urban men and urban women will reach 26.7% (UI: 23.7-29.9%) and 24.8% (UI: 21.9-28.2%), respectively by 2040. The relative increase in the prevalence of diabetes will be similar across the 20-34 years, 35-54 years and 55-69-year age groups, however, the largest absolute increase in prevalence is expected among the oldest ages. Future increases in the overall incidence of diabetes by 1.5% annually would lead to a 5.5% points higher diabetes prevalence by 2040 when compared to a constant future incidence; halts to further increases in overweight and obesity post-2015 will result in a 1-2% point lower prevalence of diabetes.

Conclusion: The prevalence of diabetes is expected to more than double between 2010 and 2040. Such estimates will be useful in planning the future healthcare

needs of India's urban population, and the model allows for the testing of policies aimed at controlling future diabetes on the future prevalence.

8.2 Background

In India, over 70 million people have diabetes; currently the second highest prevalence globally[11]. South Asians have been found to develop diabetes at younger ages[22,283] and tend to progress much faster from pre-diabetes to diabetes as compared with whites of comparable BMI[24,284]. As diabetes can show no symptoms for a long time, resulting in complications without detection, constant monitoring and estimation of overall prevalence, burden and risk factors is particularly important, and interventions must be enacted early enough to yield noticeable progress. Reliable predictions of the future prevalence of diabetes, and the identification of the most vulnerable subpopulations will be crucial in developing appropriate future health policy and anticipating future health expenditures in India.

The NHP 2017 has specified its aims to increase the screening and treatment of 80% of individuals with diabetes by 2025, in addition to reducing premature diabetes-related mortality by 25% in the same time frame[21,33]. Despite the importance of evidence-based forecasts of the future prevalence of diabetes needed to effectively monitor the progress of such goals, there is a notable lack of reliable predictions of the future prevalence of diabetes. The IDF Diabetes Atlas in 2017 estimated that by 2045, India will surpass China as the country with the most diabetes cases (134 million) with almost double the number of cases as in 2017[11]. However, these estimates are likely to be conservative due to their assumption of a fixed future prevalence for each age group, wherein the future changes in the number of cases is determined by future changes to the age structure and urbanisation. Additionally, IDF estimates fails to consider future changes in the prevalence of key risk factors for diabetes, such as overweight and obesity, which have increased considerably in the past two decades[18–20]. On the other hand, models that simultaneously models future prevalence as a function of previous, current and future changes to diabetes incidence, in addition to changes in the demographic structure of the population is likely to produce more realistic predictions of future diabetes prevalence.

In light of this rationale, I aimed to forecast the prevalence of diabetes among urban men and women aged 20-69 years in India using forecasted prevalence estimates of overweight and obesity (reported in Chapter 7) and carefully collected data on the prevalence and incidence of diabetes in urban India. Additionally, I aimed to examine the effect on the future prevalence of diabetes of a number of hypothetical scenarios.

8.3. Parameters and data sources

The forecasting model used measures of age- and BMI-specific incidence of diabetes from the Centre for cArdiometabolic Risk Reduction in South-Asia study (CARRS)[214,215], mortality rates from the SRS (published annually by the Office of the Registrar General & Census Commissioner[216–221]), and age-specific prevalence from the Indian Council of Medical Research–INdia DIABetes (ICMR-INDIAB) study.

Age-specific incidence of diabetes in urban India

CARRS is an urban based cohort study conducted in three megacities in India (Chennai and Delhi) and Pakistan (Karachi). The baseline cross-sectional survey was conducted in 2010-11 and included 13384 individuals across the three sites. Using 2010 as the baseline year, and following up 9812 participants to 2018, the incidence of diabetes was measured using a standardised estimation technique across the three sites. Diabetes status was determined via either estimation of fasting plasma glucose (FPG), Glycated haemoglobin (HbA1C) or whether one is seeking diabetes treatment[285]. In the CARRS cohort, the incidence of diabetes was obtained separately for 9812 men and women aged 20 years or more. Diabetes cases defined as those with FPG ≥ 126 mg/dl, HbA1c ≥6.5% or seeking diabetes treatment. The incidence rates were reported separately for those with a BMI<25.0kg/m^2, between 25.0 and 29.9kg/m^2, and ≥30.0kg/m^2.

Age-specific prevalence of diabetes in urban India – Baseline

The ICMR-INDIAB study used stratified multistage sampling to obtain capillary oral glucose tolerance tests from 57117 Indians between 2008 and 2015. The population covered 14 states and 1 Union Territory from the north of India (Chandigarh and Punjab); North East (Jharkhand, Bihar, Assam, Mizoram, Arunachal Pradesh, Tripura, Manipur, and Meghalaya); West (Gujarat and Maharashtra); and South (Andhra Pradesh, Karnataka, and Tamil Nadu). Investigators measured 8 hour fasting capillary blood glucose (CBG) using a glucometer. Using 82.5g oral glucose load they also performed an oral glucose tolerance test with CBG measured 2 hours after the glucose was given. If an individual already self-reported diabetes, fasting glucose was only measured[22]. Diabetes diagnosis was based on an individual having a CBG equal to or above 126mg/dl, a 2-hour post glucose load CBG or more than or equal to 220mg/dl, or both. The results of the ICMR-INDIAB study to inform 2010 prevalence was obtained stratified by 5-year age groups from 20-24, through 65-69 years, and by sex, and by urban residence.

Current and future age-, sex- and urban residence- specific mortality rates

Using the Lee-Carter method with age-specific mortality rates reported by the SRS, I forecasted the population mortality rate to 2040. The SRS reports abridged lifetables separately for the urban population for between 1997 and 2013. I extracted the mortality rates from the probabilities of dying (which were contingent on survival to particular ages) using standard demographic procedures. The Lee-Carter method was chosen as the preferred method as it offers an easily interpretable and elegant process to mortality forecasting, using the age-specific deviations from an average age pattern of mortality, obtained from empirical data, and extrapolating the overall level of mortality into the future. Further details on this methodology are included in Chapter Four, section 4.2.

Urban forecasts of overweight and obesity prevalence by age and sex

I obtained predictions of overweight and obesity in Chapter 7. Using a system of multi-status lifetables, and assuming the incidence of overweight and obesity would remain constant between 2010 and 2040, the study predicted an increase in the prevalence of overweight among urban men from 19.0% to 37.1%, and an increase in obesity prevalence from 4.0% to 11.4% between 2010 and 2040. Among women, the model predicts that the prevalence of overweight will increase from 23.2% to 32.1%, and the prevalence of obesity will increase from 8.2% to 19.7% over the same period. Similar trends were also observed amongst men. Overweight and obesity are strong risk factors for diabetes. One meta-analysis reported an over eight times higher risk of diabetes among obese women compared to normal weight women, whereas a nearly four times higher risk of diabetes has been reported for overweight women compared to normal weight women[222].

Forecast of the consumption of smokeless tobacco

I obtained estimates of the prevalence of smokeless tobacco consumption in 2009-10 and 2016-17 from the second-round report published by Global Adult Tobacco Survey (GATS)[213] that reported the prevalence of smokeless tobacco consumption in urban and rural India by age and sex. In 2016-17, 29.6% of men and 12.8% of women consumed smokeless tobacco, compared to 32.9% and 29.6% respectively in 2009-10. I applied the average annual change in smokeless tobacco consumption prevalence between GATS surveys to obtain future predictions of future prevalence to 2040 by age (Figure 20).

Relative risk of dying among smokeless tobacco consumers relative to non-consumers

Using the Mumbai voter's list and a follow-up period of 5.5 years, Gupta et al (2005)[286] estimated a 1.16- and 1.25-times higher risk of dying among 97,244 men and women, respectively, who consumed smokeless tobacco, compared to those who did not, after adjusting for age.

Relative risk of dying among overweight/obese people relative to non-overweight/obese people

I obtained the relative risks of dying by BMI group, relative to the normal weight category from a study that assessed the association of BMI with mortality in Mumbai[209]. In this study, 148,173 people aged 35 and above were recruited between 1991-97 and followed up to 1997-2003. Overweight and obese women were found to have 1.03 and 1.2 times the risk of mortality compared to normal weight women, whereas overweight and obese men had 0.89 and 1.22 times the risk of mortality, respectively, relative to normal weight men.

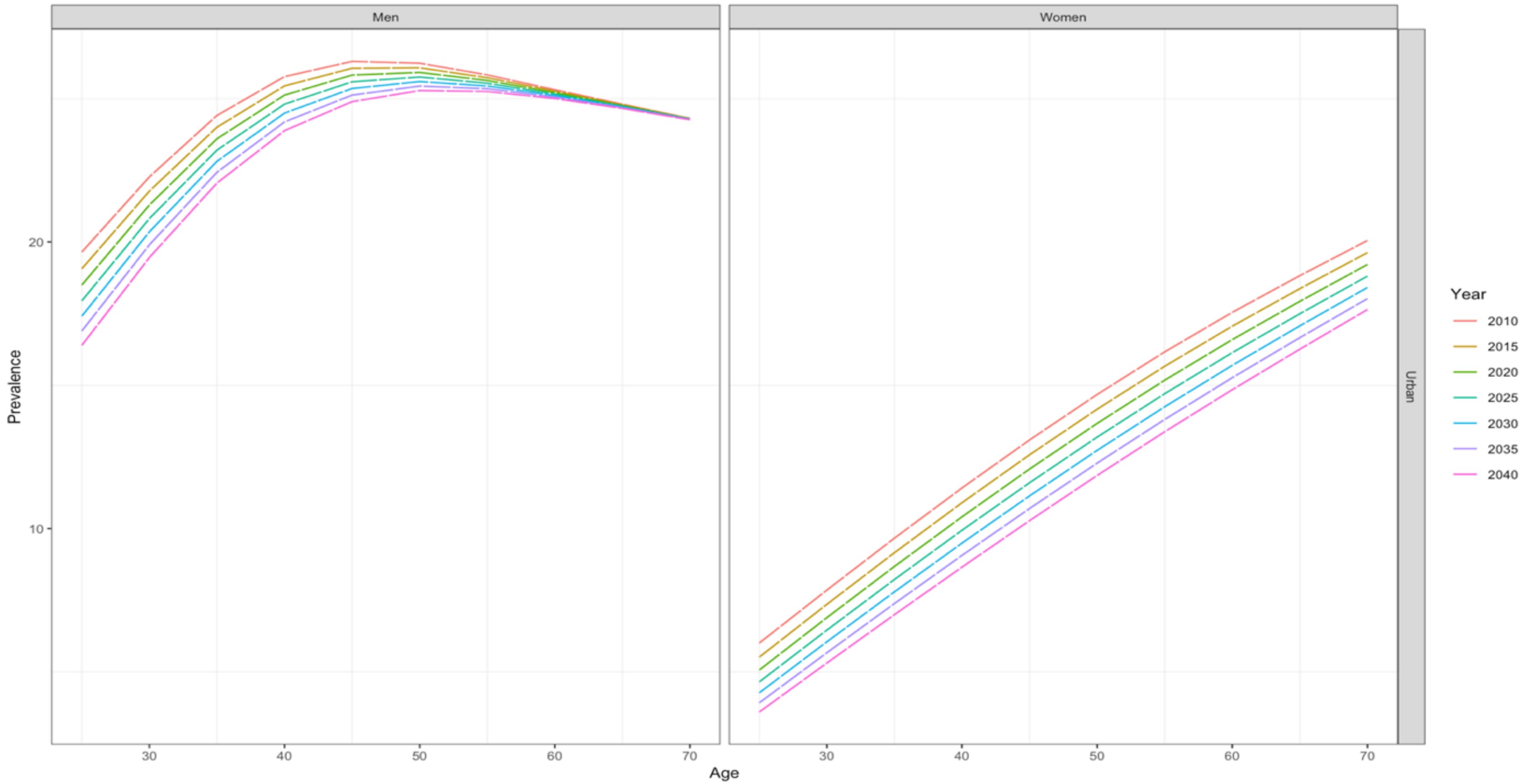
Relative risk of dying among those with diabetes relative to those without diabetes

I obtained estimates of the relative risk of dying among individuals with diabetes relative to those without diabetes from a meta-analysis of 35 published articles, mainly from economically developed countries, between 1990 and 2010, using data from 220,689 patients, with a mean follow-up period of 10.7 years[287]. The authors found a 1.85 times higher risk of dying from all causes among men; the equivalent relative risk among women was 2.0.

Relative risk of diabetes for smokeless tobacco consumers relative to non-consumers

I used the relative risk of diabetes among smokeless tobacco users from a prospective cohort study in Sweden[223], that found a 1.15 times higher risk of diabetes among users of snus (a smokeless tobacco product common in Scandinavia). Their study was based on pooled data from 5 cohorts, with data collected between 1990 and 2013 and 2441 incident cases of type 2 diabetes, which were defined as cases identified through screening, self-report and hospital or prescription registries[223].

Figure 20. Predicted smokeless tobacco consumption prevalence among urban Indians between 2010 and 2040



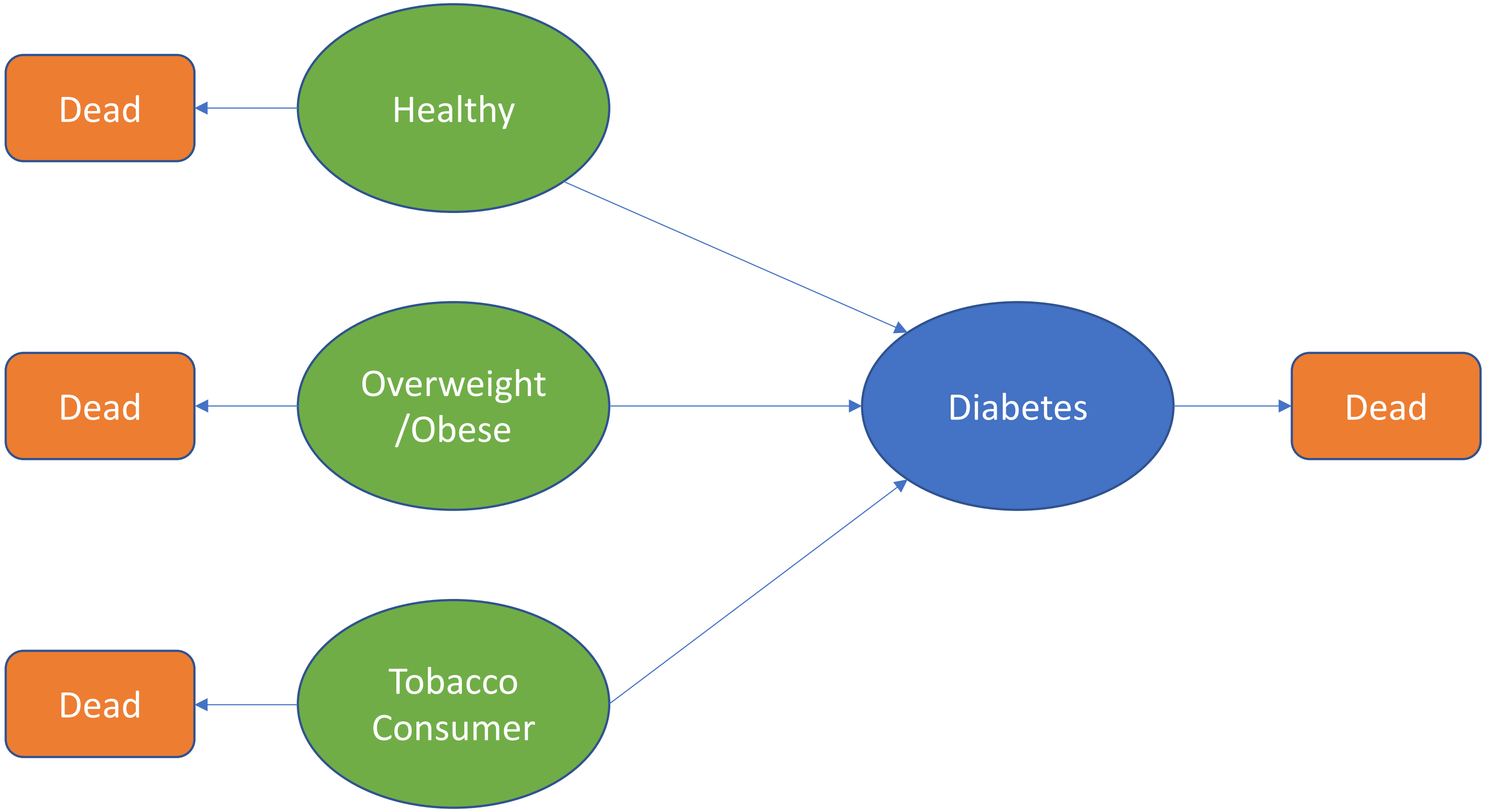
8.4. The Model

I forecasted the future prevalence of diabetes using a dynamic Markov model based on the MEDCHAMPS IMPACT diabetes model used in a number of other country contexts[128–132,211]. The original MEDCHAMPS IMPACT model feeds forecast of future smoking and obesity prevalence to forecast future diabetes prevalence. My slightly modified version included both forecasted overweight and obesity, and used smokeless tobacco instead of smoking, as there are almost twice the number of smokeless tobacco consumers in India compared to tobacco smokers[213].

The mortality and incidence rates I calculated informed a transition matrix, which calculated transition probabilities based on the intensity of flows between the groups. The model followed an absorbing Markov process, in discrete 5-year time steps (Figure 21). I grouped overweight and obesity into one category. The parameter values assigned to this category were a weighted average of the parameter values for separate overweight and obese categories.

A key criterion of the model is that the initial health states are mutually exclusive. As in previous studies[128–132,211] the 'Overweight/Obese' state only contained individuals classified as overweight/obese, but not with diabetes, leaving overweight/obese individuals with diabetes exclusively in the 'Diabetes' health state. The 'Tobacco consumer' state included smokers who were neither classified as 'Overweight/Obese' nor as having diabetes. The 'Healthy' state included individuals who were neither in the 'Overweight/Obese', 'Tobacco consumer' nor 'Diabetes' state. A 'Tobacco consumer' state was included in order to enable the estimation of a more accurate population who are at risk of developing diabetes. Individuals who consume smokeless tobacco have been found to have an elevated risk of mortality compared to those who do not consume smokeless tobacco[286], and failure to account for this may lead to an overestimation of the future prevalence of diabetes by including tobacco consuming individuals that may have otherwise died. A higher risk of dying among tobacco consumers, compared to non-consumers, was incorporated using the relative risk of dying described in section 8.3.

Figure 21. Compartmental model to future diabetes prevalence in urban India



Assumptions

I made a number of simplifying assumptions in my model. Firstly, I assumed that individuals cannot transition back from the 'Diabetes' state to non-diabetes states. A study in the US aiming to estimate the incidence of remission in adults with type 2 diabetes found a seven-year cumulative incidence of complete remission of 0.14% and prolonged remission of 0.007%[288]. Given the rarity of remission from diabetes, I believe this assumption is appropriate. Secondly, I assumed that the higher risk of mortality among smokers, among diabetes cases and among overweight/obese individuals is constant over time. I decided upon this as the possible future scenarios are unlimited, therefore, I deemed this the simplest assumption. Finally, I assumed that the new entrants aged 20-24 years into the model at each time step had the same prevalence of diabetes as in the baseline year.

Sensitivity Analysis

In my forecasts, as a baseline scenario, I assumed that the future incidence of diabetes, independent of overweight and obesity would remain constant between 2010 and 2040, and that changes to population level incidence would be driven by changes in the overall prevalence of overweight and obesity. Scenario 1 estimated the predicted prevalence of diabetes in the presence of a 1.5% annual increase in population incidence of diabetes annually through to 2040. Such increases may occur if the BMI distribution within the broad BMI groups selected increase over the forecast period. Scenario 2 estimated the effect on future prevalence of diabetes if overweight/obesity prevalence was held at the level of 2015. Although I know this to be both untrue and optimistic, I aimed to analyse the sensitivity of the model's output to future changes in excess weight. Uncertainty intervals (UI) were based on multiple simulations, each time drawing random parameter values from their uncertainty range.

8.5. Results

The forecasted prevalence of diabetes to 2040 is presented in Figure *22*, with accompanying age-specific forecasts by broad age-groups in Table 18. The higher prevalence of diabetes among urban men in my baseline year is expected to reverse by around 2020. My model predicts that the prevalence of diabetes in urban India will increase from 9.2% (UI: 8.9-9.4%) in 2010 to 26.7% (UI: 23.7-29.9%) by 2040 among women, and 11.6 % (UI: 11.2-11.9%) in 2010 to 24.9% (UI: 21.9-28.2%) by 2040 among men.

Similar relative increases are expected to be observed in all of the three broad age groups; however, larger absolute increases are expected in older age groups (Figure 23). Urban Indians in the age group 55-69 will have the highest prevalence amongst my study population, whereby diabetes prevalence is predicted to more than double from 25.7% (UI: 24.8-27.0%) in 2010 to 60.0% (UI: 53.9-67.3%) in 2040 among women, and 29.9% (UI: 28.5-31.3%) to 54.4% (UI: 48.5-61.5%) among men. On the other hand, the prevalence is expected to be lowest among urban Indians in the 20-34 age group, whereby 4.1% (UI: 3.4-4.9%) and 4.9% (UI: 4.1-6.0%) of women and men, respectively, are predicted to have diabetes in 2040.

Table 18. Forecasted percentage prevalence of diabetes in urban India to 2040

Sex	*Year*	*20-34*			*35-54*			*55-69*			*All*		
		Point Est	*Lower*	*Upper*	*Point Est*	*Lower*	*Upper*	*Point Est*	*Lower*	*Upper*	*Point Est*	*Lower*	*Upper*
Women	*2010*	1.6	1.5	1.7	11.2	10.8	11.6	25.7	24.8	27.0	9.2	8.9	9.4
	2020	3.6	2.9	4.3	21.2	19.3	23.9	37.4	34.4	41.3	17.2	15.6	19.3
	2030	3.7	3.1	4.5	26.8	23.8	30.6	52.7	47.5	58.8	23.3	20.8	26.2
	2040	4.1	3.4	4.9	29.0	25.7	33.1	60.0	53.9	67.3	26.7	23.7	29.9
Men	*2010*	2.7	2.5	2.9	14.1	13.5	14.6	29.9	28.5	31.3	11.6	11.2	11.9
	2020	3.8	3.0	4.7	20.8	18.6	23.1	40.0	37.1	43.3	17.3	15.7	19.1
	2030	4.3	3.5	5.3	26.7	23.1	30.3	47.0	42.3	52.1	21.6	19.1	24.5
	2040	4.9	4.01	6.0	29.4	25.6	33.7	54.4	48.5	61.5	24.8	21.9	28.2

Figure 22. Forecasted prevalence of diabetes in urban India to 2040

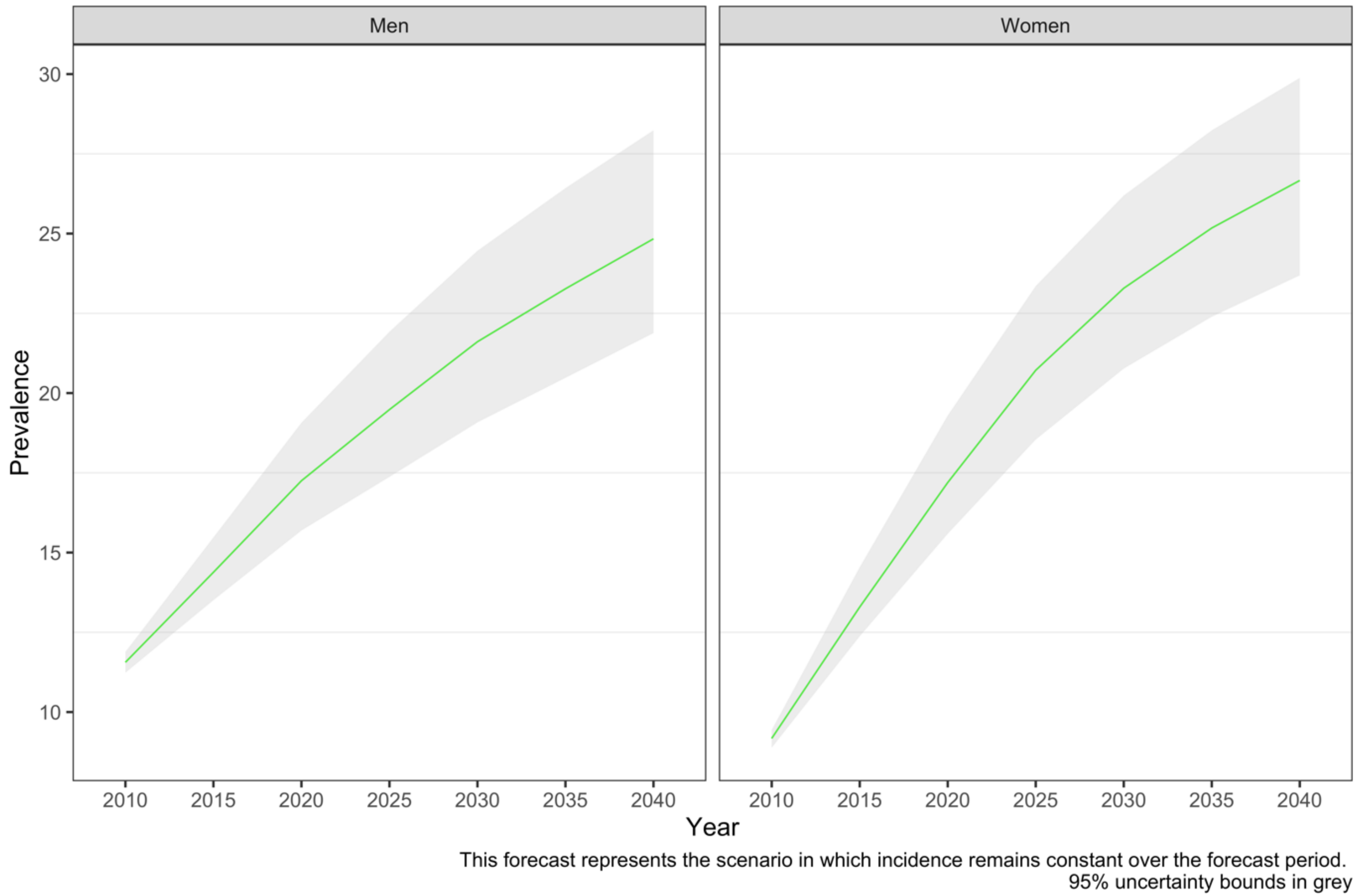
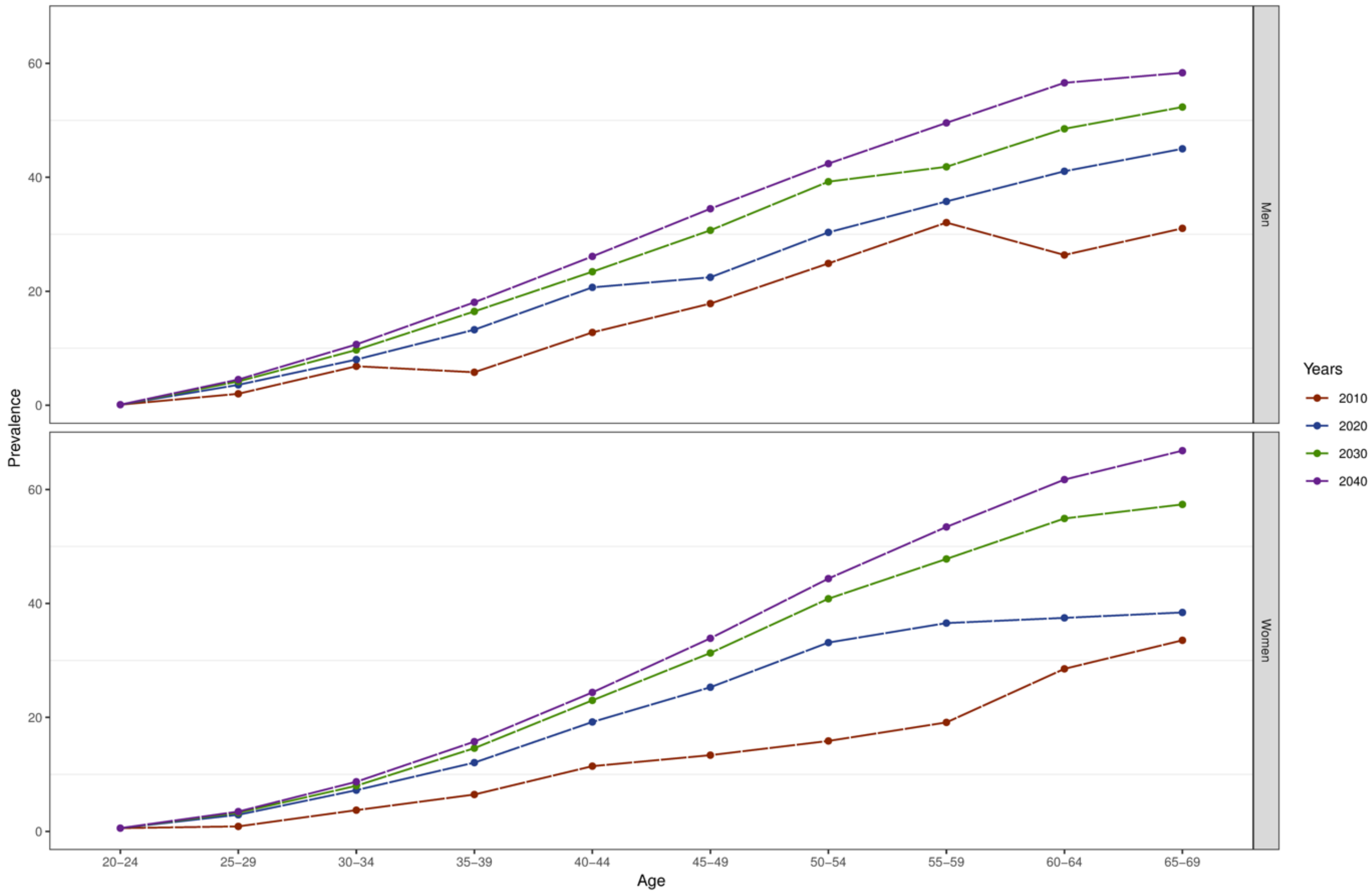


Figure 23. Forecasted prevalence of diabetes in urban India to 2040, by age



I tested two different scenarios to demonstrate the sensitivity of my output to the potentially modifiable model inputs. Under the assumption of a 1.5% annual increase in the incidence of diabetes irrespective of BMI group, my model predicted that diabetes prevalence would reach 32.2% (UI: 28.3-35.8%) among women (5.5 percentage points higher than under the assumption of constant age-specific incidence over the forecast period), and 30.3% (UI: 26.7-34.9%) among women (5.5 percentage points higher than under the constant incidence scenario), with particularly large increases in prevalence among the 55-69 year age group (Table 19).

If the prevalence of overweight and obesity was held at the 2015 level, I would expect the prevalence of diabetes to be between 1 and 2 percentage points lower in 2040 than if the prevalence of overweight and obesity followed its expected path, representing a relative reduction in diabetes prevalence of 6% among women and 9% among men (Table 20).

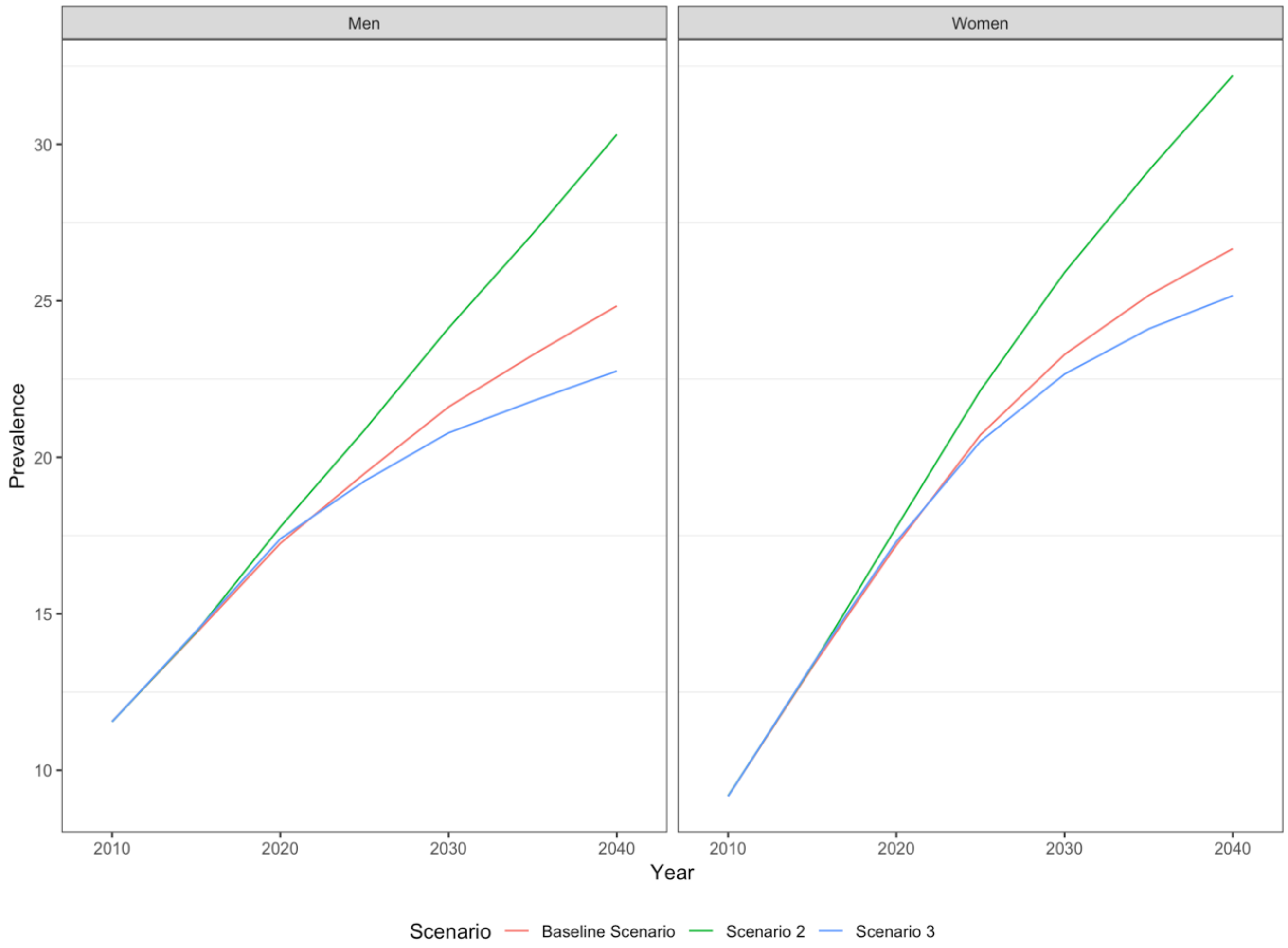
Table 19. Forecasted percentage prevalence of urban Indians with diabetes to 2040 (Scenario 1: Incidence increases by 1.5% annually)

Sex	*Year*	*20-34*			*35-54*			*55-69*			*All*		
		Point Est	*Lower*	*Upper*	*Point Est*	*Lower*	*Upper*	*Point Est*	*Lower*	*Upper*	*Point Est*	*Lower*	*Upper*
Women	*2010*	1.6	1.4	1.7	11.2	10.8	11.6	25.7	24.5	27.1	9.2	9.0	9.5
	2020	3.8	3.1	4.4	22.0	19.5	24.1	38.2	34.4	41.8	17.8	15.8	19.6
	2030	4.4	3.6	5.2	30.3	26.3	33.9	56.9	50.8	63.3	25.9	22.7	28.9
	2040	5.5	4.5	6.5	36.4	31.6	40.6	69.4	62.0	76.8	32.2	28.3	35.8
Men	*2010*	2.7	2.5	3.0	14.0	13.5	14.5	29.9	28.7	31.2	11.6	11.2	11.9
	2020	4.1	3.3	5.1	21.5	19.2	24.5	40.8	37.5	44.6	17.8	16.1	20.1
	2030	5.3	4.3	6.6	30.0	26.3	35.0	51.0	45.6	57.9	24.1	21.2	28.0
	2040	6.8	5.6	8.5	36.9	32.3	42.7	63.1	56.6	71.6	30.3	26.7	34.9

Table 20. Forecasted percentage prevalence of urban Indians with diabetes to 2040 (Scenario 2: Overweight and Obesity does not increase beyond 2015)

Sex	*Year*	*20-34*			*35-54*			*55-69*			*All*		
		Point Est	*Lower*	*Upper*	*Point Est*	*Lower*	*Upper*	*Point Est*	*Lower*	*Upper*	*Point Est*	*Lower*	*Upper*
Women	*2010*	1.6	1.5	1.7	11.2	10.8	11.8	25.7	24.6	26.9	9.2	8.9	9.5
	2020	3.6	3.1	4.3	21.4	19.4	23.5	37.6	34.3	41.2	17.3	15.7	19.1
	2030	3.5	3.0	4.1	26.3	23.5	29.5	51.0	46.1	56.3	22.7	20.3	25.3
	2040	3.6	3.0	4.3	27.6	24.5	31.1	56.7	51.1	62.9	25.2	22.5	28.1
Men	*2010*	2.7	2.5	2.9	14.0	13.5	14.5	29.9	28.3	31.1	11.6	11.2	11.9
	2020	3.9	3.2	4.8	21.0	18.9	23.8	40.2	37.4	43.4	17.4	15.8	19.5
	2030	3.9	3.2	4.8	25.7	22.4	30.0	45.4	41.1	51.0	20.8	18.3	23.9
	2040	4.1	3.3	5.0	26.8	23.2	31.5	50.9	45.4	57.5	22.8	19.9	26.3

Figure 24. Forecasted percentage (%) prevalence of urban Indians with diabetes to 2040



8.6. Discussion

My model predicts that by 2040, 24.8% of urban Indian men, and 26.7% of urban Indian women will have diabetes. These estimates hide a nuanced age-pattern of diabetes prevalence, whereby I predict that 60.0% of women and 54.4% of urban men aged 55 years or more will have diabetes by 2040, whereas the prevalence will be 4.1% among urban women, and 4.9% among urban men aged 20-34 years, respectively, by 2040. My sensitivity analysis revealed that an annual increase of 1.5% in the incidence independent of future increases in the prevalence of overweight and obesity will result in a further increase in the total prevalence of diabetes of approximately 5.5 percentage points. The effect of the prevalence of overweight/obesity remaining at 2015 levels, with no further increases, will result in a decline in total prevalence by 1-2 percentage points compared to the baseline scenario.

There have been previous attempts to forecast the future burden or prevalence of diabetes in India. The simplest, in which age-specific prevalence was held constant, and the total future number and prevalence was driven by projected changes to the population structure, was used by the IDF to project the number of diabetes cases from 2017 to 2045. Under this conservative assumption, the IDF still predicted an increase in the number of cases from 73 million in 2017 to 134 million in 2045 across the whole of India (an increase in total prevalence from 8.8% to 11.6%)[11]. Another recent study using the evolving demographic profile and urbanicity as the sole drivers of changes to total diabetes prevalence estimated a total prevalence, in urban and rural areas combined, of 9.9% in 2030[133]. Additionally, applying mean annual changes to the age- and sex-specific prevalence and extrapolating into the future, the authors predicted a further increase in total prevalence to 12.5% by 2030. Despite this improvement on assuming constant age-specific prevalence rates into the future, this is still considerably lower than my estimate. This is likely due to the fact that they apply the annual change in prevalence for all LMICS to India, a region with a slower growth in diabetes prevalence when compared to India[11]. Additionally, due to the higher prevalence of overweight and obesity in urban areas compared to rural areas of India[19], the future predictions of urban-specific diabetes prevalence in this study was expected to be considerably higher than previous national prevalence estimates.

Very few studies have attempted to forecast future diabetes prevalence in India using a dynamic simulation model[134]. Using a simple three-state simulation model (where alive individuals either have diabetes or do not), one study identified an increase in prevalence from 5.4% in 2016 to 6.7% in 2030. However, the study neither considered differential transition probabilities by age and sex, nor considered future changes to key risk factors for diabetes in the model, the latter of which is likely to make their estimates very conservative, given an almost doubling in the prevalence of combined overweight and obesity in the past decade in India[18,19]. More complex models, incorporating prediabetes and undiagnosed/diagnosed cases, have been adopted to forecast future prevalence in India, however, with emphasis on smaller geographical areas. One study, focusing on the city of Varanasi, estimated that 35.6% of Varanasi's residents will have diabetes by 2030, equivalent to 0.52 million people[136].

The relative reduction in the prevalence of diabetes that could be achieved through halting future increases in overweight and obesity are similar to what has been reported in a similar study. Sözmen et al (2015) found that halts in the prevalence of obesity at 2010 levels would result in a 7.9% relative reduction in the prevalence of diabetes by 2025, compared to their baseline scenario of a linear increase in obesity; similar to my finding of a 6% relative reduction among women and 9% among men.

In order to validate output of a model, predictions can be compared to actual data. Although the IDF report that 8.8% of 20-79-year olds will have diabetes in India in 2017, urban-specific estimates are not reported. The National Nutrition Monitoring Bureau (NNMB) report[276] that in 2017, 21.5% of men and 19.4% of women in urban India had diabetes. In my study I estimate that the 2020 prevalence among urban men and women is 17.3 % (UI: 15.7-19.1%) and 17.2% (UI: 15.6-19.3%), respectively, implying a possible underestimation of my results.

The most likely explanation for this discrepancy is that my study population differs to the sampled population in the NNMB in that I do not include individuals aged 70 years or more. Globally in 2017, aged people are at a considerably higher risk of diabetes than younger individuals[11], and the overall ICMR-INDIAB estimate for diabetes among 20-69 year olds is lower than among 20-79 year olds.

My 2040 estimate of overall diabetes prevalence in urban India is similar to levels currently observed in small Polynesian and Micronesian islands, where the total prevalence of combined overweight and obesity is nearly 100%[11289]. Moreover, the prevalence in urban India is expected to be considerably higher than national estimates of future diabetes in the USA. A recent study has estimated the 2040 diabetes prevalence in the USA to be 15.7% among people aged 18 years or more, around half the 2040 predicted prevalence in urban India[122]. Even among Black Females, a high diabetes-risk population in the USA, the forecasted prevalence in 2040 is still expected to be lower than among urban Indians.

My model is subject to a number of limitations. Firstly, I was unable to predict future prevalence among individuals under age 20 and above the age of 69 due to a lack of data to inform my parameters at these ages. Whereas I don't expect my final estimates to be greatly impacted by the omission of the population under 20 years, not including people over 70 could bias my results. For instance, a recent study, reported a prevalence of 19.9% and 16.4% among men and women aged 75-79 years, compared to 1.0% and 0.9% among men and women, respectively, aged 15-19 years in 2016.

Secondly, in my model I neither account for undiagnosed diabetes cases, nor different transitions to diabetes among the population with pre-diabetes compared to the population without pre-diabetes. I opted not to include health states relating to prediabetes as it would involve calculating extra parameters in my model, adding further uncertainty to my estimates. Furthermore, the addition of these extra health states would add further complexity to the model and take away from its simple structure. It is also unclear what assumptions would be appropriate for the future incidence of prediabetes in a country as large and as heterogenous as

India. For instance, in less economically developed Indian states the number of individuals with prediabetes far exceeds those with diabetes, whereas in the most developed states, the ratio of diabetes to prediabetes cases is equal to, or even exceeds, one[22]. Regarding the forecast of undiagnosed cases, one can make an estimate of the prevalence of undiagnosed cases based on the IDF estimates that 57.9% of diabetes cases are undiagnosed, equivalent to around 42.2 million people in 2017[11].

Thirdly, in my model I do not allow the transition from diabetes to non-diabetes. As remission from diabetes accounts for a very low percentage of all cases[288], I do not expect this assumption to significantly bias my predictions.

Finally, my main predictions are based on the assumption of a constant rate of diabetes incidence throughout the forecasting period, in addition to a constant relative risk of mortality for those with diabetes relative to those without diabetes. However, it is reasonable to assume there could be future changes to incidence, for example due to a feedback effect, where increases in future diabetes prevalence could result in a reduction in future incidence due to the population becoming more aware of diabetes-related complications[109]. I attempted to overcome such limitations by testing different scenarios regarding the future incidence of diabetes.

Despite these limitations, my study's main strength comes from its attempt to account for expected increases in the prevalence of both overweight and obesity, derived from a data-driven model, in addition to regulating the population at-risk by accounting for expected trends in smokeless tobacco consumption. This improves upon previous attempts to estimate future diabetes prevalence at the national level using a Markov matrix model, which make no accommodation for the changing prevalence of diabetes risk factors. Additionally, an improvement on studies assuming an *a priori* trajectory of future diabetes prevalence, my model recognises that the changing prevalence is a function of a society's changing demographic profile, in addition to the past, present and current changes in the incidence of diabetes.

Although urban India is expected to have a prevalence of diabetes as high as societies that have almost 100% prevalence of overweight and obesity, and even higher than high-risk subpopulations in the USA by 2040, the challenge of dealing with the future diabetes burden will be significantly more difficult in India given that it is expected to be the world's most populous country by 2025[37]. Such challenges include health complications associated with diabetes, including long term vascular complications of the kidneys and nerves[290]. The realisation of diabetes complications among people with diabetes can be expected to increase given the significant increases in diabetes prevalence predicted at younger ages (where I expect an almost quadrupling in prevalence between 2010 and 2040 among 20-34-year olds) implying an increasing proportion of an individual's life spent with diabetes. My forecasts show that even the extremely optimistic scenario of future overweight and obesity prevalence remaining at 2015 levels would not do much to reduce the extent of these implications for population health.

Given this, it can be argued that attention on preventative measures, targeting reductions in overweight and obesity may be unwarranted, and that future increases in diabetes prevalence are an inevitability due to ageing of the population. Even if halting future increases in overweight and obesity prevalence will have no notable effects by 2040 however, the effects may be noticed later when the youngest people in the study population have transitioned through older ages. Interventions targeting incidence of diabetes within broad BMI groups may also help modify the overall population prevalence of diabetes by 2040, as shown in Scenario 2. Previous studies examining the effect of interventions in India, including culturally tailored LSI, in combination with courses of medication such as metformin, have reported reductions in diabetes incidence by as much as a third among individuals with prediabetes[291]. However, such studies are limited to small sites, and further understanding of the effectiveness of such interventions at higher levels of geographical aggregation is needed.

Furthermore, given that 57.9% of all diabetes cases are undiagnosed in India (IDF), assuming this proportion remains constant to 2040, approximately 14% of India's urban population is expected to have undetected diabetes. This suggests that measures to detect cases as early as possible, such as population screening may be warranted. Caution is urged however in the rollout of such programs, as modelling studies have found large-scale rollout of such screening to produce many false positives[279].

8.7. Conclusion

In conclusion, using a dynamic model incorporating future demographic trends and forecasts of overweight and obesity, one of the main drivers of diabetes at the individual level, the prevalence of diabetes in urban India is expected to more than double between 2010 and 2040. Measures to halt the increasing prevalence of overweight and obesity will have limited effect on the population-level diabetes prevalence in the future due to population ageing, however reducing overall population-level incidence may yield positive results in reducing diabetes prevalence.

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Student ID Number	1300428	**Title**	Mr
First Name(s)	Shammi		
Surname/Family Name	Luhar		
Thesis Title	Trends in the socioeconomic patterning of overweight and obesity and predictions of the future prevalence of diabetes in India		
Primary Supervisor	Lynda Clarke		

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

SECTION B – Paper already published

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Stage of publication	**Not yet submitted**

SECTION D – Multi-authored work

For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)	Led the research conceptualisation; study design; data analysis; manuscript preparation; and revisions based on author's comments - Lead Author

SECTION E

Student Signature	[redacted]
Date	23.09.14

Supervisor Signature	
Date	

Chapter Nine. Alarming lifetime risk of diabetes in urban India

9.1. Abstract

Background: Lifetime risk estimates effectively communicate the individual-level burden of a disease, making it a useful public health metric. However, little is known about the lifetime risk of diabetes in India, a country where the importance of diabetes as a public health concern is increasing at an alarming rate.

Objective: To estimate the age-, sex- and BMI-specific lifetime risk of diabetes in urban India among individuals aged 20-79, in addition to measuring the diabetes-free life expectancy.

Data and Methods: Incidence data (by age, sex and BMI) from the Centre for Cardiometabolic Risk Reduction in South Asia Study (2010-18) was used alongside prevalence of diabetes from the Indian Council for Medical Research India Diabetes Study (2008-15), and mortality data from the SRS (1997-2013). I used a multistate Markov model to measure the outcomes of interest.

Outcomes: Remaining lifetime risk of diabetes and diabetes-free life-expectancy (by age, sex and BMI).

Results: Lifetime risk of diabetes among women at age 20 was 74.7% and decreased to 42.5%; among men the lifetime risk decreased from 69.0% to 36.2% between ages 20 and 60. Lifetime risk increased with age and BMI. Among women, for example, the lifetime risk among underweight/normal weight women aged 20 was 56.4%, compared to 92.9% among obese women aged 20. The largest increase in lifetime risk was observed between underweight/normal weight and overweight populations, whereas the increase in risk was considerably smaller between overweight and obese individuals. The proportion of remaining life spent with diabetes among obese people without diabetes aged 20 is more than double the proportion among underweight/normal weight people.

Conclusions: Urban Indians have an alarmingly high lifetime risk of diabetes at all ages and BMIs, even in comparison to high-risk populations in HICs. This highlights the importance of interventions to reduce diabetes incidence in a country where the urban population is increasing at a rapid pace.

9.2. Introduction

Diabetes is a major global public health problem with 425 million currently affected and projected to reach 629 million by 2045[11]. Most studies concerning the global diabetes burden focus on estimating prevalence. Whereas prevalence is useful in expressing the overall burden of disease, estimates of lifetime risk allow a more effective way of communicating the probability of developing diabetes during the lifetime at various ages, and in various risk groups. Furthermore, prevalence and incidence estimates say little about how a particular disease impacts people[35]. On the other hand, lifetime risk estimates effectively communicate a disease risk at the individual level and is thus a powerful public health tool. However, although diabetes prevalence is increasing at a faster pace in low- and middle-income countries (LMICs) the few studies estimating the lifetime risk of diabetes are based on data from HICs[35,139–141].

Research from HICs such as the USA[35,140,142], Australia[139], and the Netherlands[141] have found high lifetime risks of diabetes[35]. Recent studies have found a 31.3% remaining lifetime risk among 45-year-olds in the USA, and 38.0% remaining risk among 25-year-olds in the Netherlands. The lifetime risk among severely obese people in the USA has also been found to be as high as ten times that of underweight individuals[140]. The combination of a high BMI distribution, high incidence of diabetes, and high life expectancy drive a high overall lifetime risk in HICs. It is not clear, however, how the lifetime risk of diabetes may differ in LMICs, which may still have a comparatively lower BMI and life expectancy. For example, India, while at the epicentre of the diabetes epidemic, still has a lower BMI distribution[36], lower overall life expectancy[37], but a comparatively higher propensity to develop diabetes, both at younger ages[25,26] and at lower BMI levels[23,34,38].

In this study, I estimate the lifetime risk of diabetes in India; a country with a fast progressing diabetes epidemic[21]. Specifically, I measure the lifetime risk for ages 20 through 79, by sex and by BMI in urban India. I used objectively measured data on diabetes incidence by age and BMI in urban India from the Centre for Cardiometabolic Risk Reduction in South Asia (CARRS), estimates of urban mortality rates by age and sex from the SRS, and constructed a simple Markov model to measure lifetime risk overall, by age and gender, and by BMI.

9.3. Inputs

To estimate lifetime risk of diabetes, estimates of diabetes prevalence were obtained from the Indian Council of Medical Research–INdia DIABetes (ICMR-INDIAB) study, incidence of diabetes were obtained from blood samples carried out by the CARRS cohort study[214,215], and mortality rates were taken from lifetables published by the SRS.

I used age-specific prevalence of diabetes by 5-year age groups provided by the ICMR-INDIAB study, which sampled 57117 Indians between 2008 and 2015 from 14 of India's 28 states. The sampled population came from states covering the large broader regions of India: the North (Chandigarh and Punjab); the South (Andhra Pradesh, Karnataka, and Tamil Nadu); the East (Jharkhand, Bihar, Assam, Mizoram, Arunachal Pradesh, Tripura, Manipur, and Meghalaya); and the West (Gujarat and Maharashtra). Blood tests were conducted by trained investigators who measured 8-hour fasting CBG, and using an 82.5g oral glucose load, 2-hour post glucose CBG; the latter of which was only conducted if an individual self-reported diabetes. Individuals with an 8-hour CBG greater than or equal to 126mg/dl, a 2-hour post load greater than or equal to 220mg/dl, or both, were diagnosed with diabetes.

Incidence of diabetes was calculated in previous studies using 2010 as the baseline year, and 9812 participants included in the calculation were followed up until 2018[214,215]. The CARRS study is an urban based cohort of with around 4000 participants in each of three sites across South Asia (Delhi, Chennai and Karachi)[285]. Diabetes cases in the CARRS cohort were defined as those with FPG ≥ 126 mg/dl, Glycated haemoglobin (HbA1c) ≥6.5% or those seeking diabetes treatment. Incidence for the following age groups were provided: 20-24, 25-34, 35-44, 45-54, 55-64, ≥65. I estimated age specific rates using a smoothing spline. Incidence rates were provided separately for the normal/underweight, overweight, and obese population.

The SRS contains abridged lifetables for 2014 by sex and urban residence[219]. The SRS dually records deaths using representative samples[149] and its data is published by the Office of the Registrar General and Census Commissioner in India. I firstly estimated the mortality rates from the provided conditional probabilities of death provided in the data using an inversion of Chiang's formula to obtain age-specific mortality rates[205], and obtained mortality by single-years by fitting a Gompertz-Makeham mortality curve to the log-mortality distribution and extracting predicted values. The parametric Gompertz-Makeham mortality distribution is composed of the sum of an age-dependent function, whereby the rate of mortality increases exponentially with age, and an age-independent component, accommodating external causes of death. The Gompertz-Makeham curve was fitted using the MortalityLaws[292] package in R.

In order to obtain differential mortality rates among those with diabetes and those without, and among different BMI groups, I modified population-level inputs using relative risks obtained from the literature. A meta-analysis of 35 published articles between 1990 and 2010, including information from 220,689 patients in high-income countries and a mean follow-up period of 10.7 years informed the differential mortality between individuals with and without diabetes. The study found an 85% higher risk of all-cause mortality among men with type-2 diabetes compared to those without. On the other hand, women with type-2 diabetes were found to have double the risk of dying of all causes, compared to women without diabetes[287]. I accounted for differential rates of mortality among populations with different BMI status by applying relative risks of dying by BMI group obtained from a study that examined the association of BMI with mortality in urban Mumbai between 1991-97 and 1997-2003[209]. The study, comprising 148,173 individuals, reported an 11% lower risk of dying among overweight men aged 35 and older, and a 22% higher risk of dying among obese men, compared to men of a normal weight. On the other hand, overweight women have 1.03 times the risk of dying, and obese women 1.20 times the risk of dying, compared to normal weight women.

9.4. The Model

I adopted a multistate Markov model to estimate the lifetime risk of diabetes from the inputs. The multistate model compartmentalises a population into three separate age, sex and BMI specific groups: No Diabetes, Diabetes, and Dead. The transition probabilities derived from the parameters simulate movements between the three states, which are mutually exclusive, and the resultant transition matrix is used to generate measures of both lifetime risk and diabetes-free life expectancy[225–227] (see Chapter 4, section 4.4). I also used this transition matrix to estimate the number of YLL to diabetes, in addition to Quality-Adjusted Life Years (QALYs) lost to diabetes (see Appendix and Table 30).

In my study I made a number of assumptions. Firstly, similar to period lifetables, I estimated a set of age-specific transition probabilities and assumed that these probabilities hold constant throughout the lifetime of the cohort. Secondly, I assumed that once the transition to diabetes is made, one cannot transition back to not having diabetes. This is a reasonable assumption given that remission from diabetes is relatively rare, and that once diabetes develops, risk of future complications is increased[288]. Thirdly, I assumed that the relative risk of dying among those with diabetes, relative to those without, will remain constant into the future. A final assumption I made is that the incidence of diabetes will remain constant at the level measured in the CARRS study.

Instead of inputting the point estimate of the rates to estimate the required estimates, I inserted incidence values from the 95% confidence range to obtain uncertainty intervals around my measure of lifetime risk. To examine the accuracy of my model, I compared its estimates of life expectancy at the ages of interest in my study, with those reported in the same period by the SRS abridged lifetable. Any difference in life expectancy estimates were negligible (within one year).

9.5. Results

Among women, irrespective of BMI, I found that the lifetime risk of diabetes at age 20 is 74.7% (UI: 65.4%-83.3%), whereas at ages 40 and 60, the lifetime risk decreases to 67.3% (UI: 57.4%-77.1%) and 42.5% (UI: 33.8%-52.9%). Among men, the lifetime risk among urban Indians without diabetes is slightly lower at 69.0% (UI: 58.9%-78.7%) at age 20 and decreases to 36.2% (UI: 28.4%-45.56%) by age 60 (Figure 25). This age pattern persists across all three BMI groups examined. As expected, I found a higher age-specific lifetime risk of diabetes in higher BMI groups compared to higher ones. For instance, among normal weight or underweight individuals, the lifetime risk at age 20 was 54.2% and 56.4% among men and women, respectively, compared to 92.4% and 92.9% among obese men and women, respectively.

Between BMI groups, the largest increase in lifetime risk was between individuals classified as neither overweight nor obese, and overweight individuals. For instance, among urban men aged 20, the lifetime risk increased by nearly 30 percentage points from 54.2% to 85.1% between the not overweight/obese group and the overweight group, whereas the lifetime risk between overweight and obese men increased from 85.1% to 92.4%, an increase of 7.3 percentage points. This effect was apparent over all ages, however, the overweight and obese men at age 60 are considerably more similar in their remaining lifetime risk of diabetes (54.3% and 55.1%, respectively) when compared to urban women of the same age (55.6% and 65.7%, respectively).

Figure 25. Remaining lifetime risk of diabetes (panel A=Men; panel B=Women) in Urban India

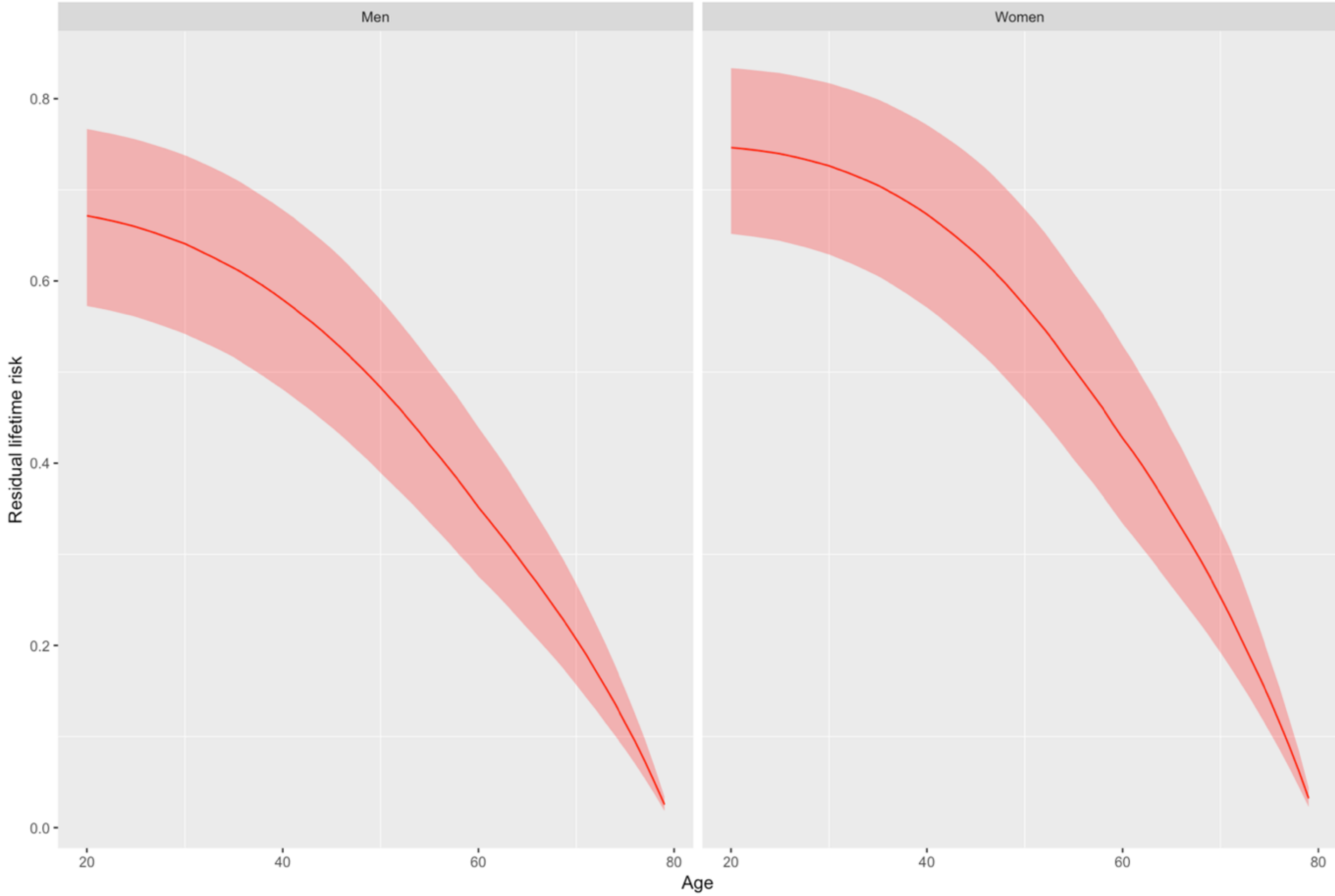

Table 21. Remaining lifetime risk (%) of diabetes by age and BMI in urban India

		Men			*Women*		
BMI	***Age (years)***	***LTR***	***Lower***	***Upper***	***LTR***	***Lower***	***Upper***
Underweight/ Normal weight	*20*	54.20	44.5	64.6	56.4	46.9	66.3
	40	47.2	38.0	57.3	49.8	40.5	59.8
	60	30.2	23.4	38.5	32.3	25.0	40.9
Overweight	*20*	85.1	76.7	91.6	84.8	76.8	91.1
	40	76.5	66.7	85.1	77.2	67.5	85.3
	60	54.3	44.2	65.0	55.6	45.1	66.2
Obese	*20*	92.4	86.6	96.1	92.9	88.0	96.0
	40	81.6	73.0	88.6	86.5	79.1	91.7
	60	55.1	45.0	65.6	65.7	55.1	75.2
Total Population	*20*	69.0	58.9	78.7	74.7	65.4	83.3
	40	59.9	49.7	70.1	67.3	57.4	77.1
	60	36.2	28.4	45.6	42.5	33.8	52.9

The life expectancy of urban Indians at age 20, and 40 years decreases with BMI, with the largest decrease observed between overweight and obese individuals (Figure 26). Among the population as a whole, men and women without diabetes aged 20 can expect to live 35.2% and 37.7% of their remaining life from 20 with diabetes. Men and women without diabetes at age 60 can expect to live 19% and 22.7% of their remaining life with diabetes.

However, the remainder of life spent with diabetes varies considerably between BMI groups. Whereas men and women aged 20 without diabetes, who are neither overweight nor obese, can expect to live 23.9% and 25.5% of remaining years with diabetes, obese 20-year-old men and women without diabetes can expect to live 64.4% and 60.2% of their remaining life with diabetes (Table 22 and Figure 26).

Figure 26. Life expectancy and amount of time expected to live with diabetes (Panel A=Men; Panel B=Women) in urban India by BMI

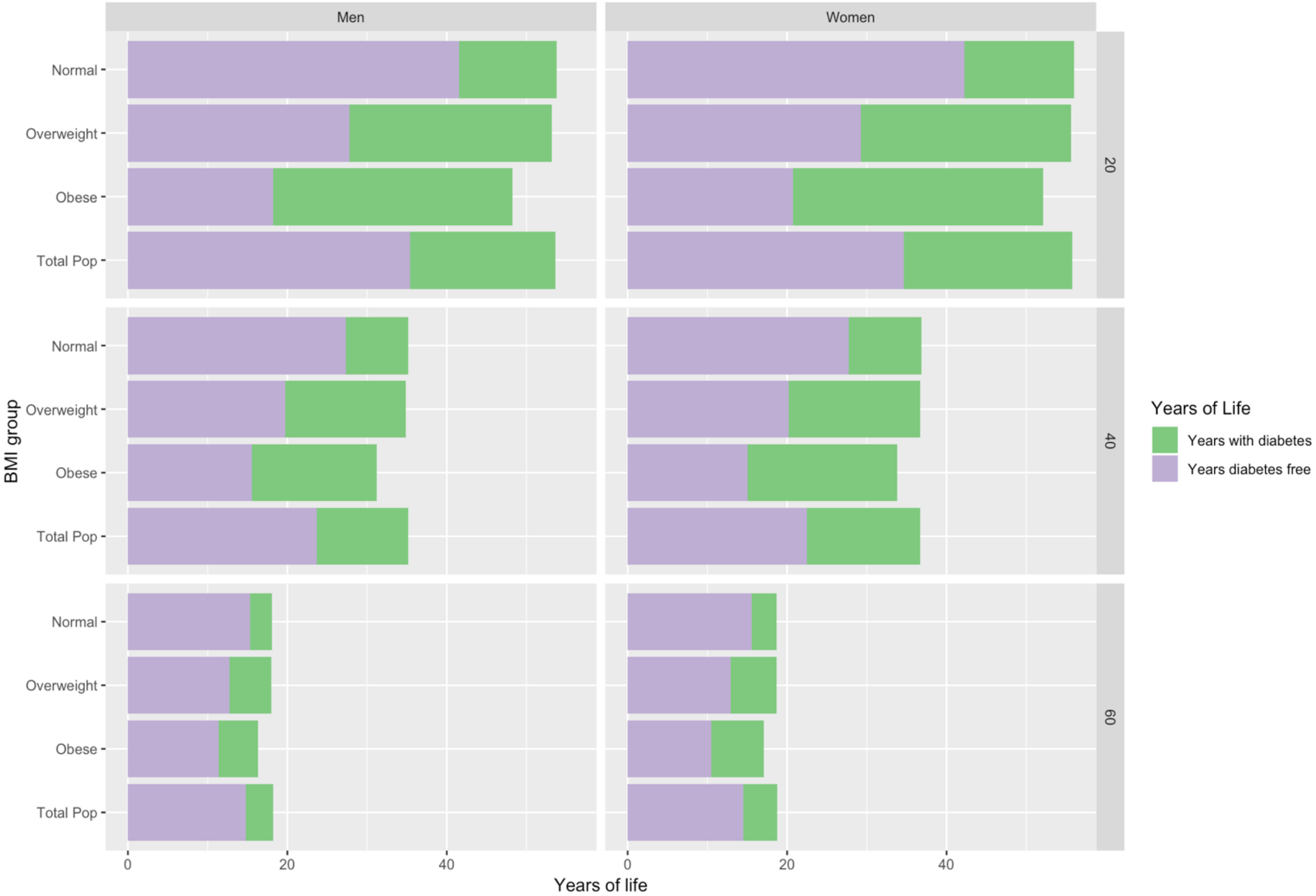

Table 22. Percentage (%) of remaining life spent with diabetes in urban India

BMI	***Age (years)***	***Men***	***Women***
Normal Weight	*20*	23.9	24.5
	40	23.4	24.8
	60	15.4	16.5
Overweight	*20*	49.2	47.5
	40	44.9	44.9
	60	30.2	30.9
Obese	*20*	64.4	60.2
	40	52.6	55.6
	60	31.6	38.7
Total Population	*20*	35.2	37.7
	40	33.4	38.7
	60	19.0	22.7

9.6. Discussion

I found that at age 20 years, men and women in urban India have a 69% and 75% probability, respectively, of developing diabetes in their lifetime. Among obese people aged 20, the remaining risk was almost double that of underweight/normal weight people (92% vs 54% among men and 93% vs 56% among women). Although decreasing at higher ages, the remaining risk of developing diabetes was still considerable; among 60-year-old men and women, respectively, the remaining probability was 36% and 42%. Among obese men and women, respectively, the remaining risk at age 60 years was 55% and 66%, dropping to 30% and 32% among underweight/normal weight people. Whereas underweight/normal weight men and women aged 20 years without diabetes can expect to live 24% and 25% of their remaining life with diabetes, respectively, the remaining proportion of life with diabetes increases considerably with BMI group; obese men aged 20 years can expect to live 65% of their remaining life with diabetes, whereas obese women can expect to live 60% of their remaining life with diabetes.

My findings indicate an alarmingly high lifetime risk of diabetes at every age in urban India, and comparably much higher than remaining risks reported in HICs. Urban Indians aged 25 years have approximately double the remaining lifetime probability of developing diabetes compared to Australians of the same age[139]. Similarly, among urban Indians there is almost twice the remaining risk of diabetes at 45 years compared to adults of the same age in the Netherlands[141]. Whereas the remaining risk among US adults aged 30 years was 31% and 36% among men and women, respectively, I found remaining risks more than twice as high[35]. Although the remaining risk is still greater in urban India, it bears a closer resemblance to high-risk subpopulations in the United States, for instance Hispanic and Black women, where the remaining probability of developing diabetes from age 20 years consistently exceeds 50%[35,142].

The higher lifetime risk among urban Indians even compared to high risk populations in HICs is driven by comparatively higher rates of diabetes incidence;

a recent study reports consistently higher incidence in urban India at all ages and BMIs[215]. Remaining risk of diabetes among urban Indians, especially among overweight and obese people, closely resembles values reported among individuals with pre-diabetes in the Netherlands[141], where those with prediabetes at 45 years have remaining risk as high as 74%.

Indian men and women in urban areas can expect to live a considerably longer period of their remaining life with diabetes. A study in Australia found that people aged 25 can expect to spend, on average 86% of their remaining years free of diabetes[139], whereas another study in the USA found that obese women aged 18 can expect to spend over 80% of their remaining years free of diabetes; the equivalent figure among normal-underweight women being around 95%. On the other hand, I found that 65% and 62% of the remaining lifespan of 20 year old urban Indian men and women, respectively, without diabetes can be expected to be spent diabetes-free, decreasing considerably with higher BMI and lower age, presumably due to a selection effect; those who survive to older ages without diabetes are not as likely to develop diabetes.

Overall, my results demonstrate that Indians at every age and all BMI categories have an alarming high probability of developing diabetes before they die, and overweight and obese urban Indians, and younger people, are particularly high-risk groups.

My study is subject to a number of limitations. Firstly, similar to a period lifetable, I assign to a population a set of age-specific mortality and incidence rates, and pass a synthetic cohort through the life course, assuming that my set of age-specific rates will prevail into the future. However, the prevalence of overweight and obesity has increased in recent decades[18,19], and if it continues to increase into the future it may slightly downwardly bias my lifetime risk estimates for the *total population*. Additionally, the life expectancy at all ages in India has increased in recent decades[216–221,293] and is expected to continue to increase for the coming years[202]. Longer life expectancies potentially increase the remaining lifetime risk of diabetes, making my results possible underestimates. Another potential source of underestimation is an increasing prevalence of overweight and obesity among people of lower socioeconomic background[258], who generally have an elevated risk of dying compared to higher socioeconomic status counterparts[294].

These results should be interpreted with some caution, given India's considerable subnational heterogeneity, with regards ethnicity, geography and customs. These results relate to an average individual in India, however, the extent of variation in lifetime risk and YLL (see Appendix) to diabetes will depend on how much a particular individual differs from this average in regards their risk of diabetes[35,140].

Despite these limitations, there are various strengths of my study. Ours is the first study to estimate remaining lifetime risk of diabetes in a country with a considerably lower BMI distribution and life expectancy compared to HICs (where all previous studies have been conducted), however a higher propensity to develop diabetes, both at younger ages[25,26] and at lower BMI levels[23,34,38]. Secondly, the model inputs are derived from carefully and objectively measured blood tests, in addition to objectively measured BMI[18,19,271], rather than self-reports. Studies assessing the validity of self-reported diabetes have found considerable misclassification; one found that self-reported diabetes in urban China had a sensitivity of 58%[295], and its use has the potential to underestimate the lifetime risk estimates of previous studies[140]. Finally, I also use geographically-representative sources of data to measure mortality, prevalence of BMI categories, and diabetes. As national-level incidence estimates of diabetes are not available, I obtained incidence rates from a large cohort in urban areas of both North and South India, suggesting a good geographical spread. Consequently, I expect my results to be geographically-representative and generalisable to the wider urban population.

An extension of this work may involve examining the lifetime risk separately for people with prediabetes, amongst whom other studies have found the risk to be considerably higher[141]. Such studies may serve as useful baseline data to examine the effects of interventions targeting the population with prediabetes. Additionally, given the heterogeneity in the prevalence of different BMI groups[19], diabetes prevalence[21,22] and mortality, primarily driven by wide variation in culture and dietary patterns across India, this study may mask considerable subnational variation in lifetime risk for diabetes in India. Examination of these statistics by state or other geographical areas is encouraged.

Overall, I find that urban Indians have a considerably higher lifetime risk of diabetes even compared to high risk groups in HICs, and that proportion of remaining life spent with diabetes at all ages among the obese population is double that of the underweight/normal weight population. Although India has a lower BMI distribution to most HICs, the remaining lifetime risk is considerably higher due to a high incidence of diabetes, emphasising the need for proactive efforts to prevent diabetes and diabetes-related complications in urban India, especially as the urban population continues to increase and represent a larger proportion of the total population[9].

Chapter Ten. Discussion

In this thesis I have addressed the trends in the socioeconomic patterning of overweight and obesity in India over the past two decades, examined how these trends have varied between India's most and least economically developed states, forecasted the future prevalence of overweight and obesity to 2040, estimated the consequent diabetes burden, and finally estimated the lifetime risk of diabetes by BMI. In this final section, I will provide a summary of the findings, discuss the general strengths and limitations of this body of work, discuss potential avenues for future research in light of my research, provide suggestions to improve survey instruments that facilitate this type of research, before drawing some implications of the findings in this thesis.

10.1. Thesis rationale and summary of findings

The past two decades have seen considerable increases in overweight and obesity in India[18–20]. In countries undergoing economic, demographic and epidemiological transitions, the association between overweight and obesity with SEP changes from a positive to a negative one, implying a higher prevalence increase among lower SEP individuals[30,32,39,41]. Understanding previous trends, and India's current position within this transition is useful in identifying the SEP groups previously and currently at highest risk of overweight and obesity, and consequently, those groups in most need of policy attention. Moreover, national level analysis of this association may mask considerable heterogeneity in this association when examining trends at the state level, due to wide variation in customs, diets, and levels of urbanisation. Identifying factors that may modify this association, such as state-level economic development, is of particular importance as the Constitution of India devolves healthcare delivery and nutritional improvement to individual states[281]. Recent additions to the literature body has recognised the need for reliable and detailed state-level disease burden data, in addition to information on risk factors and associations[15].

The increase in the prevalence of overweight and obesity in India in the last two decades has also been higher than the global average[36]. This has led to a significant increase in the global population classified as overweight or obese since a sixth of the world's population resides in India[37]. This has led to a considerable rise in NCDs associated with overweight and obesity, whereby its contribution to DALYs in most Indian states exceeds DALYs attributable to communicable or undernutrition related diseases[15]. Reliably forecasting the future prevalence of overweight and obesity, in light of future expected changes to the demographic structure and urbanisation, helps understand future health challenges, especially in regard to the most vulnerable subpopulations and future NCD burden. It can also provide an empirical basis upon which decisions related to resource allocation can be made and can be used to test the impact of policy decisions on future prevalence.

Future increases in overweight and obesity is also likely lead to increases in the proportion of the population encountering overweight and obesity related diseases, such as diabetes. Reliable forecasts can be vital in monitoring the progress of nationwide programmes with diabetes related targets. Despite this, high quality existing forecasts of future diabetes in India are lacking, and the most sophisticated analyses, incorporating future expected demographic changes and previous changes to the incidence rates, are limited to HICs. The most conservative estimates however still predict that India will have the highest number of people with diabetes by 2045[11].

Further to forecasts of diabetes prevalence, estimates of lifetime risk of diabetes allow a more detailed understanding of the diabetes burden and risk within a society[140]. For instance, calculating separate lifetime risks based on BMI allows one to detect subpopulations that are in most urgent need of prevention efforts, and can be used as an effective metric to communicate the reduction in remaining probability of developing diabetes that can be achieved by managing body weight.

In light of these rationales, I aimed to fulfil the following objectives:

- Examine trends in the socioeconomic patterning of overweight and obesity between 1998 and 2016 among women (15-49 years) and between 2005 and 2016 among men (15-54 years).

- Assess how trends in the socioeconomic patterning of overweight and obesity have differed between India's most and least economically developed states.

- Forecast the future prevalence of overweight and obesity among Indian adults to 2040 by urban and rural residence (by age, sex and urban/rural residence).

- Forecast the future prevalence of diabetes, in light of forecasted overweight and obesity, among urban Indian adults, to 2040 (by age and sex).

- Estimate the lifetime risk of diabetes among urban Indian adults (by age, sex, and BMI).

In **Chapter Five**, I examined the trends in the socioeconomic patterning of combined overweight and obesity (referred to in the paper as overweight/obesity) in India using repeated nationally representative cross-sectional surveys from 1998-99, 2005-06, and 2015-16. I used measures of educational attainment and SoL as the main SEP exposures and a measure of overweight/obesity ($BMI \geq 25kg/m^2$) as the main outcome variable. The research question was addressed using multilevel regression analysis. Overweight/obesity was consistently higher in urban areas and among higher SEP individuals in all of the three surveys for both adult men and women. However, the extent of the increase in prevalence over the analysis period in urban areas was higher for lower SEP individuals compared to higher SEP Indians, suggesting a convergence of overweight/obesity prevalence across SEP in urban India. On the other hand, similar increases in overweight/obesity prevalence was observed in both higher and lower SEP individuals in rural areas. These results demonstrate an increasing prevalence of overweight/obesity among all Indians, and especially in urban areas the prevalence has been converging across SEP.

In **Chapter Six**, I aimed to assess how the trends in the socioeconomic patterning of overweight/obesity varied by state-level economic development. I adopted multilevel regressions and used NFHS data limited to five of India's most economically developed states and the five least economically developed states to assess these trends in urban and rural areas between 1998 and 2016. As in **Chapter Five**, I used a measure of educational attainment as the main SEP exposure and supplemented findings with sensitivity analysis using a SoL index. I identified variation in trends in the socioeconomic patterning of overweight/obesity between the most and least developed states. As expected, among women, the most pronounced case of convergence of overweight/obesity by SEP was among urban areas in the most developed states, driven by higher increases in overweight/obesity among poorer respondents compared to richer ones. However, some evidence of convergence in the least developed states and in rural areas was also identified. The convergence was only observed to any notable extent among women, and not men. The findings of this study imply that the urban women in the most economically developed states are likely to be the first of my identified subgroups to show a negative association between overweight/obesity and SEP. Lower SEP urban women in India's most developed states are a particularly vulnerable population to overweight/obesity.

In **Chapter Seven**, I developed a system of multi-state lifetables to forecast both the prevalence of overweight and obesity separately among Indians aged 20-69 years to 2040. I parametrised the model using nationally-representative data and modified rates using relative risks obtained in the body of literature. The prevalence of overweight is predicted to increase from 14.7% to 27.3% among women, and from 12.6% to 30.4% among men, respectively between 2010 and 2040. On the other hand, the prevalence of obesity is predicted to increase from 4.4% to 14.0% among women, and from 2.4% to 9.6% among men, between 2010 and 2040. I predicted relatively larger increases in overweight and obesity in rural, compared to urban, India and among older age groups, compared to younger groups.

In **Chapter Eight**, I forecasted the future prevalence of diabetes to 2040 in urban India using the forecasted future prevalence of overweight and obesity from Chapter 7. I used age and sex-specific incidence of diabetes derived from the CARRS study, age-specific prevalence of diabetes from the ICMR-INDIAB study, and mortality data from abridged lifetables reported by the SRS. The model predicted that the overall prevalence of diabetes will increase from 9.2% to 26.7% among adult women, and 11.6% to 24.8% among men, between 2010 and 2040. A considerably higher proportion of urban Indians aged 55 years or more will have diabetes compared to younger ages. For instance, among women aged 55 years or more, 54.4% are expected to have diabetes in 2040, compared to 4.9% of 20-34-year olds. Similar results were observed among men. In this study, a number of hypothetical scenarios to test the model's sensitivity to the key assumptions were tested. Rather than a constant rate of incidence of diabetes, a 1.5% annual increase in diabetes incidence, independent of increases in overweight and obesity, will lead to a further 5.5 percentage point increase in prevalence by 2040; and holding overweight and obesity prevalence at 2015 levels will lead to a decline in total prevalence of diabetes by 2 percentage points (a relative reduction of prevalence of 6% among women and 9% among men compared to the constant incidence scenario).

Finally, **Chapter Nine** estimated both the lifetime risk of diabetes by BMI groups and diabetes-free life expectancy in urban India, among 20-79-year olds, using a compartmental simulation model. As in Chapter 8, diabetes incidence from the CARRS study was used, along with mortality rates from the SRS abridged lifetables, and baseline prevalence from the ICMR-INDIAB study. The study reported that men and women aged 20 have a remaining lifetime risk of 69.0% and 74.7% of developing diabetes, with considerably higher risk in higher BMI groups. The largest increase in lifetime risk was observed between the normal weight/underweight and overweight BMI groups, compared to between the overweight and obese categories. As expected, at all ages, obese individuals without diabetes can expect to live a greater proportion of their remaining life with diabetes, when compared to lower BMI groups (24.5% among underweight/normal weight women aged 20 years vs 60.2% among obese women aged 20 years).

These results collectively demonstrate a complicated and evolving picture of overweight and obesity prevalence, and the profile of diabetes in India. Notably, the burden of overweight and obesity is shifting towards lower socioeconomic groups, and the overall prevalence of overweight and obesity is expected to continue to increase considerably to 2040, with notable increases among the elderly population and in rural areas. In combination with expected increases in diabetes prevalence and high overall lifetime risk of diabetes, especially with increasing BMI, these results demonstrate the need for interventions designed to both control the increasing prevalence of overweight and obesity, and provide sufficient healthcare, affordable medicine, and lifestyle advice to the populations who are most vulnerable to developing overweight and obesity related conditions, such as diabetes.

10.2. General strengths and limitations

In Chapters Five to Nine I discuss the strengths and limitations of the individual studies. Below I describe the general strengths and limitations of my research.

10.2.1. Thesis strengths

One of the main strengths of this thesis comes from the use of geographically-representative survey data from a broad range of sources to inform my findings. Consequently, the results I obtained are generalisable to the broader study population.

Secondly, the use of the most up-to-date data to inform the modelling studies and studies on trends in the socioeconomic patterning of overweight and obesity make the findings some of the most reliable to date and applicable to contemporary policy issues. This implies that the future predictions reported may be the most likely predictions to transpire compared to previous attempts. This was particularly facilitated by consistency across NFHS surveys in the sampling method, study population and estimation of the key variables.

Thirdly, the measures of overweight, obesity, and diabetes used in all of the studies were obtained from objective measures of height, weight, blood glucose, ensuring that misclassification of outcome status was kept to a minimum.

Fourth, instead of modelling solely secular trends in the prevalence of overweight, obesity and diabetes, the models used benefit from incorporating the real-life lag between changes in demographic profile, incidence and mortality on future age-specific prevalence of these conditions.

Fifth, the models used to forecast overweight, obesity, and diabetes, in addition to estimating the lifetime risk of diabetes were intended to be sufficiently flexible to allow the replication of my findings in other countries or even at the state-level in India settings where data availability is commonly an issue. Demographic characteristics of many populations are available in public repositories such as those provided by the UN, and transition parameters can be estimated either using community studies or DHS survey data, both of which are available for a number of LICs and MICs. The flexibility of the models is further demonstrated by the ability to test multiple scenarios that affect the input parameters and how the parameters evolve over time. This allows policy makers to understand the potential impact on the future prevalence of overweight, obesity, and diabetes of certain policy decisions.

Finally, in addition to estimating standard metrics that are internationally comparable, including predicted population prevalence, I expressed the burden of diabetes in India in additional easily understandable ways that provide new insights into the diabetes-related challenges that India faces, for instance, inferences about age of onset of diabetes from measures of diabetes-free life expectancy.

10.2.2. Thesis limitations

Despite the strengths of this thesis, my research is subject to a number of limitations.

Firstly, the use of repeated cross-sectional data to estimate trends in the socioeconomic patterning of overweight and obesity limits the ability to examine the direction of causality between SEP and BMI group.

Secondly, basing the SoL index merely on the ownership of assets makes no accommodation for variance in the *quality* of assets between households, which could lead to the misclassification of households in their relative ranking based on living standards, however this was likely to be partially corrected for by using broad three broad SoL categories. I also attempted to correct for differences in the relative importance of assets between urban and rural areas by calculating separate indices by residence however there may still remain differences in the importance of assets between other levels of geographical aggregation not considered.

Thirdly, BMI may be an imperfect measure of measuring overweight and obesity, as it does not contain information about an individual's body fat percentage. Ideally, I would have liked to have complemented findings with additional adiposity measures, such as WC, if they were available at all ages. Despite this, I do not expect the conclusions to be considerably altered, given the high correlation between WC and BMI in India[238]. Furthermore, the use of BMI enables direct comparison with other studies in the body of literature as the majority use BMI as the main measure of excess weight.

Fourth, this thesis consistently used the standard BMI thresholds in the analyses. However, some controversy exists as to the appropriateness of global BMI cut-offs when analysing South Asian populations[234] as South Asians have been reported to have a higher percentage of body fat for the same BMI when compared to Caucasians[185,186]. I provided some sensitivity analyses of the socioeconomic patterning of overweight and obesity using the South Asian-specific BMI cut-offs[234], in addition to overweight and obesity forecasts (see Appendix). The use of global-cut-offs in the final forecasts enable direct comparison with similar studies in other countries, however, not using the Asian cut-offs could have led me to substantial underestimation of the predicted prevalence (see Chapter 7 and Appendix)[186]. Despite this, I do not expect the forecasts of diabetes that used the forecasted overweight and obesity based on global cut-offs as inputs, to be biased by this as the separate incidence rates from CARRS that were specific to BMI groups were based on the global-cut-offs.

Finally, the results reported in Chapters Eight and Nine do not distinguish between type 1 and type 2 diabetes, the latter of which is positively associated with adiposity. Although the proportion of diabetes cases that are type 2 in LICs and MICs have not been explored in detail in the literature, in HICs type 2 diabetes represent a great majority of all cases (87-91% of all cases[11]).

10.3. Future potential research

The results presented in this thesis give rise to a number of additional research questions that should be addressed in future research. Firstly, regarding the results of Chapters Five and Six, further research should aim to understand the relative importance of the different pathways through which overweight and obesity is associated with different SEP measures. For instance, understanding the extent to which the association is mediated by diet or sedentary lifestyle can lead to a more nuanced understanding of the necessary issues to target in interventions. Data on dietary intake among respondents is included in NFHS surveys to facilitate a start to such research.

Regarding the forecasts of overweight and obesity, future research could aim to incorporate the changing socioeconomic patterning of overweight and obesity into future forecasts. Although I aimed to incorporate future changes to the urbanicity and demographic profile of India into my forecasts, as has been suggested in literature advising the design of health outcome models in India[296], the modelling of future changes to the association of overweight and obesity with SEP would have added extra layers of uncertainty and complexity into my model, which I sought to avoid.

Another possible extension of the overweight and obesity forecasts involves replication of my model at the state-level. State-level forecasts may be of particular importance in light of the fact that the Constitution of India devolves the delivery of healthcare and raising of living standards to the level of the state[281], and due to India's considerable population heterogeneity in terms of customs and diet.

Modelling the future economic costs of overweight, obesity, and diabetes in India will further emphasise the seriousness of its increasing prevalence and help understand the effect of the country's future disease profile on its economic aspirations. In the USA, additional medical costs associated with obesity were estimated at $75 billion in 2003[111,297], and between 4 and 7% of total health care expenditure[111,298]. These costs are likely to be considerably higher in India due to the combination of lower disposable incomes and its considerably larger population size. Regarding the cost of diabetes, in 2005, a survey covering all of India found that total costs of diabetes per capita was approximately US$ 429.70 annually[290,299].

Moreover, as suggested with overweight and obesity forecasts, state-level forecasts are desirable in light of wide variation in the prevalence of diabetes between India's states[22].

Finally, as with previous studies in the USA[126], forecasts incorporating differential transitions to diabetes among the population with prediabetes may provide more accurate and detailed predictions. The proportion of the population with prediabetes is not insignificant, whereby it is higher than the population with diabetes in most states, particularly states at lower levels of economic development[22].

10.4. Future survey recommendations

Further to future research recommendations, I provide a number of suggestions for future surveys that may help address important related research questions in India.

My first recommendation involves more detailed collection of data on caste. This uniquely Indian social hierarchy has been found to be a positive correlate of overweight and obesity[91] and could be used to complement my findings related to the socioeconomic patterning of overweight and obesity. The NFHS collects caste data categorised into very broad groups defined by the government. Additionally, the assignment of India's many different 'jatis', or castes, into these broad categories are subject to considerable change over time. In 2019 the state government of Uttar Pradesh added 17 castes to 'Other Backward Caste' category from the 'Scheduled Caste' category[198]. These broad categorisations and changing definitions allow very little scope for assessing the changing socioeconomic patterning by this variable.

Secondly, I suggest more survey data collected from older Indians. The limited power of the SAGE study led me to estimate the age-specific incidence of overweight and obesity via an indirect method among Indians aged 50 years or more.

Finally, I recommend that geographically-representative survey data be collected and made available at shorter intervals. Although this may not always be possible, especially due to the size of India's population, other DHS surveys have had follow-up surveys published, in some cases, within three years of a previous survey[300]. More regular collection can help externally validate previous forecasts of overweight or obesity using other datasets and update previous forecasts with the most up-to-date data. Forecasting studies have shown that predictions of future health outcomes using older data can vary considerably from those that update forecasts with more recent data[120–122].

10.5. Implications of the findings

In light of the findings, this following section will outline some policy implications. Firstly, as my research identified that lower SEP individuals, those in less developed states and those in rural areas will become increasingly exposed to combined overweight and obesity, and consequently, related diseases, policy interventions may wish to emphasise these vulnerable subpopulations.

Secondly, in light of the finding that combined overweight and obesity is expected to increase in all ages and subpopulations in India to 2040, I encourage the inclusion of overweight and obesity targets in the national programmes focused on controlling the increasing NCD burden in India.

Thirdly, in response to the expected increases in diabetes prevalence at all ages to 2040 and high lifetime risk of diabetes at all ages and BMI levels, improving affordable healthcare will be critical in relieving some of the inevitable increase in diabetes related expenditures at the individual level.

Fourthly, given that I identified attenuated increases in diabetes prevalence to 2040 under low diabetes incidence scenarios, and given the large reduction in lifetime risk of diabetes that can potentially be achieved through reductions in diabetes incidence via BMI, measures to reduce the incidence of diabetes at all ages both within and across BMI groups should be implemented.

Finally, as the number of individuals with diabetes continues to increase to 2040, the number of undiagnosed cases, that represent a high proportion of the total diabetes cases, will continue to increase. Research into cost-effective measures to identify these individuals, in addition to individuals at high risk of diabetes will be important in preventing or delaying the onset of diabetes and its complications.

Implication 1

The first policy implication involves a future focus on increasingly vulnerable subpopulations. In Chapter Five, I found that over the past two decades the prevalence of combined overweight and obesity among lower SEP individuals has been of a greater magnitude than among higher SEP Indians. In Chapter Six, I found that this was particularly the case among lower SEP individuals in India's most developed states and in urban areas. Additionally, in Chapter Seven, I identified that that rural areas are forecasted to experience relatively larger increases in both overweight and obesity prevalence than urban areas through 2040. Future health targets should be designed in light of increasing overweight and obesity in rural areas and among more disadvantaged Indians, and address the dietary implications of globalisation, increases to spending power and ways in which farming and rural lifestyles are evolving[243].

Controlling the increasing prevalence of overweight and obesity among marginalised segments of society, along with consequent increases in related diseases in these social groups, may be partly accommodated by the launch of the Ayushman Bharat Arogya Yojana in 2018, which addresses healthcare issues at the primary, secondary and tertiary level, and aims to provide funded Universal Health Care to around 500 million marginalised Indians[301]. It additionally includes the extensive provision of healthcare services (150,000 Health and Wellness Centres to address the primary care of leading diseases[21]) to avoid excessive OOP expenditures[301]. Complementary initiatives are encouraged including state-level public health initiatives, for instance, promoting the consumption of healthier foods at younger ages[243], and discouraging consumption of excessively unhealthy foods[137]. A study aiming to model the effects of a tax on sugar sweetened beverages in India found potentially mitigating effects on the future expected increases in obesity and type 2 diabetes in India[137].

Implication 2

The National Programme for Prevention and Control of Cancer, Diabetes, Cardiovascular Disease and Stroke (NPCDCS)[179], aims to provide federal financial and technical support to state initiatives to control NCDs in India. Such initiatives include behaviour and lifestyle changes. Furthermore, the NHP, initiated in 2017 in response to the WHO's Sustainable Development Goals (SDG-3: Ensure healthy lives and promote well-being for all at all ages), aims to reduce premature mortality attributable to either cancers, chronic respiratory diseases, CVD or diabetes by 2025[33]. Results from Chapter Seven find that both overweight and obesity prevalence will increase through 2040 even under the most conservative assumptions. Despite this no national-level emphasis is currently being specifically placed on the reduction of overweight and obesity even in light of expected increases in future urbanisation and the association of overweight and obesity with some NCDs. Culturally tailored initiatives, targeting vulnerable populations by residence and age should aim reduce the incidence of overweight and obesity, with emphasis on changing the distal determinant of positive perceptions of body size which is still prevalent in India[302].

Implication 3

In response to the predicted increase in diabetes prevalence at all ages through to 2040 (Chapter Eight), and the high lifetime risk of diabetes at all ages and BMI levels (Chapter Nine), affordable health care will be imperative to relieve potentially catastrophic financial burdens on households. In India, up to 33% of household income in low-income families can be allocated to diabetes care[303]. Due to slow and gradual rollout of the NPCDCS across the country[21], out of pocket (OOP) expenditures on private sector diabetes care is highly prevalent and should be addressed[304]. This may involve addressing a wider expansion of NCD centres, beyond the current coverage of 55% of India's districts, improving the supply of doctors and nurses per individual in the population (a problem across many LMICs), or the affordable widespread provision of diabetes drugs, such as metformin[304], which in some circumstances can account for more than half of household expenditure[305,306]. Efforts like the ones explained above, to achieve the Planning Commission of India's commitment to provide universal health care by 2022[305,307], is encouraged in light of the findings.

Implication 4

Given the high lifetime risk of diabetes at all ages and in all BMI groups (Chapter Nine) and the large reductions in lifetime risk that can be achieved through lower BMI, I recommend the introduction of measures to reduce diabetes incidence at all ages both within and across broad BMI groups. Although the diabetes forecasts to 2040 were not considerably sensitive to changes in future incidence, attenuated increases in diabetes prevalence are likely to be observed further into the future as cohorts with previously high incidence, and relatively high prevalence, have passed through the forecasted population.

A meta-analysis of effectiveness studies that examined the impact of diabetes interventions, primarily in HICs, have found reductions in incidence of diabetes even at small reductions in body weight[308] in the presence of lifestyle interventions (LSI) and medication; the most effective intervention being group education delivered by professional healthcare providers[308]. A specific focus on reducing diabetes incidence in younger ages can also reduce the extent of the younger onset of diabetes among Indians[157,309–311] and help reduce the extent of expected future increases in prevalence at older ages.

Although targeting high-risk groups with such interventions - for instance the overweight and obese populations - can considerably reduce the extent of the diabetes prevalence increase (Chapter Eight), the rollout of LSI programmes to the general population, rather than targeting specific BMI groups may be crucial in reducing the incidence across the BMI spectrum. Broad population interventions such as this may be vital in light of the fact that South Asians are more susceptible to diabetes compared to other ethnic-groups in every BMI group. One study in the United States found that South Asians have a higher insulin resistance and lower beta-cell function at any given BMI up to approximately 40kg/m^2, when compared to most broad ethnic groups in the United States[312]. Studies on the impact of rolling out such interventions to the whole population is encouraged to understand its potential benefits, however, existing studies have found only moderate decreases in diabetes among high-risk individuals receiving LSI and medication in India[291].

Implication 5

This thesis forecasts that the prevalence of diabetes will reach 26.7% among men and 24.8% among women, by 2040 (Chapter Eight). As almost 50% of diabetes cases are undiagnosed in India[25] there is a high probability of individuals encountering diabetes-related complications without detection. To reduce both the chances that an individual with diabetes goes undetected, and to reduce the mortality rate amongst people with diabetes, which has been estimated to be as high as double that of people without diabetes[287], the final implication pertains to increased efforts to detect as many cases as possible.

The NHP (2017) includes an aim to use screening to detect and treat 80% of Indians with diabetes, in addition to reducing diabetes related mortality by 25% in under a decade[21,33]. The manner of mass screening is an important topic to address in light of evidence of high validity of tools in certain areas[313], and variation between geographical areas in the ability of screening instruments to detect both individuals at high risk and with diabetes[279,314]. A microsimulation model examining the performance and cost-effectiveness of various screening instruments, including random glucose screening and survey screening found that mass rollout is likely to lead to low specificity of screening instruments, with total costs of administering such programmes ranging from US$169 to 567 million[279]. This suggests that mass population screening may not be cost-effective and can be improved through combining it with screening for other risk factors, including hypertension[315,316].

Rather than mass population screening using standardised instruments, locally appropriate instruments that keep false positives to a minimum may be more effective in detecting a higher proportion of diabetes cases. Additionally, screening of only those with certain risk factors, for instance obesity, may be more cost-effective than mass screening or no screening[316,317]. Further research into the cost-effectiveness of such measures across different Indian populations is advised. Additionally, considerations regarding the involvement of stakeholders at different levels of screening delivery should be made to make screening more cost-effective. This may involve, for instance, large organisations to donate screening equipment, training of local staff to increase general awareness and concern for diabetes or the adoption of innovative screening methods[318,319].

10.6. Conclusion

This thesis has examined trends in the socioeconomic patterning of overweight and obesity nationally and sub-nationally in India, forecasted the future prevalence of overweight and obesity in urban and rural India to 2040, and resultant diabetes in urban areas, before reporting urban-specific estimates of the lifetime risk and diabetes free-life expectancy. I conclude that combined overweight and obesity can no longer be considered solely a condition of the affluent, and that the most notable increases in recent decades has been observed among poorer segments of society. Moreover, the prevalence of overweight and obesity is expected to continue to increase to an alarming degree into the future, along with the future prevalence of diabetes and the proportion of the population at very high risk of developing diabetes at some point in their lifetime. Collectively, these results indicate that explicit and realistic overweight and obesity targets should be designed and implemented as part of National Health

Programmes that have been launched, with particular emphasis on vulnerable subpopulations, for instance the poor and elderly. Additionally, innovative approaches to screening diabetes cases that minimise the number of false positives should be investigated due to the combination of a high future number of diabetes cases, and consequently, undetected cases. Finally, given the slow rollout of existing policies, the expected future increases in diabetes, and the high overall lifetime risk, efforts to minimise OOP expenditure on diabetes-related healthcare is strongly suggested.

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Appendix One. Ethical approval documents

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Observational / Interventions Research Ethics Committee

Mr Shammi Luhar
LSHTM

10 April 2019

Dear Shammi

Submission Title: Forecasting the prevalence of Overweight in India to 2040

LSHTM Ethics Ref: 16190

Thank you for responding to the Observational Committee Chair's request for further information on the above research and submitting revised documentation.

The further information has been considered on behalf of the Committee by the Chair.

Confirmation of ethical opinion

On behalf of the Committee, I am pleased to confirm a favourable ethical opinion for the above research on the basis described in the application form, protocol and supporting documentation as revised, subject to the conditions specified below.

Conditions of the favourable opinion

Approval is dependent on local ethical approval having been received, where relevant.

Approved documents

The final list of documents reviewed and approved is as follows:

Document Type	File Name	Date	Version
Protocol / Proposal	FRIND2	01/10/2000	1
Consent form	SAGESurveyManualFinal	01/01/2006	1
Protocol / Proposal	SAGESurveyManualFinal	01/02/2006	1
Protocol / Proposal	report with qaire	01/09/2007	1
Protocol / Proposal	SAGEIndiaReport	01/09/2013	1
Protocol / Proposal	India nfhs 4	01/12/2017	1
Investigator CV	Shammi CV	29/10/2018	1
Consent form	Protecting the privacy of DHS Survey Respondents	01/02/2019	1
Covering Letter	Leo_cover_Clarification	15/03/2019	1
Protocol / Proposal	Ethics_res_protocol	19/03/2019	1

After ethical review

The Chief Investigator (CI) or delegate is responsible for informing the ethics committee of any subsequent changes to the application. These must be submitted to the committee for review using an Amendment form. Amendments must not be initiated before receipt of written favourable opinion from the committee.

The CI or delegate is also required to notify the ethics committee of any protocol violations and/or Suspected Unexpected Serious Adverse Reactions (SUSARs) which occur during the project by submitting a Serious Adverse Event form.

An annual report should be submitted to the committee using an Annual Report form on the anniversary of the approval of the study during the lifetime of the study

At the end of the study, the CI or delegate must notify the committee using the End of Study form.

All aforementioned forms are available on the ethics online applications website and can only be submitted to the committee via the website at: http://leo.lshtm.ac.uk.

Further information is available at: www.lshtm.ac.uk/ethics.

Yours sincerely,

Professor John DH Porter
Chair

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Observational / Interventions Research Ethics Committee

Mr Shammi Luhar
LSHTM

29 June 2017

Dear Shammi,

Study Title: Sociodemographic patterning of overweight and obesity between 1998 and 2015: Evidence from India

LSHTM Ethics Ref: 12097

Thank you for responding to the Observational Committee's request for further information on the above research and submitting revised documentation.

The further information has been considered on behalf of the Committee by the Chair.

Confirmation of ethical opinion

On behalf of the Committee, I am pleased to confirm a favourable ethical opinion for the above research on the basis described in the application form, protocol and supporting documentation as revised, subject to the conditions specified below.

Conditions of the favourable opinion

Approval is dependent on local ethical approval having been received, where relevant.

Approved documents

The final list of documents reviewed and approved by the Committee is as follows:

Document Type	File Name	Date	Version
Covering Letter	Cover Letter Shammi		
Protocol / Proposal	FRIND2	01/10/2000	1
Protocol / Proposal	report with qaire	01/09/2007	1
Investigator CV	SHAMMI LUHAR CV	01/01/2017	1

After ethical review

The Chief Investigator (CI) or delegate is responsible for informing the ethics committee of any subsequent changes to the application. These must be submitted to the Committee for review using an Amendment form. Amendments must not be initiated before receipt of written favourable opinion from the committee.

The CI or delegate is also required to notify the ethics committee of any protocol violations and/or Suspected Unexpected Serious Adverse Reactions (SUSARs) which occur during the project by submitting a Serious Adverse Event form.

At the end of the study, the CI or delegate must notify the committee using an End of Study form.

All aforementioned forms are available on the ethics online applications website and can only be submitted to the committee via the website at: http://leo.lshtm.ac.uk

Additional information is available at: www.lshtm.ac.uk/ethics

Yours sincerely,

[redacted]

Professor John DH Porter
Chair

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Observational / Interventions Research Ethics Committee

Mr Shammi Luhar
LSHTM

17 July 2019

Dear Shammi ,

Study Title: Forecasting future diabetes in India to 2040 based on overweight/obesity and smoking forecasts

LSHTM ethics ref: 17568

Thank you for your application for the above research, which has now been considered by the Observational Committee.

Confirmation of ethical opinion

On behalf of the Committee, I am pleased to confirm a favourable ethical opinion for the above research on the basis described in the application form, protocol and supporting documentation, subject to the conditions specified below.

Conditions of the favourable opinion

Approval is dependent on local ethical approval having been received, where relevant.

Approved documents

The final list of documents reviewed and approved by the Committee is as follows:

Document Type	File Name	Date	Version
Protocol / Proposal	Ethics_Diab_FC	01/05/2019	1
Investigator CV	CV	01/05/2019	1
Consent form	CARRS QAIRE	01/05/2019	1

After ethical review

The Chief Investigator (CI) or delegate is responsible for informing the ethics committee of any subsequent changes to the application. These must be submitted to the Committee for review using an Amendment form. Amendments must not be initiated before receipt of written favourable opinion from the committee.

The CI or delegate is also required to notify the ethics committee of any protocol violations and/or Suspected Unexpected Serious Adverse Reactions (SUSARs) which occur during the project by submitting a Serious Adverse Event form.

An annual report should be submitted to the committee using an Annual Report form on the anniversary of the approval of the study during the lifetime of the study.

At the end of the study, the CI or delegate must notify the committee using an End of Study form.

All aforementioned forms are available on the ethics online applications website and can only be submitted to the committee via the website at: http://leo.lshtm.ac.uk

Additional information is available at: www.lshtm.ac.uk/ethics

Yours sincerely,

[redacted]

Professor Jimmy Whitworth
Chair

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Improving health worldwide

Appendix Two. Thesis related publications

BMJ Open

Trends in the socioeconomic patterning of overweight/obesity in India: a repeated cross-sectional study using nationally representative data

Shammi Luhar,[1] Poppy Alice Carson Mallinson,[2] Lynda Clarke,[1] Sanjay Kinra[2]

To cite: Luhar S, Mallinson PAC, Clarke L, *et al*. Trends in the socioeconomic patterning of overweight/obesity in India: a repeated cross-sectional study using nationally representative data. *BMJ Open* 2018;**8**:e023935. doi:10.1136/bmjopen-2018-023935

► Prepublication history and additional material for this paper are available online. To view these files, please visit the journal online (http://dx.doi.org/10.1136/bmjopen-2018-023935).

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ABSTRACT

Objectives We aimed to examine trends in prevalence of overweight/obesity among adults in India by socioeconomic position (SEP) between 1998 and 2016.

Design Repeated cross-sectional study using nationally representative data from India collected in 1998/1999, 2005/2006 and 2015/2016. Multilevel regressions were used to assess trends in prevalence of overweight/obesity by SEP.

Setting 26, 29 and 36 Indian states or union territories, in 1998/99, 2005/2006 and 2015/2016, respectively.

Participants 628 795 ever-married women aged 15–49 years and 93 618 men aged 15–54 years.

Primary outcome measure Overweight/obesity defined by body mass index >24.99 kg/m^2.

Results Between 1998 and 2016, overweight/obesity prevalence increased among men and women in both urban and rural areas. In all periods, overweight/obesity prevalence was consistently highest among higher SEP individuals. In urban areas, overweight/obesity prevalence increased considerably over the study period among lower SEP adults. For instance, between 1998 and 2016, overweight/obesity prevalence increased from approximately 15%–32% among urban women with no education. Whereas the prevalence among urban men with higher education increased from 26% to 34% between 2005 and 2016, we did not observe any notable changes among high SEP urban women between 1998 and 2016. In rural areas, more similar increases in overweight/obesity prevalence were found among all individuals across the study period, irrespective of SEP. Among rural women with higher education, overweight/obesity increased from 16% to 25% between 1998 and 2016, while the prevalence among rural women with no education increased from 4% to 14%.

Conclusions We identified some convergence of overweight/obesity prevalence across SEP in urban areas among both men and women, with fewer signs of convergence across SEP groups in rural areas. Efforts are therefore needed to slow the increasing trend of overweight/obesity among all Indians, as we found evidence suggesting it may no longer be considered a 'diseases of affluence'.

Strengths and limitations of this study

- Our use of the most recent nationally representative data available for Indian adults make our results the most up-to-date estimates of the socioeconomic patterning of overweight/obesity, and their trends, in India.
- Using a large nationally representative data set also enabled us to generate both precise and nationally generalisable overweight/obesity prevalence trends.
- Body mass index was the only measure used to define overweight/obesity, and prevalence estimates may vary based on the adiposity measure used and the cut-offs used. However, we would not expect the reported socioeconomic patterning of overweight/obesity, and trends, to change considerably between measures.
- Our results may mask subnational variation in overweight/obesity prevalence and trends, especially given large subnational differences in economic growth, demography and culture between India's states.

INTRODUCTION

Overweight and obesity present considerable challenges to the maintenance of global health improvements due to its association with many non-communicable diseases (NCDs).[1] WHO's aim to reduce global obesity to 2010 levels by 2025[1] is threatened by the increasing prevalence of overweight and obesity in India,[2] where nearly a sixth of the global population lives.[3]

In India, economic growth and rising incomes have been accompanied by increases in the proportion of Indians classified as overweight or obese. The proportion of adult women classified as either overweight or more than doubled for adult women from 9% to 21% between 1998 and 2016, while increasing from 11% to 19% among adult men between 2005 and 2016.[2 4 5] At the same time, undernutrition and infectious diseases continue to threaten population health,[6–9] presenting dilemmas about the appropriate allocation of scarce public finances and policy attention.

In low-income countries, overweight and obesity is usually more prevalent among higher socioeconomic position (SEP) groups,[2 10–13] whereas the opposite is observed in most high-income countries, where lower SEP individuals are more likely to be overweight or obese.[10 13] Although considered a lower middle-income country,[14] India has experienced considerable economic growth between 1998 and 2015,[15] and how this has impacted the proportion classified as overweight or obese in different SEP groups is unknown.

In this study, we aim to estimate recent trends in the proportion of Indians considered overweight or obese by SEP in India. Our results are intended to inform health policy decisions by identifying groups currently most at risk of being overweight or obese and those who have experienced the largest increases in prevalence between 1998 and 2016.[16] We hypothesise that between 1998 and 2016, the proportion classified as overweight or obese has increased in all SEP groups, in both urban and rural areas, however, with greater increases among lower SEP individuals than higher SEP individuals.

METHODS

Study population

The National Family Health Surveys (NFHS) 2, 3 and 4, collected in 1998–1999, 2005–2006 and 2015–2016, respectively, gathered health and demographic data on 89 199, 124 385 and 699 686 eligible women in surveys 2, 3 and 4, respectively, in addition to 74 369 and 112 122 eligible men in surveys 3 and 4, respectively.[2 4 5] As NFHS-2 only collected data on ever-married women, we restricted the sample across surveys to this population to allow comparability over time. Pregnant women were not included in our analysis as their pregnancy may bias their assessment of weight status. From this restricted sample, we further excluded women (1998–1999: n=6182 (7.4%); 2005–2006: n=3673 (4.2%); 2015–2016: 7810 (1.6%)) and men (2005–2006: n=5160 (6.8%); 2015–2016: n=3422 (3.1%)) with missing height and weight data. The analytic sample used in our main analysis consisted of 628 795 women aged 15–49 years and 93 618 men aged 15–54 years across all three surveys, representing respondents with complete data across all the key variables. In each of the surveys, multistage sampling approaches were adopted, and sampling weights were provided in the data sets.[2 4 5] Between surveys, the number of states, or union territories, in India increased from 26 in 1998–99 in to 36, due to the creation of new states from existing ones, for instance, the creation of Jharkhand from Bihar, and Telangana from Andhra Pradesh.

Outcome

In each survey, the participants' height and weight were measured and used to calculate body mass index (BMI). To make the interpretation of our results more straightforward, we categorised the continuous BMI variable using a meaningful qualitative cut-off that facilitate comparison with other studies and adequately capture excess adiposity. Overweight, as well as obese, adults have been reported to be at higher risk of NCDs and all cause-mortality,[17 18] therefore we categorised individuals as either overweight/obese (BMI over 24.99 kg/m^2), or not overweight/obese (BMI less than or equal to 24.99 kg/m^2), based on the WHO definition.[1] We additionally used cut-off values recommended for use among Asian populations to verify the trends we initially identified,[19] whereby individuals with a BMI greater than 22.99 kg/m^2 were classified as overweight/obese and included the results in the online supplementary appendix. Lower BMI cut-off values may be more appropriate among Asian populations, given a potentially higher risk of overweight/obesity related diseases at lower BMI levels compared with populations on which initial classifications were based.[19]

Independent variables

We considered two measures of SEP: an index of standard of living (SoL) and educational attainment. It was not possible to include occupation as an independent variable because it was collected on a limited subsample of respondents in the 2015–2016 survey.

We allocated individuals in all the surveys to one of the following four education categories, based on the number of years of schooling: none (0 years), primary (1–5 years), secondary (6–12 years) and higher (12+ years). We used education as a measure of SEP as it may indicate employable skills that expose individuals to more opportunities to earn higher incomes.

The NFHS contains a wealth index, constructed using Principal Components Analysis (PCA) in each survey separately, using information on household asset ownership and household characteristics. As the original wealth index cannot be appropriately compared over time, and as we intended to stratify our analysis by urban and rural areas, we constructed a new index, as an alternative measure of SEP, using PCA from 26 assets and characteristics available in all the surveys.[2 4 5] Based on our new wealth scores derived from weightings given to each asset or characteristic, households were classified as either 'lower', 'medium' or 'higher' SoL. Asset-based indices are commonly used in cross-sectional studies conducted in low-income and middle-income countries, where income data may be an unreliable indicator of overall SEP, particularly in rural areas.[20] For instance, households may receive income from a variety of sources, which may be difficult to recall, or income may be received in kind[20 21] rather than monetarily. Consequently, a household's stock of assets may provide a more reliable measure of current SEP.[20]

We adjusted our final models for the respondent's age (categorised as 15–29 years, 30–39 years and 40–49 years (40–54 years) for women (men)), as it has been reported in previous studies that overweight/obesity prevalence increases with age.[22] Additionally, older adults may have accumulated more assets over a longer lifespan, potentially, confounding the association between SEP and overweight/obesity. Research has found overweight/obesity to be higher among married individuals, and therefore could confound the reported association between SEP and overweight/obesity.

Statistical analysis

We initially calculated the prevalence of overweight/obesity in each SoL index and educational attainment category by sex and urban/rural residence. We accounted for the complex survey design of the data using sampling weights. Separately for urban and rural areas, we calculated the ratio of the prevalence between the highest and lowest socioeconomic status group of our two main SEP variables (eg, higher to lower SoL, and higher to no education) in each of the surveys. Additionally, we calculated the percentage change in the prevalence of overweight/obesity by each category of SoL and educational attainment.

Separately for urban and rural areas and sex, we fitted multilevel logistic regression models with random intercepts for primary sampling units and states. We chose to include Primary Sampling Unit (PSU)-level and state-level random intercepts due to the hierarchical nature of the NFHS data, whereby individuals are nested within PSUs, which are nested within states. SEs calculated in our models would have been underestimated if we did not account for this clustering. We modelled the log OR of overweight/obesity in each category of the SEP variable of interest in each of the surveys by fitting a survey-specific interaction term. The regression models were adjusted for the covariates mentioned in the independent variables section, in addition to the remaining SEP variable. No evidence of multicollinearity of independent variables with the main exposure of interest was detected when examining changes in the SE once new variables were added. Finally, we derived and reported the predicted prevalence of overweight/obesity from the model, in addition to their 95% confidence bounds. Adjusted analyses were also carried out using Asian specific BMI cut-offs to observe if the trends identified varied depending on the outcome measure used (online supplementary appendix).

Patient and public involvement

Publicly available survey data were used for the analysis, and no patients were involved in the study.

RESULTS

The study population generally experienced increasing educational attainment and SoL over the period of analysis in both urban and rural areas. Whereas the percentage of respondents with no education declined over the study period, particularly among the rural population, the percentage with secondary education in the 2015–2016 survey was generally higher than in 1998–1999 and 2005–2006. Additionally, in both rural and urban areas, the percentage of individuals from lower SoL households declined, while the percentage from higher SoL households increased between 1998 and 2016 (tables 1 and 2).

The prevalence of overweight/obesity increased in each successive survey for both of our samples of men and women. In rural India, the prevalence among men almost tripled from 0.059 to 0.148 between 2005 and 2016, and

Table 1 Characteristics of rural study participants across NFHS surveys with recorded BMI information

	Women						Men			
	NFHS 2 (1998–1999)		NFHS 3 (2005–2006)		NFHS 4 (2015–2016)		NFHS 3 (2005–2006)		NFHS 4 (2015–2016)	
	Freq	Proportion	Freq	Proportion	Freq	Proportion	Freq	Proportion	Freq	Proportion
Not overweight/ obese	49 596	0.93	42 979	0.9	2 89 482	0.83	32 304	0.93	64 133	0.86
Overweight/obese	3496	0.07	4912	0.1	61 124	0.17	2255	0.07	10 550	0.14
Age 15–29 years	23 888	0.45	19 279	0.4	1 26 796	0.36	16 537	0.48	34 589	0.46
Age 30–39 years	17 488	0.33	16 892	0.35	1 22 520	0.35	8951	0.26	18 965	0.25
Age 40-49 years (54 males)	11 716	0.22	11 720	0.24	1 01 290	0.29	9071	0.26	21 129	0.28
No education	31 724	0.6	24 314	0.51	1 46 302	0.42	6904	0.2	11 709	0.16
Primary	9469	0.18	8417	0.18	55 652	0.16	6620	0.19	10 545	0.14
Secondary	9971	0.19	13 872	0.29	1 31 722	0.38	18 199	0.53	43 737	0.59
Higher	1916	0.04	1285	0.03	16 930	0.05	2824	0.08	8692	0.12
Low SoL	28 408	0.54	21 262	0.44	64 998	0.19	14 615	0.42	11 842	0.17
Middle SoL	18 616	0.35	15 929	0.33	1 20 050	0.36	12 508	0.36	25 338	0.35
High SoL	5869	0.11	10 645	0.22	1 49 191	0.45	7409	0.21	34 202	0.48
Married	49 674	0.94	44 763	0.93	3 31 883	0.95	22 352	0.65	47 948	0.64
Not married	3418	0.06	3128	0.07	18 723	0.05	12 207	0.35	26 735	0.36

BMI, body mass index; NFHS, National Family Health Surveys; SoL, standard of living.

Table 2 Characteristics of urban study participants across NFHS surveys with recorded BMI information

	NFHS 2 (1998–1999)		NFHS 3 (2005–2006)		NFHS 4 (2015–2016)		NFHS 3 (2005–2006)		NFHS 4 (2015–2016)	
	Freq	Proportion	Freq	Proportion	Freq	Proportion	Freq	Proportion	Freq	Proportion
Not overweight/obese	18473	0.75	25454	0.7	87695	0.64	28669	0.83	25285	0.74
Overweight/obese	6048	0.25	10808	0.3	49443	0.36	5981	0.17	8732	0.26
Age 15–29 years	8950	0.36	12401	0.34	41893	0.31	17434	0.5	15581	0.46
Age 30–39 years	9253	0.38	13954	0.38	52032	0.38	8652	0.25	8742	0.26
Age 40–49 (54 males)	6318	0.26	9907	0.27	43213	0.32	8564	0.25	9694	0.28
No education	6493	0.26	9048	0.25	28878	0.21	3016	0.09	2884	0.08
Primary	4025	0.16	4959	0.14	16818	0.12	4143	0.12	3407	0.1
Secondary	8814	0.36	16655	0.46	67583	0.49	19902	0.57	19563	0.58
Higher	5181	0.21	5596	0.15	23859	0.17	7574	0.22	8163	0.24
Low SoL	16444	0.67	17263	0.48	33609	0.25	17329	0.5	8773	0.27
Middle SoL	5682	0.23	10147	0.28	50027	0.38	9613	0.28	11925	0.36
High SoL	2310	0.09	8832	0.24	49540	0.37	7694	0.22	12389	0.37
Married	22931	0.94	33845	0.93	128279	0.94	19656	0.57	20375	0.6
Not married	1590	0.06	2417	0.07	8859	0.06	14994	0.43	13642	0.4

BMI, body mass index; NFHS, National Family Health Surveys; SoL, standard of living.

among women, the prevalence increased from 0.059 to 0.182 between 1998 and 2016. In urban India, the prevalence among women increased to 0.385 in 2015–2016, from 0.236 in 1998–1999, whereas the prevalence among urban men increased from 0.167 to 0.276 between 2005 and 2016 (figure 1).

In all surveys, and for men and women in both urban and rural areas, the prevalence of overweight/obesity was

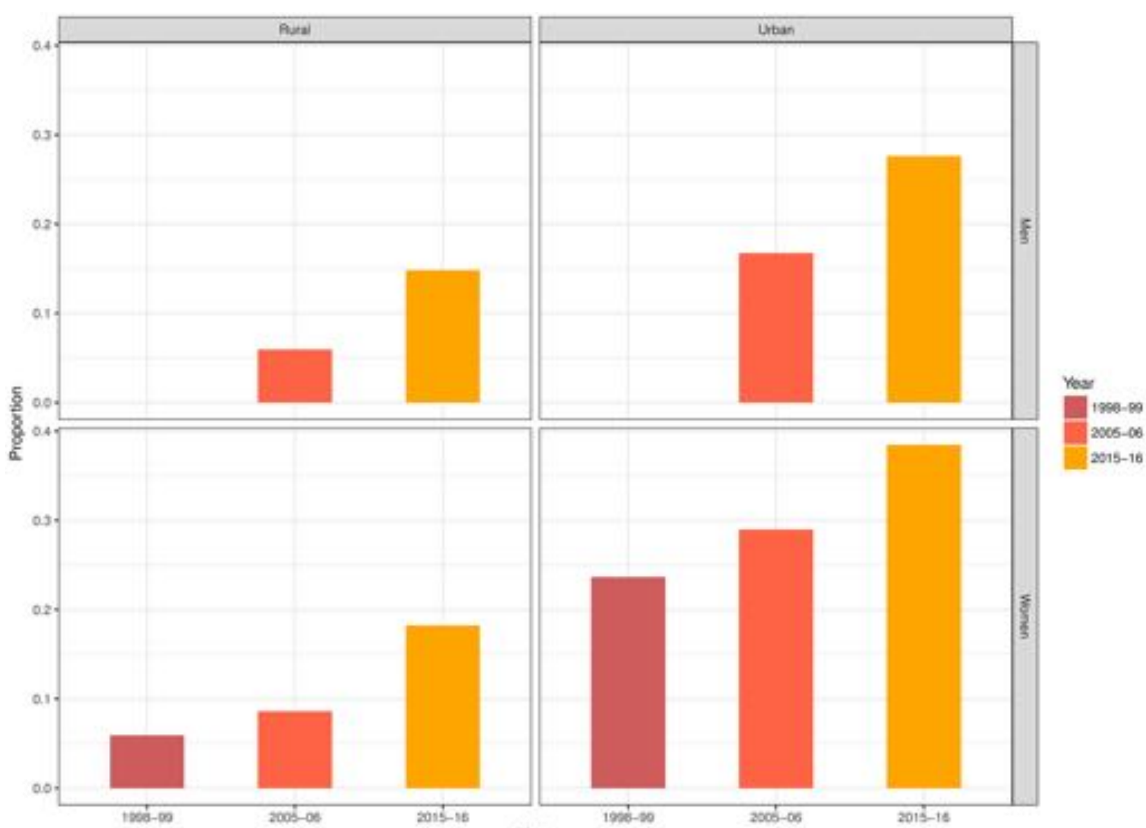

Figure 1 Prevalence (weighted) of overweight/obesity in urban and rural India among men and women.

Table 3 Percentage of respondents classified as overweight/obese by education level (1998–2016)

	Women				Men		
	1998–1999	2005–2006	2015–2016	% change	2005–2006	2015–2016	% change
	%	%	%	1998–2016	%	%	2005–2016
Rural							
Education*							
No education	3.38	5.26	13.91	311.54	3.05	10.79	253.77
Primary	7.93	10.01	18.45	132.66	4.22	14.06	233.18
Secondary	10.8	14.19	21.82	102.04	6.57	14.56	121.61
Higher	15.85	22.79	26.73	68.64	15.32	22.32	45.69
Ratio†	4.69	4.33	1.92		5.02	2.07	
Urban							
Education*							
No education	13.53	18.49	32.17	137.77	7.73	18.28	136.48
Primary	19.45	24.45	37.21	91.31	10.9	23.86	118.90
Secondary	27.18	33.04	40.15	47.72	15.24	26.33	72.77
Higher	35.35	41.79	41.56	17.57	28.39	34.87	22.82
Ratio†	2.61	2.26	1.29		3.67	1.91	

*χ^2 test p value of each Strata's association with overweight/obesity: p<0.001.
†Ratio of the percentage among individuals with higher education and no education.

highest among participants with higher education and from a higher SoL, whereas the lowest prevalence of overweight/obesity was found among participants with no education and from a lower SoL.

However, over the study periods for both men and women, the greatest percentage increase in overweight/obesity prevalence was observed among participants from the lowest SoL category and participants with no education. Consequently, the ratio of the prevalence of overweight/obesity in all of the highest, compared with the lowest, SEP groups, reduced over time (tables 3 and 4).

After adjusting for marital status and age, in urban areas, the predicted prevalence of overweight/obesity among lower SEP women increased over the study period for both men and women, whereas no notable changes were observed among higher SEP women. Among urban men, we observed some increase in the prevalence

Table 4 Percentage of respondents classified as overweight/obese by standard of living (SoL) (1998–2016)

	Women				Men		
	1998–1999	2005–2006	2015–2016	% change	2005–2006	2015–2016	% change
	%	%	%	1998–2016	%	%	2005–2016
Rural							
SoL*							
Lower SoL	2.35	3.01	6.65	182.98	1.79	4.96	177.09
Middle SoL	8.22	8.88	12.94	57.42	5.66	9.47	67.31
Higher SoL	22.93	25.15	27.74	20.98	17.49	22.3	27.50
Ratio†	9.76	8.36	4.17		9.77	4.50	
Urban							
SoL*							
Lower SoL	16.32	17.36	24.91	52.63	8.92	16.01	79.48
Middle SoL	39.11	35.01	38.83	–0.72	20.61	26.89	30.47
Higher SoL	46.93	48.4	46.87	–0.13	30.59	35.77	16.93
Ratio†	2.88	2.79	1.88		3.43	2.23	

*χ^2 test p value of each strata's association with overweight/obesity: p<0.001.
†Ratio of the percentage in the highest and lowest socioeconomic group.

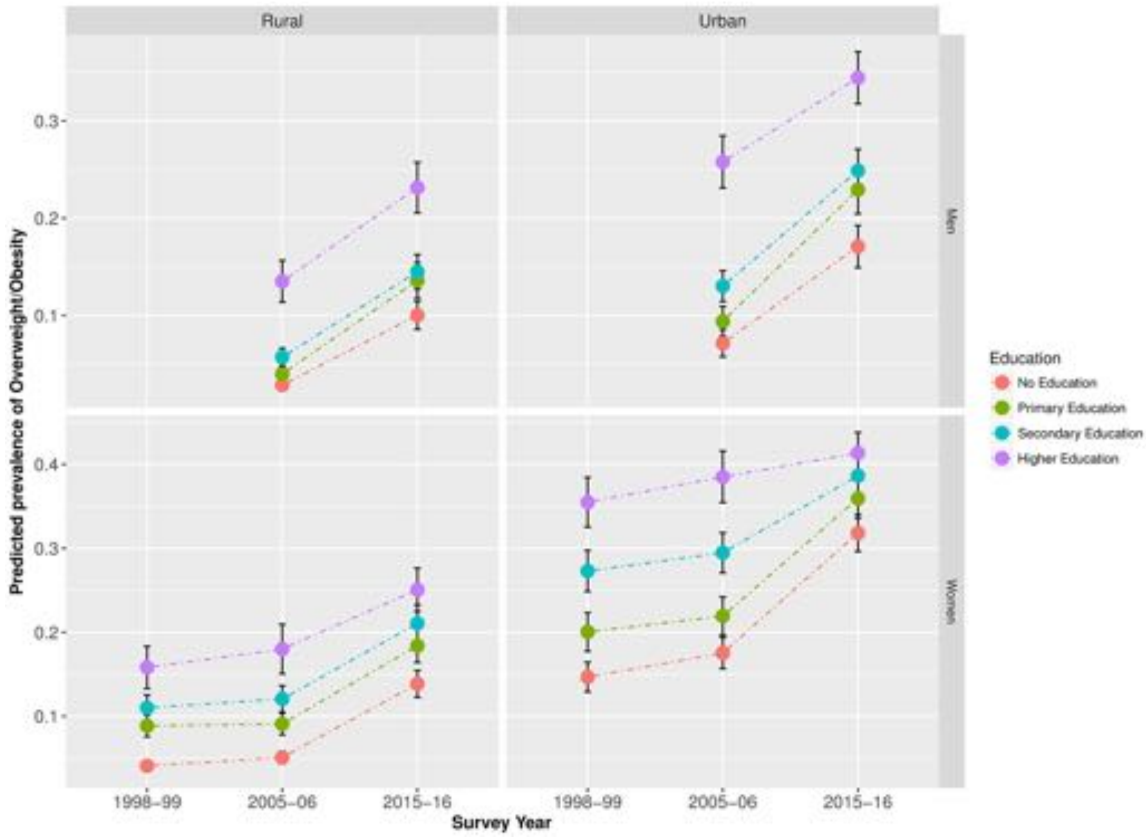

Figure 2 Predicted prevalence* of overweight/obesity in India by educational attainment (1998–2016).

of overweight/obesity among high SEP respondents; however, the increase among low SEP men was greater. Among both rural men and women, more similar increases were observed among individuals from all SEP groups over the study period (figures 2 and 3). Equivalent trends were found when using the BMI cut-offs recommended for Asian populations (online figures A1 and A2 in supplementary appendix).

DISCUSSION

We found that, although overweight/obesity prevalence increased with SEP, in urban areas no notable change in the prevalence of overweight/obesity was observed among higher SEP women, whereas the prevalence among lower SEP women increased considerably between 1998 and 2016. The prevalence increase of overweight/obesity was greater among lower SEP urban men compared with higher SEP counterparts between 2005 and 2016. Consequently, some convergence of overweight/obesity across SEP was observed in urban areas among both men and women. In rural areas, however, overweight/obesity prevalence increased similarly among individuals in all SEP groups, with fewer signs of convergence across SEP groups yet.

Strengths and limitations

The main strength of our study is our use of the most recent nationally representative data available for India, making our results the most up-to-date estimates of overweight/obesity trends by SEP.

Our study however has some limitations. First, we derive our only measure of overweight/obesity from BMI, rather than complement our results with alternative measures of overweight/obesity, such as waist circumference[23 24] and body fat percentage. Consequently, prevalence estimates may vary depending on the adiposity measure and the exact definitions/cut-offs used. However, given the high correlation between BMI and measures including waist circumference among Indians,[25] we would not expect the reported associations between overweight/obesity and SEP, and trends, to change considerably between measures.

Second, to ensure the population of sampled women was comparable over time, we limited our analysis to ever-married women, as this was the selection criteria in the NFHS-2 survey. Prevalence of overweight/obesity is generally lower among never-married women,[26] for instance in the NFHS-4 survey data, the prevalence of overweight/obesity was 6.6% among never-married women, compared with 25.0% among currently married women. This may have lead us to overestimate overweight/obesity prevalence among women, as the weighted percentage of never-married women were 19.8% and 22.5% in the 2005–2006 and 2015–2016 samples, respectively. However, although individual point estimates may be affected, we do not expect the

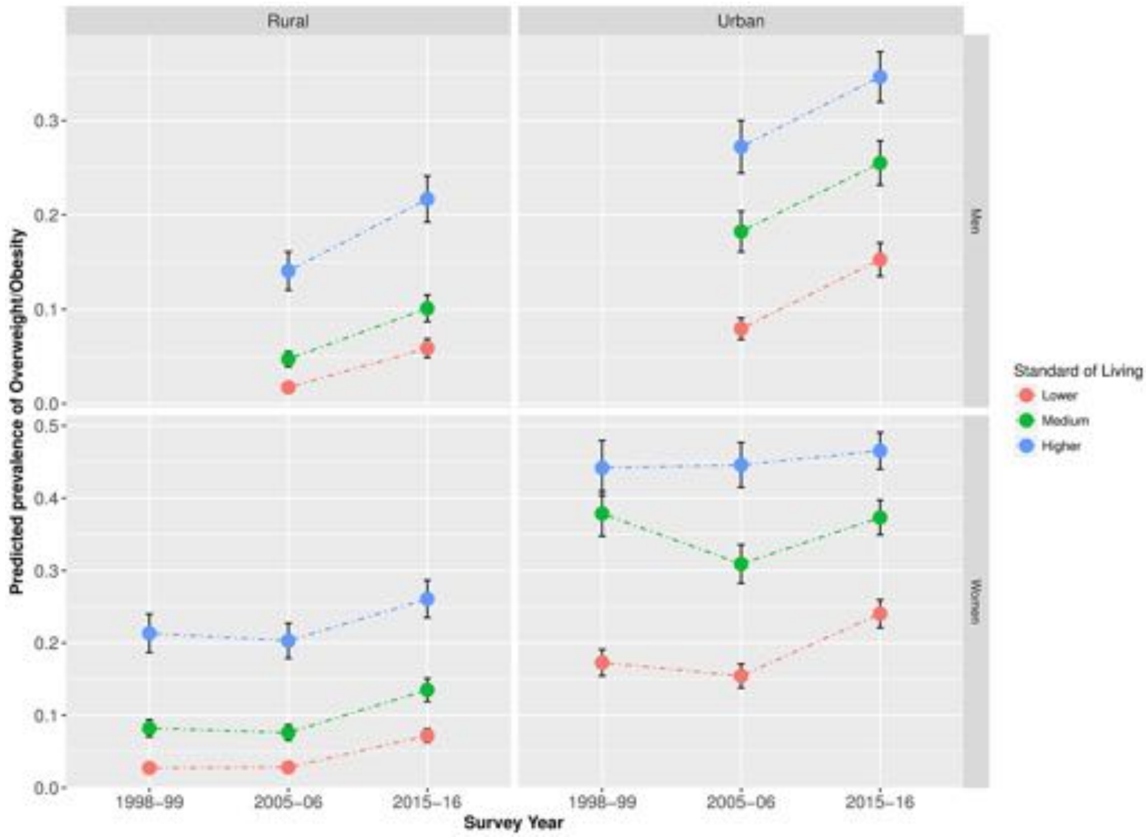

Figure 3 Predicted prevalence* of overweight/obesity in India by standard of living (1998–2016).

association between overweight/obesity and SEP we identified to be overestimated.

Our SoL index may also imperfectly capture household wealth. For instance, no indication about the quality of assets used in the measure were included, potentially misclassifying certain households.[20 27] However, as three broad SoL groups across a large data set were defined, we do not expect any misclassification to substantially bias our results. Additionally, the association between the true SEP and certain assets included in the SoL index may differ between urban and rural areas. We attempted to account for differences in the value of certain assets by calculating separate indices for urban and rural areas; however, differences in the value of some assets may still exist within broader geographical areas, for instance between states.

Finally, our results may mask variation in subnational prevalence and trends, especially given subnational differences between states in economic growth, demography and culture. For instance, research in India has found that in states with a higher prevalence of overweight, lower and higher SEP group may show a converging risk of overweight/obesity, whereas divergent trends have been identified in states with the highest proportion of underweight individuals.[28]

Comparison with other research

The only other India-specific national study we found on this topic did not identify any change in the overweight/obesity-SEP association between 1998–1999 and 2005–2006 in urban or rural India, with a persisting higher prevalence among high SEP groups.[29] Beyond 2005–2006, the authors predicted that future overweight/obesity prevalence would show a similar social patterning as they expected future economic gains to almost solely benefit higher SEP individuals. By contrast, the converging socioeconomic patterning of overweight/obesity we have identified in urban areas indicates that economic growth in the past decade may either have been more egalitarian than previously expected, the cost of high calorie food may have become less expensive or even the pool of susceptible higher SEP individuals may be becoming saturated.

Converging overweight/obesity prevalence between higher and lower SEP groups has been identified subnationally in India, when restricted to states defined by a high overall prevalence of overweight,[28] mirroring our finding in urban areas. This may suggest that convergence is restricted to areas that have moved beyond the earliest stages of the epidemiological transition.

Though not reported in previous nationally representative studies in India, a converging socioeconomic patterning of overweight/obesity has been noted in some other low-income and middle-income countries, where the highest increases in overweight prevalence have been found among women working in manual labour,[30] among the lowest wealth and income groups[31–33] and among rural residents.[34]

Potential mechanisms

In rural areas, we identified similar increases in prevalence among individuals from all SEP groups. Some studies suggest that in low-income settings, increases in overweight and obesity are restricted to higher SEP individuals, which may be due to changing dietary patterns towards fatty and sugary convenience foods[9–13 35]; however, the rising prevalence among lower SEP individuals indicates that they may also be increasingly exposed to high-calorie foods. Some researchers have also suggested that this mechanism is stronger in low-income or rural settings due to more favourable perceptions of large body sizes across socioeconomic status.[13 36–38]

In urban India, the greater increase in overweight/obesity prevalence among lower SEP individuals mirrors similar findings from places at relatively later stages of economic development, where some researchers have suggested that lower SEP individuals may be priced out of affording relatively expensive low-calorie healthy diets.[13 39–41] Additionally, lower SEP individuals in urban areas may be more exposed to sedentary lifestyles driven by technological advances replacing manual energy-exerting labour and improved transport links.[42 43] Increased health consciousness, in combination with the ability to afford low calorie diets, may explain why no notable change in overweight/obesity prevalence among the higher SEP urban population was found[13 44 45] in addition to the potential saturation of individuals susceptible to becoming overweight or obese.

Implications

Some studies argue that in India, NCD risk factors are almost exclusively an issue for higher SEP individuals.[46] However, our finding that overweight/obesity prevalence has increased among lower SEP individuals in both urban and rural areas implies that to consider overweight/obesity as 'diseases of affluence'[47] may not be appropriate in India's current context. Efforts to tackle the overall increasing overweight/obesity trend must be inclusive of both the urban and rural poor. This may be especially urgent due to the compounding effect of overweight/obesity and associated NCDs on infectious diseases, which are still highly prevalent among the poor.

Recent initiatives to raise population health include the launch of an integrated National Health Mission,[48] which aims to address deficiencies in healthcare delivery across the socioeconomic spectrum in urban and rural areas. Such initiatives may benefit from information about the increasing prevalence among low SEP Indians, as future action aimed at preventing overweight and obesity can be targeted accordingly. Due to the positive association of overweight and obesity with NCDs such as stroke and diabetes,[49 50] urgency is required in addressing this modifiable risk factor especially as it could compound existing health complications among poorer Indians, where communicable disease and undernutrition-related diseases already tend to be more prevalent.

CONCLUSION

Although India is still considered as a lower middle-income country, we have identified some convergence of overweight/obesity prevalence across SEP in urban areas among both men and women, with fewer signs of convergence across SEP groups in rural areas. Our findings suggest that an urgent response is needed to slow the increasing trend among poorer Indians, particularly as increasing exposure to overweight and obesity related diseases may compound an already high exposure to infectious diseases.

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Patient consent Not required.

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Provenance and peer review Not commissioned; externally peer reviewed.

Data sharing statement All datasets in this analysis are available at http://www.measuredhs.com.

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Do trends in the prevalence of overweight by socio-economic position differ between India's most and least economically developed states?

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Abstract

Background: India's economic development and urbanisation in recent decades has varied considerably between states. Attempts to assess how overweight (including obesity) varies by socioeconomic position at the national level may mask considerable sub-national heterogeneity. We examined the socioeconomic patterning of overweight among adults in India's most and least economically developed states between 1998 and 2016.

Methods: We used state representative data from the National Family Health Surveys from 1998 to 99, 2005–06 and 2015–16. We estimated the prevalence of overweight by socioeconomic position in men (15–54 years) and women (15–49 years) from India's most and least economically developed states using multilevel logistic regressions.

Results: We observed an increasing trend of overweight prevalence among low socioeconomic position women. Amongst high socioeconomic position women, overweight prevalence either increased to a smaller extent, remained the same or even declined between 1998 and 2016. This was particularly the case in urban areas of the most developed states, where in the main analysis, the prevalence of overweight increased from 19 to 33% among women from the lowest socioeconomic group between 1998 and 2016 compared to no change among women from the highest socioeconomic group. Between 2005 and 2016, the prevalence of overweight increased to similar extents among high and low socioeconomic status men, irrespective of residence.

Conclusions: The converging prevalence of overweight by socioeconomic position in India's most developed states, particularly amongst urban women, implies that this subpopulation may be the first to exhibit a negative association between socioeconomic position and overweight in India. Programs aiming to reduce the increasing overweight trends may wish to focus on poorer women in India's most developed states, amongst whom the increasing trend in prevalence has been considerable.

Keywords: State economic development, India, Overweight, Socioeconomic status, Urban/rural

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Background

The considerable rise in the prevalence of overweight (including obesity) in India, where over a billion people reside [1–4], presents a serious public health concern given the association of overweight with increased non-communicable disease (NCD) risk [5].

In the early stages of economic development and urbanisation, overweight and obesity prevalence tends to be higher among individuals of a higher socioeconomic position (SEP), arguably due to an increased financial capability to meet and exceed nutritional requirement [6–9]. As societies develop economically, the prevalence of overweight increases among the poor and rural population [6–14].

Since India's economic liberalisation in the early 1990 [15], economic growth has not been uniformly distributed across the country. In addition to considerable heterogeneity in culture, customs and diet, the current levels of economic development between India's states varies substantially. For example, the Gross Domestic Product of Delhi is eight times greater than that of the state of Bihar [16]. Consequently, the prevalence of overweight, and the extent of the increase in its prevalence in recent decades, varies considerably sub-nationally [1–3]. For instance, in Bihar, the prevalence of overweight among women increased from 3.7 to 11.7% (an absolute increase of 8%) between 1998 and 2016, whereas in Delhi, the prevalence increased from 12 to 33.5% over the same period (an absolute increase of 21.5%) [1]. However, little is known about variation in the sub-national socioeconomic patterning of overweight.

In this paper, we aimed to understand how recent trends in the association between overweight and SEP differ between India's most and least economically developed states between 1998 and 2016, a period in which India's Gross Domestic Product per capita quadrupled from US$432 to US$1750 [17]. The main rationale for this study was to unmask subnational heterogeneity in trends in the association of overweight and SEP in India not observed when analysing national trends. Demonstrating this would imply that national-level trends may not be generalisable at a subnational level [18]. A study of this nature is of importance as health policy is dictated at the state level; therefore, estimating the prevalence by state development and urban and rural areas may highlight different immediate health policy priorities between less and more developed states.

We conducted secondary analysis, using repeated cross-sections from state-representative data from 1998 to 2016 to estimate the prevalence of overweight in India by SEP in the five most and least economically developed states in India. In more economically developed societies, there is usually higher prevalence of overweight among poorer individuals where, for instance, there is a higher exposure to relatively cheaper fatty foods [6, 9, 19]. This is more likely to be the case in urban areas, where risk factors for overweight are usually much greater. We therefore hypothesise that in India's most developed states, we will observe a considerable increase in the prevalence of overweight among lower SEP individuals and relatively smaller increases among higher SEP individuals. On the other hand, in India's least developed states, we expected to find larger increases among higher SEP individuals, compared to lower SEP individuals. This is supported by the fact that poorer individuals in societies with lower levels of economic development are more likely to be unable to afford to meet nutritional requirements, whereas the relatively rich may be more exposed to overweight due to a greater access to excess food [6, 9].

Data

We used the National Family Health Survey (NFHS) Surveys 2 (1998–99), 3 (2005–06) and 4 (2015–16). All three surveys collected health and demographic data on women aged 15–49, whereas surveys 3 and 4 collected data on men aged 15–54. The sampling method was designed to include a nationally-representative sample of individuals within a nationally-representative sample of households. Additionally, in India, the NFHS surveys are also representative at the level of the state.

The NFHS surveys select rural and urban samples separately. Specifically, in rural areas in all three waves analysed, rural samples were selected using two-stage sampling, whereby the first stage involved selecting primary sampling units (PSUs), or villages, with a probability proportional to size (PPS), and the second stage involved selecting random households from each village. In urban areas, NFHS 2 and 3 used a slightly different sampling procedure to the one in NFHS 4. In NFHS 2 and 3, three-stage sampling was adopted whereby in the first stage wards were selected with a PPS, in the second random census enumeration blocks (CEB) were chosen in each ward and, in the third, random households were chosen from each CEB [2, 3] On the other hand, NFHS 4 adopted a two-stage approach in urban areas, whereby CEBs served as the PSU, selected using a PPS, and households from each PSU randomly selected. Were a PSU to contain fewer than 40 households, the PSU was joined to the nearest PSU. The 2011 census helped determine the sampling frame in NFHS 4 [1].

In all three surveys Interviews used a uniform questionnaire and were conducted by survey teams. A woman's eligibility for the survey was determined by whether they were between ages 15–49 and, for the NFHS 3 and 4, whether they spent the previous night in the selected households. Men aged 15–54 in the households were eligible for the Men's survey in NFHS 3. Of the selected households in NFHS 4, a random sample of households were selected to determine eligibility for the men's survey [1].

In India there are currently 36 States/Union Territories. We restricted our analysis to states that have been in existence since the collection of the NFHS 2 survey. States created between the surveys were not considered in the analysis. We selected five states to indicate the most and least developed states as the study aimed to demonstrate a divergence in the trends in their socioeconomic patterning. Our primary objective was to highlight variation in trends in the socioeconomic patterning of overweight within India. We therefore chose not to include all the states in India as this would lead to the inclusion of states that are closer to the average level of per capita net state domestic product for India. As a result, we would risk placing states at similar levels of economic development in the Most and Least developed states categories, consequently underestimating the extent of the variation in trends.

Our classification of states was based on the per capita net state domestic product (PCNSDP) in 2014–15 using the base year 2011–12. The most economically developed states were Goa, Maharashtra, Sikkim, Haryana and Kerala with a PCNSDP ranging from ₹112,444 to ₹241,081, compared to an all India average of ₹72,805. The least economically developed states included Bihar, Assam, Uttar Pradesh, Manipur, and Madhya Pradesh with NSDPPC ranging from ₹23,223 to ₹44,809 [20]. We limited our sample to non-pregnant women, whose inclusion could bias the associations we sought to identify. This left a total of 96,365 women and 18,729 men in the most developed states category, and 289,200 women and 54,669 men, respectively, in the least developed states category.

As NFHS-2 only sampled ever-married women, we restricted our samples in 2005–06 and 2015–16 to this population to allow the comparability of the study population across surveys. Additionally, respondents with missing height and weight data were also omitted from the sample, leaving 76,050 women (12, 168 in 1998–99; 14,000 in 2005–06; 49,882 in 2015–16) and 18,729 men (8518 in 2005–06 and 10,211 in 2015–16) as the study population in the most economically developed states, and 213,195 women (22, 266 in 1998–99; 20,459 in 2005–06; and 170,470 in 2015–16) and 54,669 men (19,377 in 1998–99; and 35,292 in 2015–16) in the least economically developed states. As multi-stage sampling approaches were adopted in the collection of the NFHS, we included the sampling weights included in the data set to account for unequal selection probabilities.

Outcome

We used the Body Mass Index (BMI) variable included in the surveys (measured as the respondent's weight divided by the square of their height) to separate individuals into two groups: overweight (BMI over 24.99 kg/m^2), and not overweight (BMI 24.99 kg/m^2 or under). This categorisation is based on the WHO's recommended cut-offs for BMI classification [5]. Rather than split the continuous BMI measure into multiple subcategories of overweight, we used this classification as the main aim of the paper was to analyse trends in excess adiposity, and research has found an elevated risk of NCDs and mortality beyond a BMI of 24.99 kg/m^2 [21, 22]. We did not use a continuous measure of nutritional status, as observed population-level increases in BMI we would expect to observe over the study period could be driven by a both individuals moving into overweight categories, and individuals moving from underweight to normal weight; the latter of which does not capture increases in excess adiposity.

Height and weight information on women aged 15–49 in NFHS-2, 3 and 4, and men aged 15–54 in NFHS-3 and 4, were collected by specially trained investigators. A solar-powered SECA digital scale was used to measure the weight of respondents, with the NFHS-2 report claiming an accuracy of ±100 g. The height of respondents in NFHS-2 and 3 was measured using a measuring board designed for use in survey data collection. In NFHS-4, the Seca 213 stadiometer was used to collect respondent's height information [1–3].

Independent variables

Exposure of interest

We used a measure of educational attainment as our primary indicator of SEP. This was based on the answer to a question regarding the number of completed years of schooling, and respondents were assigned to one of the following education categories: No Education (0 years); Primary Education (1–5 years); Secondary Education (6–12 years); and Higher Education (12+ years). Higher levels of education can increase earning capability, along with the accumulation of employable skills, both of which make it a suitable proxy for SEP.

For sensitivity analysis we verified our results using a standard of living (SoL) asset-based index as an alternative measure of SEP. In surveys, measures of SEP are seldom examined in isolation, as one measure cannot adequately describe all socioeconomic differences in a health outcome [23]. As education and SoL capture different aspects of SEP, the pathways through which it is associated with overweight may also differ. For example, those with high education may work in more sedentary jobs [6–9], increasing their risk of overweight, whereas SoL may be positively associated with overweight through determining the ability to afford excess food

[6–9]. Some suggest that in low/middle income settings, where there is a substantial informal employment sector and earnings not in the form of monetary enumeration, household income may not be an appropriate measure of SEP. Rather, the stock of assets may be more reliable [24]. Data on household income to proxy SEP is likely to be very sensitive to seasonal fluctuations in repeated cross-sections and may not capture the true level of wealth of the household. Additionally, in transitioning societies, it may be more common to receive income 'in-kind' rather than monetary enumeration [25], and households may draw money from multiple sources [24], limiting the ability for respondents to adequately recall all income in a questionnaire.

We created our own SoL index using principal components analysis (PCA) after pooling the household surveys over time. The inputs we used into the PCA included information on the household's stock of assets, their access to services, and other household characteristics. We completed this process for urban and rural areas separately due to differences in the importance of different assets between urban and rural residents. The percentage of respondent households in urban and rural areas by characteristics used to build the SoL index in each survey is presented in Additional file 1: Table S1. We then ranked households based on this new index and assigned the first, second and last third of the weighted sample a SoL classification of 'Higher', 'Medium' or 'Lower' Standard of Living (SoL).

We examined the validity of the SoL index we created by comparing the ranking of households using the index from the pooled data, within one survey, and the survey-specific wealth index already included in the data. The correlation coefficient in each of the three surveys used was greater than 0.95, suggesting a very strong agreement with our measure and the household rankings determined the survey-specific index.

Covariates

Our final models were adjusted for the respondent's age (15–29; 30–39; and 40–49 (40–54 for men)) and marital status. Marital status was categorised as either 'currently married' or 'not currently married' and was included as married individuals have been found to be at higher risk of being overweight [26]. We would have also preferred to control for the respondent's occupation. Higher prevalence of overweight may be expected to be observed among individuals in more sedentary jobs [6–9], and sedentary labour may be expected to be more prevalent among higher SEP individuals. However, it was not possible to control for occupation in our research due to the fact that it was collected on a very limited subsample of the respondents in NFHS 4 (approximately 5% of women in the NFHS-4 national sample).

Methods

In our preliminary analysis, we calculated the weighted prevalence of overweight in each strata of the education SEP variable, separately for India's most and least developed states, by sex and urban/rural residence. We then calculated the ratio of the prevalence in the highest educational category to the lowest in each survey.

In order to account for the hierarchical nature of the data, in our main analysis we fitted multilevel logistic regressions with PSU-level random intercepts, for each sex, and urban/rural residence, separately. Failure to account for this deliberate clustering at the sampling stage of the data collection process would have caused us to underestimate the standard errors of our results. We used survey-specific interaction terms to estimate the log odds ratio of overweight in each category of our SEP exposure variables, relative to the lowest category of each SEP variable, in each survey. We monitored changes in standard errors of the main SEP exposure variable in order to determine whether there was multicollinearity of the main exposure with added covariates. Coefficients from the adjusted models were subsequently converted to a predicted prevalence, with 95% confidence intervals, to make the results easier to interpret.

Results

The characteristics of respondents in the surveys used are presented in Table 1. In both the most and least developed states, the percentage of women with secondary education and in the Higher SoL category is higher in later surveys, compared to earlier ones. On the other hand, the percentage of women with no education and in the Lower SoL category decreases over the surveys. For example, in the most developed states, the percentage of women in the Higher SoL category increases from 16 to 65% between NFHS 2 and 4, whereas the percentage in the Lower SoL category decreases from 44 to 9%. The percentage of respondents classified as overweight increases in each successive survey. The largest increase was observed among women in the least developed states, where the percentage of overweight respondents increased from 6 to 19% between NFHS 2 and 4. Similar trends are found even when we do not limit our sample to non-pregnant and ever-married women (Additional file 1: Table S2).

In our preliminary analysis we found a consistent trend of increasing prevalence of overweight in both India's most and least developed states. This trend was found amongst both men and women in urban and rural areas (Fig. 1). As expected, the most developed states generally had a higher overall level of overweight

Table 1 Percentage* and number of study participants by key variables in each of the surveys

	Women 1998–99		Women 2005–06		Women 2015–16		Men 2005–06		Men 2015–16	
	%	Freq	%	Freq	%	Freq	%	Freq	%	Freq
Most developed states										
Overweight	18.24	2220	24.12	3377	27.26	13,598	14.19	1658	24.15	3323
Age 15–29	38.44	4677	33.84	4737	33.11	16,518	48.73	6041	44.76	7056
Age 30–39	36.05	4386	38.90	5446	36.15	18,033	25.58	3145	25.76	4054
Age 40–49 (54 males)	25.52	3105	27.26	3817	30.73	15,331	25.69	3088	29.48	4454
Urban	40.35	4910	49.40	6916	35.40	17,656	59.26	7294	37.31	5788
Rural	59.65	7258	50.60	7084	64.60	32,226	40.74	4980	62.69	9776
No Education	32.10	3905	23.64	3309	19.30	9626	6.98	1010	6.15	1292
Primary	18.85	2294	15.43	2160	13.57	6771	13.85	1741	10.20	1856
Secondary	35.93	4371	50.21	7030	54.48	27,178	63.25	7624	64.47	9784
Higher	13.13	1597	10.72	1501	12.64	6307	15.92	1895	19.18	2632
Lower SoL	44.28	5373	30.39	4250	8.97	4447	36.43	4524	8.74	1693
Middle SoL	39.74	4822	34.77	4862	26.18	12,985	34.52	4335	24.97	4418
Higher SoL	15.99	1940	34.84	4873	64.85	32,161	29.05	3406	66.29	9351
Married	93.41	11,366	93.24	13,053	94.16	46,971	58.96	7339	62.11	9961
Not Married	6.59	802	6.76	947	5.84	2911	41.04	4935	37.89	5603
Least developed states										
Overweight	6.00	1336	14.67	3002	18.51	31,546	9.56	1853	12.88	4544
Age 15–29	46.49	10,352	39.32	8044	36.88	62,868	51.00	9882	49.02	17,300
Age 30–39	32.19	7168	35.94	7353	34.71	59,173	24.87	4819	24.16	8527
Age 40–49 (54 males)	21.32	4746	24.74	5062	28.41	48,429	24.13	4676	26.82	9465
Urban	20.50	4564	40.75	8338	22.98	39,174	46.62	9034	27.55	9724
Rural	79.50	17,702	59.25	12,121	77.02	131,296	53.38	10,343	72.45	25,568
No Education	62.67	13,951	48.88	9999	44.43	75,735	16.12	3122	16.49	5820
Primary	14.22	3166	13.52	2766	14.29	24,364	13.77	2667	14.14	4990
Secondary	16.14	3594	28.94	5921	33.91	57,798	53.78	10,416	55.35	19,535
Higher	6.96	1550	8.66	1771	7.38	12,573	16.34	3164	14.02	4947
Lower SoL	69.21	15,333	55.29	11,301	30.03	47,214	51.81	10,032	28.21	9164
Middle SoL	24.98	5534	27.13	5546	38.52	60,571	28.53	5525	38.99	12,667
Higher SoL	5.81	1288	17.58	3594	31.45	49,457	19.66	3806	32.80	10,654
Married	94.24	20,984	94.61	19,356	95.42	162,655	60.84	11,788	62.35	22,006
Not Married	5.76	1282	5.39	1103	4.58	7815	39.16	7589	37.65	13,286

*All percentages are based on unweighted proportions

prevalence compared to the least developed states, and especially in urban areas and among women.

We found a higher relative increase in overweight prevalence in India's least developed states. Whereas the prevalence among urban women doubled from 17 to 34% in the least developed states between 1998 and 2016, the prevalence increased from 24 to 39% among urban women in the most developed states. Similarly, in among rural women, overweight increased nearly five-fold, from 3 to 14%, in the least developed states, compared to an increase from 10 to 23% in the most developed states.

Although the prevalence of overweight increased among individuals of all educational attainments, the extent of the increase in prevalence over the study period was consistently highest among those with lower levels of education (Table 2). This was reflected in a declining the ratio of prevalence among those with higher education compared to those with no education. For example, in urban areas of India's most developed states,

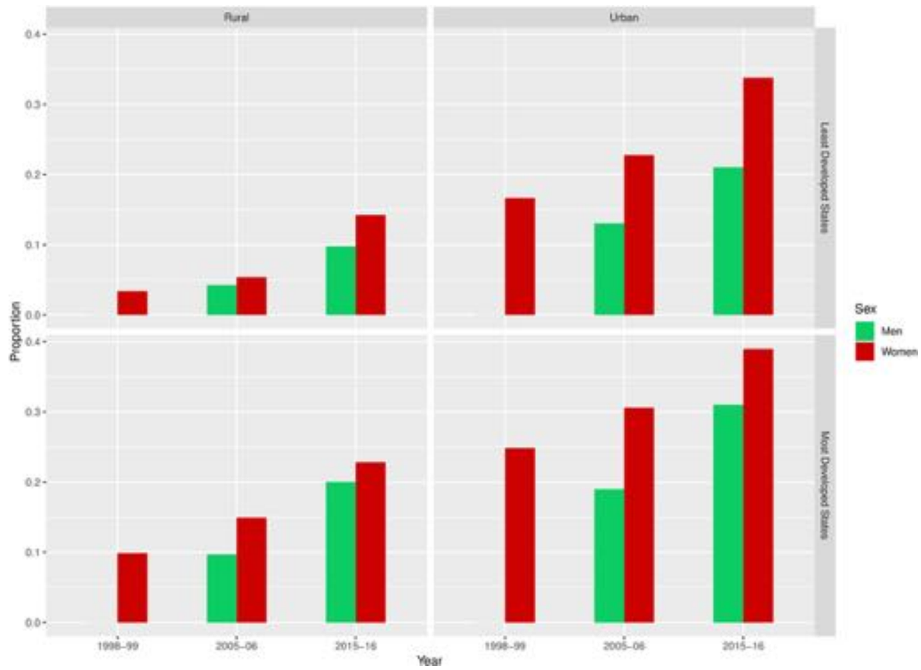

Fig. 1 Prevalence of overweight in 1998–99, 2005–06 and 2015–16 in urban and rural India

the prevalence of overweight was 5.14 times higher among highly educated women than women with no education in 1998–99 compared to 1.79 times higher in 2015–16.

Notably, the smallest ratio was reported among women in 2015–16 in urban areas of the most developed states, whereas the highest ratio among women was found in rural areas of the least developed states. Among men, the lowest ratio was found among rural residents in the most developed states, whereas the highest was found in rural areas of India's least developed states.

In our adjusted analysis we found that the difference in prevalence between the highest and lowest SEP category generally declined among women between 1998 and 99 and 2005–06 (Figs. 2 and 3). The largest decline in this difference was among women in the most developed states, where we observed

Table 2 Percentage* of respondents classified as overweight by education level

		Most developed states					*Least developed states*				
		Women			*Men*		*Women*			*Men*	
		1998–99	*2005–06*	*2015–16*	*2005–06*	*2015–16*	*1998–99*	*2005–06*	*2015–16*	*2005–06*	*2015–16*
*Education***											
Rural	*No Education*	4.09	7.90	16.52	4.31	13.85	2.43	3.69	11.74	2.21	6.29
	Primary Education	10.07	15.46	20.73	8.13	19.81	4.44	6.23	14.31	1.64	7.42
	Secondary Education	13.74	18.43	24.51	9.41	19.31	6.33	9.86	17.51	4.45	9.88
	Higher Education	20.99	28.20	29.51	19.27	25.54	11.01	16.47	22.38	15.37	18.57
	Ratio (Higher: No education)	5.14	3.57	1.79	4.47	1.84	4.53	4.46	1.91	6.94	2.95
*Education***											
Urban	*No Education*	16.62	21.27	34.77	11.71	15.90	8.98	14.38	28.74	4.61	14.59
	Primary Education	21.10	25.62	37.07	13.61	29.46	13.05	19.92	29.68	7.00	15.28
	Secondary Education	25.42	32.54	39.79	17.70	28.43	18.87	27.74	34.80	11.24	19.42
	Higher Education	35.16	37.70	40.21	27.52	40.79	29.34	37.75	42.10	26.39	30.55
	Ratio (Higher: No education)	2.12	1.77	1.16	2.35	2.56	3.27	2.63	1.47	5.72	2.09

*All percentages were calculated using sampling weights
**Chi-squared test *p* value of the variable's association with overweight: $p < 0.001$

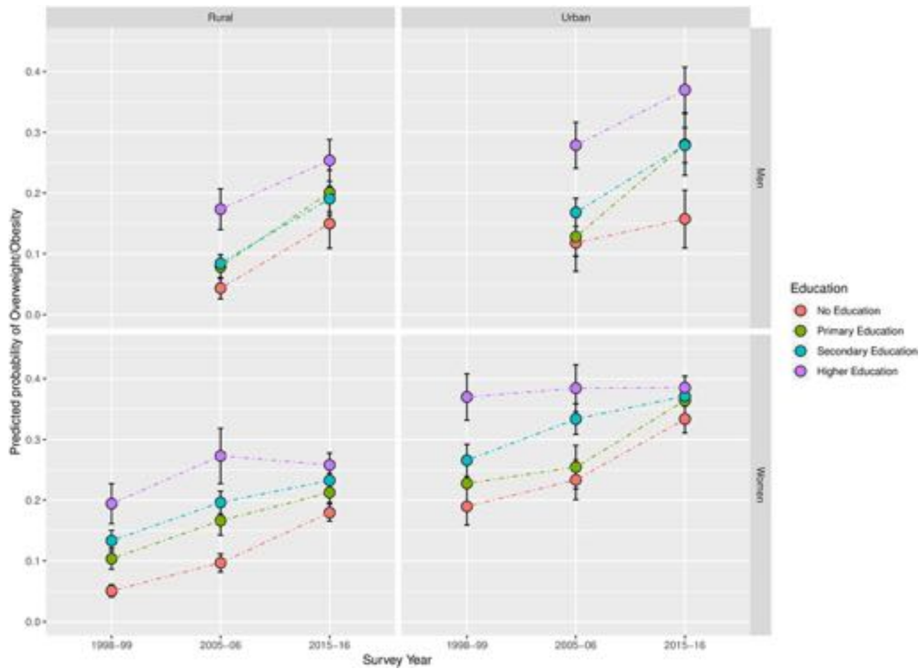

Fig. 2 Predicted prevalence of overweight by Education Level between 1998 and 99 and 2015–16 in India's most developed states

substantial increases among women with low educational attainment between 1998 and 2016, and no notable increase among women with higher education. In the least developed states, we observed increases in overweight prevalence among women of all educational attainments, however, the increases were to a greater extent among women with little or no education.

Although the overall prevalence of overweight is consistently higher among urban women than rural women, we found no notable differences between them in their socioeconomic patterning trends. We

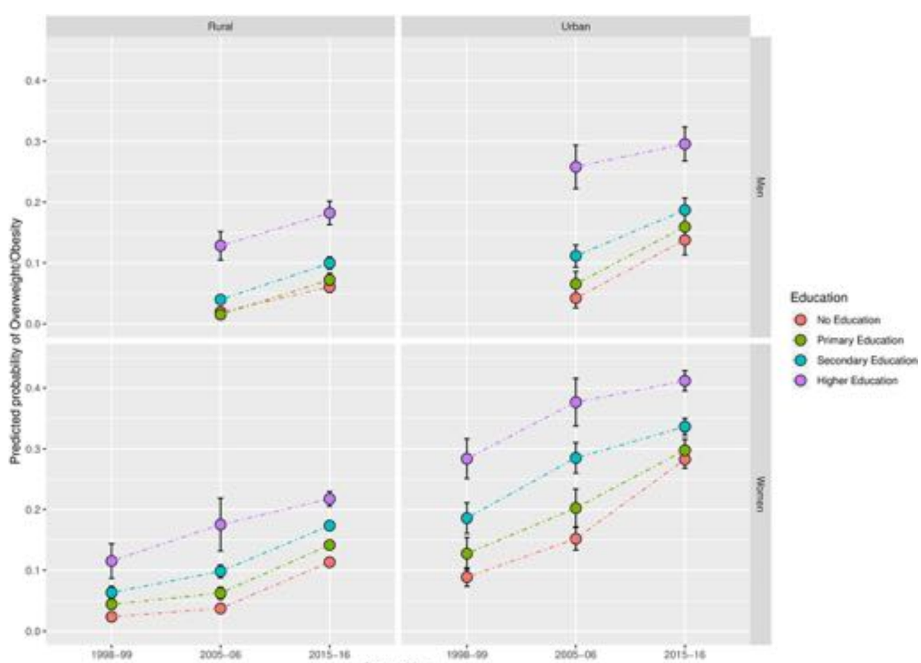

Fig. 3 Predicted prevalence of overweight by Education Level between 1998 and 99 and 2015–16 in India's least developed states

identified very limited evidence of a smaller difference of overweight prevalence between men with higher education and no education in 2015–16 compared to 2005–06.

Sensitivity analysis

Results of our sensitivity analysis are presented in Table 3, and in Figs. 4 and 5. Using the SoL index as the main exposure, shows a similar trend of a notable convergence of overweight prevalence across SEP among women, particularly in urban areas of India's most developed states. Additionally, it supports the considerably more mixed trend of overweight patterning among men we identified when using education as the exposure of interest.

Discussion

Statement of findings

This study has found that the trends in the socioeconomic patterning of overweight in India varied between India's most and least developed states between 1998 and 2016. When examining the difference between overweight prevalence in the highest and lowest SEP groups, we found a converging trend of overweight prevalence across SEP among women between 1998 and 2016. As expected, this trend amongst women was more pronounced in India's most developed states, particularly in urban areas, however, similar trends were observed in the least developed states and in rural areas. The converging trend amongst women appears to be driven by relatively smaller increases, and in some cases a decline, in the prevalence of overweight in higher SEP groups compared to lower SEP groups. This convergence appears to be limited to women, as amongst men, we did not identify any notable convergence in the socioeconomic patterning of overweight between 2005 and 2016. Using SoL as the main exposure of interest, we found similar, albeit a more attenuated convergence in the socioeconomic patterning of overweight.

Few studies have examined sub-national variation in the association of SEP and overweight in countries that have undergone rapid economic development. The only similar study we identified in India used a standard of living index as the primary exposure and reported a similar converging trend in the prevalence of overweight across SEP in states with a high overall prevalence of. On the other hand, they identified a diverging trend in Standard of Living in states with a high prevalence of underweight amongst women between 1998 and 2006 [27]. Our more up-to-date examination of sub-national trends in additional subpopulations suggests a more nuanced picture of the socioeconomic patterning. Notably we find no evidence of a diverging trend of overweight across SEP in any of the subpopulations, and that there are notable differences in the trends between the sexes and urban and rural areas.

Although there still remains a positive association between SEP and overweight across all the subpopulations we analysed in India, studies in other countries have identified a negative association between SEP and excess weight in more economically areas of countries that have undergone rapid economic development. One study in Brazil found a positive association between obesity and per capita household income in both more and less economically developed regions of Brazil in 1974/75. By 1996/97 the association was negative in the more economically developed regions, whereas the positive association in the less developed regions persisted [28]. This suggests that Brazil's more developed regions in 1996/97 may

Table 3 Percentage* of respondents classified as overweight by Standard of Living

		Most developed states					*Least developed states*				
		Women			*Men*		*Women*			*Men*	
		1998–99	*2005–06*	*2015–16*	*2005–06*	*2015–16*	*1998–99*	*2005–06*	*2015–16*	*2005–06*	*2015–16*
*SoL***											
Rural	*Lower SoL*	3.13	4.29	7.63	2.76	7.91	1.88	2.37	7.13	1.70	4.70
	Middle SoL	9.66	10.96	12.96	6.41	9.57	5.02	6.94	12.28	4.83	7.77
	Higher SoL	24.79	27.42	27.25	18.10	23.98	16.04	19.96	25.21	16.49	17.67
	Ratio (Higher: Lower SoL)	7.92	6.39	3.57	6.55	3.03	8.54	8.41	3.53	9.68	3.76
*SoL***											
Urban	*Lower SoL*	16.62	19.6	26.48	10.98	19.88	11.48	13.58	20.36	5.55	11.15
	Middle SoL	39.06	32.62	38.53	23.36	27.48	33.06	29.27	34.72	17.19	21.69
	Higher SoL	49.64	46.5	44.45	29.04	38.76	38.29	43.79	44.83	31.13	30.69
	Ratio (Higher: Lower SoL)	2.99	2.37	1.68	2.64	1.95	3.34	3.22	2.20	5.61	2.75

*All percentages were calculated using sampling weights

**Chi-squared test p value of the variable's association with overweight: $p < 0.001$

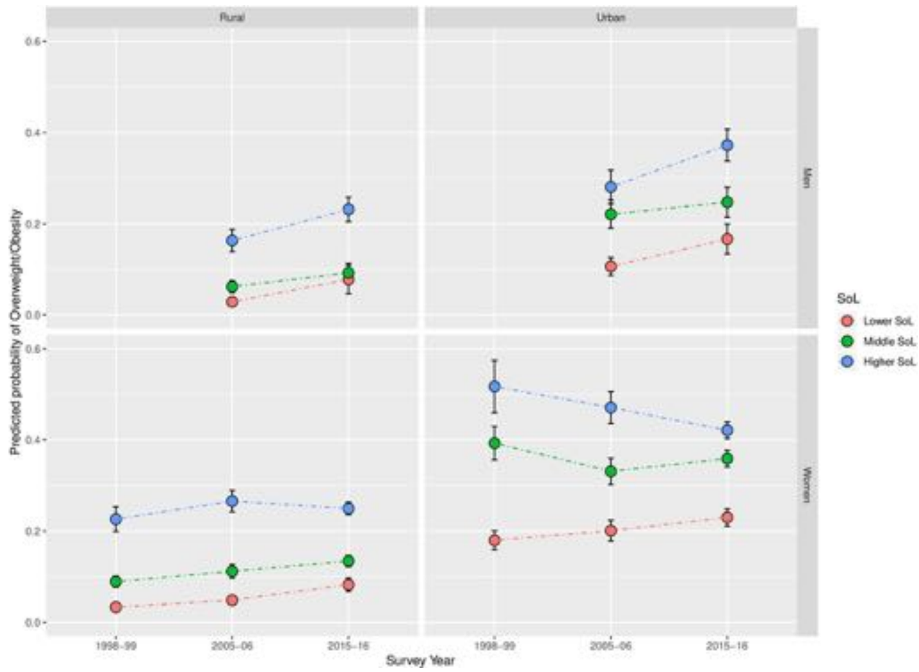

Fig. 4 Predicted prevalence of overweight by SoL between 1998 and 99 and 2015–16 in India's most developed states

have been at a more advanced stage of the epidemiological transition than India's most developed states currently. Other studies using measures of household income and educational attainment as the primary exposures and focusing on women in China's most economically prosperous regions have also found a negative association between SEP and prevalence of overweight [29, 30].

We also identified a particularly notable convergence in the prevalence of overweight by SEP among women when compared to men. Other studies have identified similar differences by sex. One study in China found

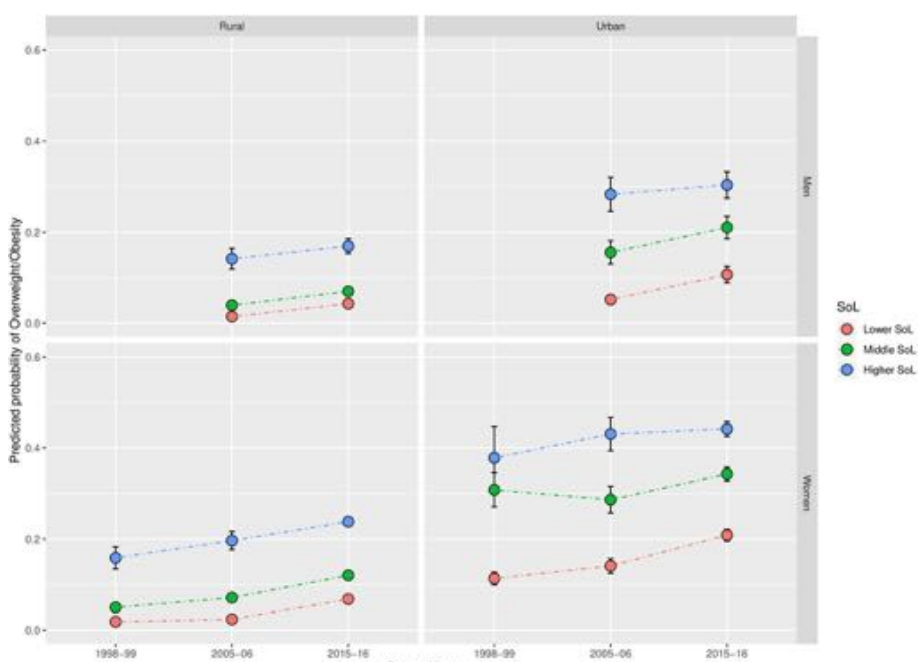

Fig. 5 Predicted prevalence of overweight by SoL between 1998 and 99 and 2015–16 in India's least developed states

high-income men and women with low education to be at highest risk of obesity in an economically prosperous province [29]. Another study in China found that higher education was associated with lower odds of overweight among women and higher odds of overweight among men [30]. In South Korea, a country that experienced a remarkable pace of economic growth in previous decades [31], one study still found a positive association of income with obesity among men, whereas they found a negative association among women [32].

The increased capacity of higher SEP individuals to afford to consume excess food [6–9] is a commonly suggested reason as to why the association between overweight and SEP is positive in low- or low-middle-income countries like India. However, the smaller difference in overweight prevalence between lower and higher SEP women in India's most developed states, particularly in the most recent period, may be due to an increased ability to afford expensive healthy foods and an increased level of health consciousness among higher SEP individuals [6, 33, 34]. On the other hand, particularly in India's most developed states, lower SEP individuals may be increasingly able to afford cheap high calorie fatty foods [6, 35].

Our study has some limitations. Firstly, we would have ideally liked to have used additional indicators of excess adiposity to complement our findings. BMI may be limited in that it cannot distinguish between lean mass and body fat, nor does it have information on the distribution of body fat, potentially making it an inaccurate measure of central adiposity [36]. However, other studies have shown a strong correlation of BMI with measures of central adiposity among Indians, such as waist circumference [37]. Consequently, we would not expect the trends we report to vary considerably between adiposity measures. Another possible limitation associated with our use of the BMI variable to inform our main outcome of interest is the potential difference in the body fat percentage at any given BMI between higher and lower SEP groups. Research amongst children from higher income countries have shown that lower SEP groups may have a higher percentage of body fat at any given BMI compared to higher SEP groups [14, 38]. Although this may be limited to high income societies, we are unable to verify the association of body fat and BMI in our data as the NFHS does not collect body fat information. Were a similar phenomenon observed in India, this would imply a more rapid convergence in the socioeconomic patterning of overweight in India than we have reported.

We limited our study population of women in 2005–06 and 2015–16 to ever-married women, as this was the sampled population in 1998–99. However, a slightly higher proportion of the sample was never-married in 2015–16 (22.5%) than in 2005–06 (19.5%). Additionally, the prevalence of overweight is lower among never-married than in currently married women (prevalence of overweight was 6.6% and 25% among never married and currently married women, respectively, in 2015–16). This may have led us to potentially overestimate the prevalence we reported for 2015–16 and therefore underestimate the extent of convergence overweight prevalence across SEP (see Additional file 1: Table S3).

There are some slight differences in the rankings of states by PCNSDP in 2005–06 and 1998–99 compared to in 2014–15. For example, in 2005–06, the state of Odisha had a slightly lower PCNSDP than Manipur. Additionally, Gujarat's economy is 19% larger than Sikkim's in 2005–06, however, Sikkim's economy almost tripled within a decade [20]. These discrepancies are however, unlikely to change the overall message of the study, and instead inclusion of these states is expected make results more relatively conservative.

Another limitation of our study involves our use of the standard of living index based in part on the ownership of assets. Common criticisms of an asset-based index like the one we used, includes the fact that it makes little accommodation for the quality of assets [24, 39], potentially leading to misclassification of households. For instance, televisions in poorer households may only receive terrestrial transmission, whereas in higher SEP households may receive digital transmission. Despite this, the simple collection of asset ownership information is not expected to affect the variable substantially [39]. Additionally, as we used three broad SoL categories across a large data set, any misclassification is not expected to be substantial. Another criticism of asset indices is that certain assets are likely to have different importance between broad geographical areas. Although we attempted to remedy this to an extent by calculating separate SoL indices in urban and rural areas, the importance of some assets may still differ between other geographical levels of aggregation [18]. Despite these issues, asset-based indices offer an affordable and stable long-term measure of household wealth for large surveys in low-income settings [24]. Furthermore, our use of two different measures of SEP in this study ensures that we have captured a large portion of the avenues through which SEP and overweight are associated.

Finally, the cross-sectional nature of the data we used did not enable us to draw conclusions about the causal relationship between overweight and SEP. Although this was not an explicit study aim, such information may have enriched our understanding of the reasons as to why overweight is more prevalent among particular socioeconomic groups in India.

Despite these limitations, we use the most recent state representative data, making our findings both generalisable and the most current estimates of these trends.

Some have suggested that overweight is a 'disease of affluence' in low and low-middle income countries [40, 41]. We find evidence of a much more nuanced picture of the socioeconomic patterning of overweight, when we examine sub-national trends. Whereas it may be an appropriate description of the positive associations between SEP and overweight we identified, were the identified trends to continue especially among women in India's more economically developed states, there may be a negative association in the coming years. We find no evidence that were past trends to continue, there would be any change to the socioeconomic pattering among men.

The markedly higher increase in overweight among lower SEP Indians will be an important consideration in the near future as state governments are already tasked with tackling the burden of infectious diseases within this demographic. A state-specific approach will be needed to face the challenge of raising general access to staple foods whilst simultaneously trying to lower demand for unhealthy foods [27, 42–44]. Additionally, attempts to close the difference in the association of overweight with SEP between men and women may wish to focus on improving health-related behaviors among men.

Conclusion

Although the association between SEP and overweight is still positive, a continuation of past trends suggests that urban areas of the most developed states in India may be the first to show a negative association commonly seen in high-income countries. The success of policies to slow the increasing prevalence of overweight may depend on understanding how trends in socioeconomic patterning of overweight have developed and may continue to develop in the future.

Additional file

Additional file 1: Table S1. Percentage of households with the following assets/characteristics by survey and urban/rural residence – presents the ownership of assets and household characteristics by urban and rural residence across India in the three NFHS surveys used. **Table S2**. Percentage of the full women's sample (including pregnant and never-married women) in each strata of the SEP exposures and the outcome – presents the distribution of the data across the SEP variables and main outcome in the full sample of women. **Table S3**. Predicted prevalence of overweight from the regression model in India's least developed states (using the full sample of women including pregnant and never married women) – demonstrates potential underestimation of the convergence in socioeconomic patterning of overweight in least developed states when including never-married women and pregnant women. (DOCX 17 kb)

Abbreviations

BMI: Body mass index; NCD: Non-communicable disease; PCNSDP: Per capita net state domestic product; SEP: Socioeconomic position; SoL: Standard of living

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Authors' contributions

The authors' responsibilities were as follows: SL and SK designed the study; SL performed the data analysis and takes responsibility for the final content; SL and PACM interpreted the results; SL drafted the manuscript; PACM, LC and SL made substantive revisions to the manuscript; PACM, LC and SK reviewed and approved the final manuscript. All authors read and approved the final manuscript.

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Availability of data and materials

The datasets supporting the conclusions of this article are available in the Measure DHS repository, https://dhsprogram.com/data/available-datasets.cfm. Data is available from the MEASURE DHS project upon reasonable online request after submission of concept paper.

Ethics approval and consent to participate

The analysis of secondary data was approved by the London School of Hygiene and Tropical Medicine's Research ethics committee (ref: 12097). We obtained approval from Measure DHS to access the data.

Consent for publication

Not Applicable.

Competing interests

The authors declare that they have no competing interests.

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Publisher's Note

Appendix Three. Additional Files to Chapter Five

Table 23. Predicted percentage prevalence of overweight/obesity in India by SEP among adult women (1998-2016)

		Rural			Urban		
Year	***Standard of Living***	***Predicted percentage prevalence***	***Lower bound***	***Upper bound***	***Predicted percentage prevalence***	***Lower bound***	***Upper bound***
1998-99	*Lower*	2.7	2.3	3.2	17.3	15.5	19.1
	Medium	8.2	7.0	9.4	37.9	34.8	41.0
	Higher	21.3	18.7	24.0	44.2	40.4	48.0
2005-06	*Lower*	2.8	2.4	3.3	15.4	13.8	17.1
	Medium	7.6	6.5	8.7	30.9	28.3	33.6
	Higher	20.3	17.9	22.7	44.6	41.5	47.7
2015-16	*Lower*	7.2	6.3	8.2	24.0	22.1	26.0
	Medium	13.5	11.9	15.1	37.3	34.9	39.7
	Higher	26.1	23.5	28.7	46.5	44.0	49.1

Table 23 continued…

		Rural			Urban		
Year	***Education***	***Predicted percentage prevalence***	***Lower bound***	***Upper bound***	***Predicted percentage prevalence***	***Lower bound***	***Upper bound***
1998-99	*No Education*	4.1	3.5	4.7	14.7	12.9	16.4
	Primary	8.9	7.6	10.2	20	17.7	22.3
	Secondary	11	9.5	12.5	27.3	24.9	29.7
	Higher	15.8	13.3	18.3	35.5	32.5	38.5
2005-06	*No Education*	5.1	4.4	5.8	17.5	15.7	19.4
	Primary	9.1	7.8	10.4	21.9	19.7	24.2
	Secondary	12.1	10.5	13.7	29.5	27.1	31.9
	Higher	18	15.1	21.0	38.5	35.4	41.6
2015-16	*No Education*	13.9	12.2	15.5	31.8	29.6	34.0
	Primary	18.4	16.4	20.4	35.9	33.6	38.3
	Secondary	21.1	18.9	23.2	38.6	36.3	41
	Higher	25.1	22.5	27.6	41.4	38.9	43.8

* Predicted percentage prevalence and confidence intervals are based on multivariate regressions, and the models adjust for the respondent's age, current marital status and the socio-economic variable not considered as the main exposure.

Table 24. Predicted percentage prevalence of overweight/obesity in India by SEP among adult men (2005-2016)

		Rural			Urban		
Year	***Standard of Living***	***Predicted percentage prevalence***	***Lower bound***	***Upper bound***	***Predicted percentage prevalence***	***Lower bound***	***Upper bound***
2005-06	*Lower*	1.7	1.4	2.1	7.9	6.8	9.1
	Medium	4.7	3.9	5.5	18.2	16.1	20.4
	Higher	14.1	12	16.1	27.2	24.4	30.0
2015-16	*Lower*	5.9	4.9	6.9	15.3	13.5	17.0
	Medium	10.1	8.7	11.5	25.5	23.2	27.8
	Higher	21.7	19.2	24.1	34.6	32	37.3

Table 24 continued…

		Rural			Urban		
Year	***Education***	***Predicted percentage prevalence***	***Lower bound***	***Upper bound***	***Predicted percentage prevalence***	***Lower bound***	***Upper bound***
2005-06	*No Education*	2.9	2.3	3.4	7.1	5.8	8.5
	Primary	4.0	3.2	4.7	9.4	7.9	10.9
	Secondary	5.7	4.8	6.6	13.0	11.4	14.6
	Higher	13.5	11.4	15.7	25.8	23.1	28.5
2015-16	*No Education*	10.0	8.6	11.5	17.1	14.9	19.3
	Primary	13.6	11.8	15.4	22.9	20.5	25.4
	Secondary	14.5	12.7	16.3	24.9	22.7	27.1
	Higher	23.1	20.5	25.7	34.4	31.8	37.1

* Predicted percentage prevalence and confidence intervals are based on multivariate regressions, and the models adjust for the respondent's age, current marital status and the socio-economic variable not considered as the main exposure.

Table 25. Predicted percentage prevalence of overweight/obesity in India by SEP among adult women (using South Asian BMI cut-offs) (1998-2016)

		Rural			Urban		
Year	***Standard of Living***	***Predicted percentage prevalence***	***Lower bound***	***Upper bound***	***Predicted percentage prevalence***	***Lower bound***	***Upper bound***
1998-99	*Lower*	7.4	6.4	8.4	29.7	27.3	32.1
	Medium	17.0	15.0	18.9	55.8	52.7	58.8
	Higher	35.8	32.5	39.1	62.4	58.9	65.9
2005-06	*Lower*	7.5	6.6	8.5	27.0	24.7	29.2
	Medium	17.3	15.3	19.2	47.8	44.9	50.6
	Higher	35.4	32.3	38.5	61.7	58.9	64.5
2015-16	*Lower*	17.3	15.5	19.1	40.0	37.6	42.3
	Medium	27.3	24.8	29.8	55.5	53.2	57.9
	Higher	44.0	41.0	47.1	65.5	63.4	67.7

Table 25 continued…

		Rural			*Urban*		
Year	***Education***	***Predicted percentage prevalence***	***Lower bound***	***Upper bound***	***Predicted percentage prevalence***	***Lower bound***	***Upper bound***
1998-99	*No Education*	10.0	8.7	11.2	26.0	23.6	28.4
	Primary	16.1	14.3	18.0	33.2	30.4	36.0
	Secondary	20.3	18.1	22.5	43.3	40.5	46.0
	Higher	30.2	26.8	33.6	51.8	48.8	54.8
2005-06	*No Education*	11.3	10.0	12.7	29.3	26.9	31.6
	Primary	17.7	15.7	19.7	36.2	33.4	38.9
	Secondary	23.4	21.0	25.7	44.6	42.0	47.2
	Higher	33.8	29.9	37.7	56.6	53.6	59.6
2015-16	*No Education*	27.6	25.1	30.0	48.4	46.1	50.8
	Primary	33.1	30.5	35.8	52.7	50.4	55.1
	Secondary	37.0	34.3	39.8	56.8	54.6	59.0
	Higher	42.1	39.0	45.1	61.3	59.1	63.6

* Predicted percentage prevalence and confidence intervals are based on multivariate regressions, and the models adjust for the respondent's age, current marital status and the socio-economic variable not considered as the main exposure.

Table 26. Predicted percentage prevalence of overweight/obesity in India by SEP among adult men (using South Asian BMI cut-offs) (1998-2016)

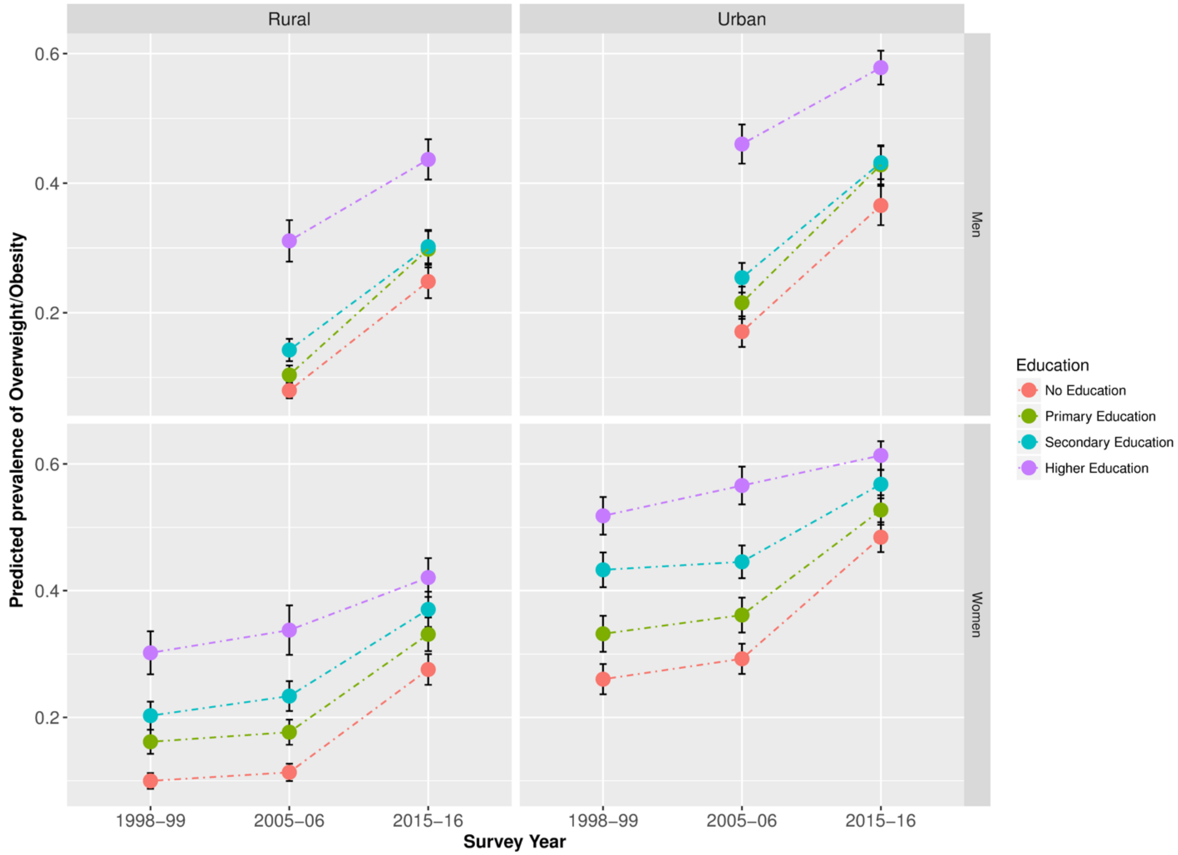
		Rural			Urban		
Year	***Standard of Living***	***Predicted percentage prevalence***	***Lower bound***	***Upper bound***	***Predicted prevalence***	***Lower bound***	***Upper bound***
2005-06	*Lower*	6.0	5.1	6.9	18.2	16.2	20.1
	Medium	13.3	11.6	15.0	33.1	30.4	35.9
	Higher	29.3	26.4	32.1	47.1	44.0	50.2
2015-16	*Lower*	17.7	15.6	19.8	31.9	29.3	34.5
	Medium	24.1	21.7	26.5	45.5	42.8	48.2
	Higher	40.0	37.1	43.0	56.8	54.2	59.5

Table 26 continued…

		Rural			Urban		
Year	***Education***	***Predicted prevalence***	***Lower bound***	***Upper bound***	***Predicted prevalence***	***Lower bound***	***Upper bound***
2005-06	*No Education*	8.0	6.8	9.2	17.1	14.7	19.4
	Primary	10.4	8.9	11.9	21.5	19.1	24.0
	Secondary	14.2	12.5	16.0	25.4	23.1	27.7
	Higher	31.1	27.9	34.3	46.0	43.0	49.1
2015-16	*No Education*	24.8	22.2	27.4	36.6	33.5	39.6
	Primary	29.8	27.0	32.6	42.8	39.8	45.9
	Secondary	30.2	27.6	32.8	43.2	40.6	45.7
	Higher	43.7	40.6	46.8	57.8	55.2	60.4

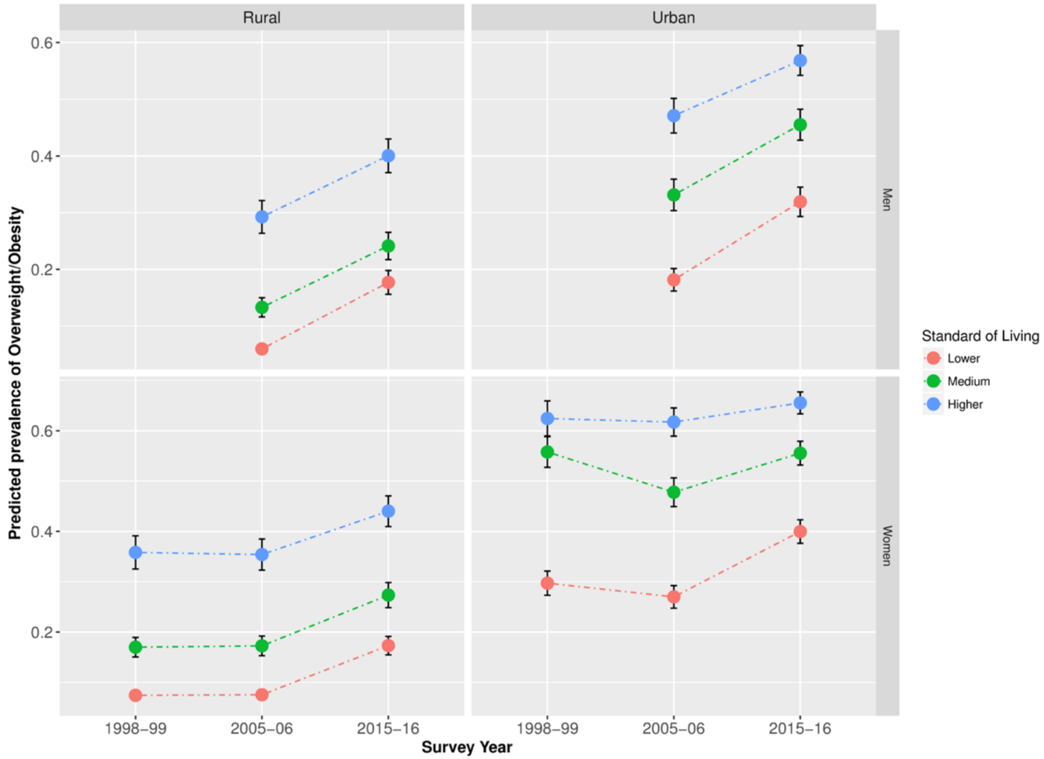
* Predicted percentage prevalence and confidence intervals are based on multivariate regressions, and the models adjust for the respondent's age, current marital status and the socio-economic variable not considered as the main exposure.

Figure 27. Predicted prevalence of overweight/obesity in India by Education (using South Asian BMI cut-offs) (1998-2016)



Predicted prevalence and confidence intervals are based on multivariate regressions, and the models adjust for the respondent's age, current marital status and the socio-economic variable not considered as the main exposure.

Figure 28. Predicted prevalence of overweight/obesity in India by Standard of Living (using South Asian BMI cut-offs) (1998-2016)



Predicted prevalence and confidence intervals are based on multivariate regressions, and the models adjust for the respondent's age, current marital status and the socio-economic variable not considered as the main exposure.

Appendix Four. Additional files to Chapter Six

Table 27. Percentage of households with the following assets/characteristics by survey and urban/rural residence

	1998-99		2005-06		2015-16	
	Urban	***Rural***	***Urban***	***Rural***	***Urban***	***Rural***
Asset						
Mattress	71.7	38.1	75.4	48.7	82.3	58.4
Pressure cooker	65.2	16.0	69.9	22.1	83.6	42.2
Chair	71.3	356.0	76.1	43.8	86.5	70.7
Cot/bed	86.1	79.4	86.3	81.2	88.5	88.3
Table	64.9	30.0	65.0	32.9	72.1	46.5
Clock/watch	90.1	57.5	91.0	71.4	90.8	71.4
Electric fan	82.2	31.4	84.7	38.6	95.1	69.1
Bike	53.5	45.7	50.1	51.6	45.0	55.9
Radio	53.2	32.2	38.9	27.0	10.3	7.0
Sewing Machine	35.5	11.9	30.9	12.6	33.5	19.0
Telephone	20.1	2.6	36.3	7.4	96.1	87.3
Refrigerator	28.8	3.7	33.5	6.6	54.2	16.4
Television (B+W)	44.8	17.0	25.6	18.7	3.1	3.5
Television (Colour)	27.3	3.5	51.5	12.5	86.0	51.5
Moped/Scooter/Motorcycle	25.0	6.0	30.5	10.8	51.5	30.3
Car	4.4	0.6	6.1	1.0	11.4	3.2
Water Pump	9.3	8.2	11.0	9.9	21.5	14.9
Thresher	0.7	2.5	0.4	2.2	0.6	1.9
Tractor	0.8	2.0	0.5	2.3	0.7	3.4
Characteristics						
Flush toilet/pit latrine	63.9	8.8	79.9	20.8	81.1	36.2
High quality house material	66.0	19.0	81.2	28.8	84.5	41.3
LPG/Electricity for cooking	47.7	5.3	59.6	8.3	79.3	23.4
Piped/handpump water source	92.6	72.3	92.3	81.1	86.4	84.6

Sources: NFHS 2 report; NFHS 3 report; NFHS 4 report

Table 28. Percentage of the full women's sample (including pregnant and never-married women) in each strata of the SEP exposures and the outcome

	Most developed states			***Least developed states***		
	1998-99	***2005-06***	***2015-16***	***1998-99***	***2005-06***	***2015-16***
Education						
No Education	31.7	18.1	15.4	62.7	40.2	34.8
Primary	18.7	13.2	11.1	14.3	12.9	12.7
Secondary	36.2	55.5	57.5	16.1	36.9	42.7
Higher	13.4	13.2	16.0	6.9	10.0	9.8
SoL						
Low SoL	44.6	29.3	8.7	69.5	53.1	29.2
Middle SoL	39.6	35.7	26.4	24.8	28.2	38.8
Higher SoL	15.8	35.1	64.9	5.7	18.7	32.1
Overweight/Obesity	17.8	19.7	22.6	5.9	11.9	14.9

Table 29. Predicted prevalence of overweight/obesity from the regression model (by Education level) in India's least developed states (using the full sample of women - including pregnant and never married women)

		Urban			*Rural*		
Survey		***Prevalence***	***Lower***	***Upper***	***Prevalence***	***Lower***	***Upper***
2005-06	*No Education*	14.6	12.9	16.3	3.5	3.2	3.9
	Primary	16.4	13.9	18.9	5.1	4.3	5.8
	Secondary	18.4	16.7	20.1	6.4	5.7	7.1
	Higher	27.6	24.7	30.5	11.6	8.9	14.4
2015-16	*No Education*	27.1	25.8	28.4	11.1	10.7	11.5
	Primary	25.3	23.8	26.8	12.0	11.5	12.6
	Secondary	23.7	22.7	24.7	11.0	10.6	11.4
	Higher	28.8	27.6	30.0	14.5	13.7	15.2

Appendix Five. Additional files to Chapter Nine

I calculated the Years of Life Lost (YLL) to diabetes as the difference of the life expectancy among the population without diabetes and the population with diabetes at every age, and calculated Quality-Adjusted Life Years Lost (QALYs) as the same difference, however, weighting a year spent with diabetes as a fraction (hereon referred to as a utility weight) of a year spent without diabetes[35]. A utility weight of one indicates that a year spent with diabetes has no detrimental effect on quality of life, whereas a utility weight of 0 indicates that the quality loss associated with a year spent with diabetes is equivalent to death. Most studies in South Asia use weights derived from developed countries[316]. However, others advocate for transferring sets of weights from existing sources calculated in proximate regional settings[320]. I used a range of utility weights from 0.50 to 0.95, by 0.05 increments, to provide a range of estimates of QALYs lost, in addition to adopting an age-distribution of diabetes-related sex-specific utility weights that were derived from a study in South Korea[321]. The former assumes that the weighing used to estimate QALYs is the same over the life course, whereas it may decrease in older age, especially given the higher propensity to develop diabetes related complications in older ages. The latter enabled me to account for the fact that years of life spent with diabetes will have less utility compared with years spent with diabetes as a people age.

In Table 30 I show the YLL and QALY to diabetes in urban India. Specifically, I find that a woman in urban India with diabetes can expect to live 2.35 fewer years at age 20, compared to women without diabetes of the same age. Among men the equivalent number of YLL at age 20 is 1.49 years. If a year spent with diabetes is weighted at half of a year with diabetes, I expect that a woman and man aged 20 with diabetes can expect to lose 18.87 and 19.07 QALYs. As expected, the remaining YLL to diabetes and QALYs decreases with age, however can be still substantial, with 4.92 and 4.54 QALYs lost by women and men, respectively, between ages 60 and 79 under the middle ground assumption of a year with diabetes having 25% lower utility than that of a year spent without diabetes (utility weight 0.75).

Assuming an age dependent distribution of utility weights extracted from the literature, I find 4.34 and 4.0 QALYs lost to diabetes at age 20 among women and men, respectively, whereas at age 60, the QALYs lost are 3.8 and 3.2 years among women and men, respectively.

The YLL to diabetes in India is less than the YLL reported in studies focusing on other countries. A recent study has reported that individuals in the United States with diabetes live 10 years less on average, compared to those without diabetes[141]. Another found 5.8 and 6.8 YLL among men and women aged 40, respectively in the United States, and a study in Australia reported a life expectancy difference of 6 years among people with and without diabetes. A national study in the United states found 4.4 YLL per person, associated with diabetes, compared to those without[322]. I generally find a considerably smaller gap in longevity among individuals with diabetes compared to those without. Even when using the same relative risk of dying among people with diabetes compared to those without diabetes, a population with a lower life expectancy will observe fewer lost YLL associated with diabetes, potentially explaining the lower YLL reported in my study compared to studies in other HICs.

Table 30. Years of Life Lost (YLL) and Quality Adjusted life years lost (QALYs) to diabetes (women) in urban India

	Age (years)	*YLL*	*QALY utility weight*										
		1	*AS**	*0.5*	*0.55*	*0.6*	*0.65*	*0.7*	*0.75*	*0.8*	*0.85*	*0.9*	*0.95*
Women	*20*	2.4	4.4	18.9	17.2	15.6	13.9	12.3	10.6	9.0	7.3	5.7	4.0
	40	2.3	3.8	13.0	11.9	10.9	9.8	8.7	7.6	6.6	5.5	4.4	3.3
	60	1.6	3.8	8.2	7.5	6.9	6.2	5.6	4.9	4.3	3.6	3.0	2.3
Men	*20*	1.5	4.0	18.1	16.4	14.8	13.1	11.5	9.8	8.1	6.5	4.8	3.1
	40	1.4	3.8	12.0	10.9	9.9	8.8	7.7	6.7	5.6	4.6	3.5	2.4
	60	1.3	3.2	7.8	7.2	6.5	5.9	5.2	4.5	3.9	3.2	2.6	1.9

*AS refers to age specific utility weights from South Korea reported in Ock et al (2015)

Appendix Six. Additional Files to Chapter Eight

Table 31. Percentage prevalence of overweight and obesity from the SAGE datasets (2002-04 and 2007-10) (Women)

	SAGE 0 (2002-04)			***SAGE 0 (2002-04)***			***SAGE 1 (2007-10)***			***SAGE 1 (2007-10)***		
Age	***Overweight***			***Obese***			***Overweight***			***Obese***		
	Point Est	***Lower***	***Upper***	***Point Est***	***Lower***	***Upper***	***Point Est***	***Lower***	***Upper***	***Point Est***	***Lower***	***Upper***
50-54	13.8	9.1	20.5	2.2	1.1	4.6	19.7	14.5	26.2	3.8	2.6	5.7
55-59	10.4	5.8	18.0	3.2	1.0	9.8	13.3	9.9	17.7	3.7	2.4	5.8
60-64	10.2	5.6	18.0	4.2	1.5	11.5	12.9	9.4	17.4	2.9	1.7	5.0
65-69	7.8	3.1	18.0	4.8	1.3	16.1	10.2	7.3	14.2	4.5	2.6	7.8

Table 32. Percentage prevalence of overweight and obesity from the SAGE datasets (2002-04 and 2007-10) (Men)

	SAGE 0 (2002-04)			***SAGE 0 (2002-04)***			***SAGE 1 (2007-10)***			***SAGE 1 (2007-10)***		
Age	***Overweight***			***Obese***			***Overweight***			***Obese***		
	Point Est	***Lower***	***Upper***	***Point Est***	***Lower***	***Upper***	***Point Est***	***Lower***	***Upper***	***Point Est***	***Lower***	***Upper***
50-54	7.8	4.1	14.1	1.0	0.3	3.3	11.6	7.4	17.7	3.1	1.7	5.5
55-59	17.8	10.0	29.6	1.9	0.5	7.0	9.6	6.8	13.5	1.0	0.4	2.3
60-64	8.1	4.5	14.4	0.3	0.1	1.1	6.5	4.4	9.5	1.1	0.5	2.2
65-69	3.8	1.9	7.3	2.3	0.4	12.1	5.9	3.3	10.3	0.9	0.3	2.7

Table 33. Percentage prevalence of overweight and obesity in NFHS datasets (2005-06 and 2015-16) (Women)

	Rural											
	Overweight (2005-06)			***Obese (2005-06)***			***Overweight (2015-16)***			***Obese (2015-16)***		
Age	***Point Est***	***Lower***	***Upper***	***Point Est***	***Lower***	***Upper***	***Point Est***	***Lower***	***Upper***	***Point Est***	***Lower***	***Upper***
20-24	3.0	2.3	4.0	0.4	0.2	0.7	6.4	5.2	7.8	1.32	1.0	1.8
25-29	5.2	3.9	7.0	0.8	0.6	1.2	11.4	9.6	13.5	2.36	1.8	3.1
30-34	7.3	5.6	9.6	1.4	0.9	2.3	15.4	13.3	17.8	3.83	2.9	5.0
35-39	9.7	7.5	12.6	2.0	1.2	3.2	17.4	15.2	19.8	4.80	3.7	6.2
40-44	10.9	8.6	13.8	2.8	1.7	4.3	18.6	16.3	21.2	5.27	4.3	6.5
45-49	12.5	9.9	15.7	3.2	2.0	5.2	20.0	17.3	22.9	5.58	4.4	7.1
	Urban											
20-24	8.9	7.4	10.8	1.9	1.4	2.6	11.7	10.3	13.3	3.3	2.6	4.0
25-29	15.9	14.1	17.9	4.3	3.5	5.2	20.5	19.0	22.1	6.6	5.5	7.8
30-34	22.3	19.7	25.2	6.8	5.5	8.4	27.4	25.5	29.4	10.6	9.4	11.9
35-39	25.3	24.1	26.5	9.9	8.4	11.6	29.7	28.4	31.0	13.3	11.8	14.9
40-44	28.4	26.6	30.3	13.5	10.8	16.7	33.4	31.8	35.1	16.1	14.5	17.8
45-49	29.4	27.5	31.4	12.8	11.0	15.0	34.1	32.7	35.5	16.9	14.9	19.2

*Lower and Upper refer to 95% confidence intervals

Table 34. Percentage prevalence of overweight and obesity in NFHS datasets (2005-06 and 2015-16) (Men)

Age	Rural											
	Overweight (2005-06)			*Obese (2005-06)*			*Overweight (2015-16)*			*Obese (2015-16)*		
	Point Est	*Lower*	*Upper*	*Point Est*	*Lower*	*Upper*	*Point Est*	*Lower*	*Upper*	*Point Est*	*Lower*	*Upper*
20-24	2.5	1.9	3.2	0.4	0.2	0.7	7.5	5.9	9.4	1.0	0.6	1.6
25-29	5.0	3.6	7.1	0.4	0.2	1.0	12.8	10.5	15.6	1.9	1.3	2.9
30-34	6.9	5.0	9.3	0.8	0.5	1.4	16.0	13.2	19.3	2.2	1.7	2.9
35-39	7.4	5.7	9.7	1.1	0.7	1.7	17.7	14.9	20.8	3.3	2.4	4.7
40-44	7.9	5.6	10.9	0.9	0.6	1.5	17.9	15.1	21.2	3.1	2.2	4.3
45-49	8.5	6.2	11.5	1.2	0.8	2.0	17.8	14.5	21.6	3.3	2.5	4.4
	Urban											
20-24	6.9	5.9	8.0	0.8	0.5	1.3	13.9	11.6	16.5	2.6	1.8	3.9
25-29	12.6	10.9	14.4	2.0	1.4	2.8	21.0	18.2	24.0	4.1	3.1	5.3
30-34	17.1	15.0	19.4	3.0	2.3	4.0	25.8	22.8	29.1	6.3	4.0	9.8
35-39	21.2	18.3	24.4	3.8	2.9	5.1	30.6	25.5	36.1	6.1	4.8	7.8
40-44	21.8	19.2	24.6	4.3	3.3	5.6	32.5	29.1	36.0	7.5	6.5	8.6
45-49	22.9	20.4	25.7	4.8	3.5	6.7	33.5	30.3	36.8	6.7	4.9	9.0

Table 35. Forecasted percentage prevalence of overweight to 2040 in Rural India (Women)

Age	*Year*	*Proportion*	*Lower Bound*	*Upper Bound*
20-24	*2010*	4.8	3.7	5.9
25-29		8.5	6.7	10.2
30-34		11.6	9.4	13.7
35-39		13.7	11.3	16.2
40-44		14.9	12.5	17.5
45-49		16.4	13.6	19.3
50-54		14.7	12.6	16.8
55-59		9.7	8.2	11.3
60-64		9.4	7.8	11.0
65-69		8.2	6.1	10.2
20-24	*2020*	8.4	6.5	10.2
25-29		12.8	10.3	15.4
30-34		16.6	13.4	19.8
35-39		19.7	15.9	23.4
40-44		21.8	17.3	26.2
45-49		22.4	17.6	28.0
50-54		22.6	17.5	27.8
55-59		23.7	18.5	29.4
60-64		22.5	17.4	28.1
65-69		18.8	14.3	23.7
20-24	*2030*	10.6	8.22	12.9
25-29		14.8	12.0	17.8
30-34		18.6	15.0	22.1
35-39		21.9	17.6	26.4
40-44		24.4	19.4	30.0
45-49		25.6	19.9	31.6
50-54		26.6	20.5	33.8
55-59		27.3	20.5	35.6
60-64		27.7	20.8	35.9
65-69		28.3	21.6	36.5
20-24	*2040*	11.1	8.6	13.6
25-29		16.0	12.9	19.2
30-34		19.8	16.0	23.6
35-39		23.0	18.5	27.7
40-44		25.5	20.3	31.1
45-49		27.0	21.0	33.6
50-54		28.2	21.4	36.0
55-59		29.4	21.9	38.0
60-64		30.5	22.9	40.0
65-69		31.0	22.9	41.4

Table 36. Forecasted percentage prevalence of obesity to 2040 in Rural India (Women)

Age	*Year*	*Proportion*	*Lower Bound*	*Upper Bound*
20-24	*2010*	0.9	0.6	1.2
25-29		1.7	1.2	2.2
30-34		2.8	1.9	3.7
35-39		3.6	2.5	4.7
40-44		4.2	3.0	5.4
45-49		4.6	3.2	6.1
50-54		3.0	1.9	4.0
55-59		2.7	1.7	3.7
60-64		1.8	0.9	2.6
65-69		3.4	2.1	4.8
20-24	*2020*	2.0	1.3	2.7
25-29		3.3	2.3	4.3
30-34		4.4	3.2	5.7
35-39		6.0	4.4	7.7
40-44		7.3	5.1	9.8
45-49		7.8	5.3	10.6
50-54		7.7	4.9	10.6
55-59		7.4	4.2	11.2
60-64		5.1	2.2	8.3
65-69		3.7	1.3	6.2
20-24	*2030*	2.6	1.7	3.5
25-29		4.3	2.9	5.7
30-34		6.2	4.4	8.0
35-39		8.2	6.0	10.5
40-44		9.7	7.1	12.6
45-49		10.8	7.5	14.5
50-54		11.2	7.0	15.8
55-59		10.6	5.9	15.7
60-64		9.5	4.6	14.4
65-69		8.3	3.1	14.1
20-24	*2040*	2.7	1.8	3.6
25-29		4.9	3.3	6.4
30-34		7.2	5.1	9.3
35-39		9.5	6.9	12.1
40-44		11.5	8.4	14.8
45-49		13.0	9.2	17.1
50-54		13.4	8.8	18.6
55-59		13.4	8.0	19.0
60-64		12.6	6.2	19.1
65-69		10.9	4.3	17.5

Table 37. Forecasted percentage prevalence of overweight to 2040 in Urban India (Women)

Age	*Year*	*Proportion*	*Lower Bound*	*Upper Bound*
20-24	*2010*	10.5	8.8	12.0
25-29		18.3	16.6	20.0
30-34		25.0	22.6	27.3
35-39		27.5	26.3	28.8
40-44		30.9	29.2	32.7
45-49		31.8	30.1	33.5
50-54		33.9	29.3	38.5
55-59		22.6	18.6	26.4
60-64		21.6	17.6	25.7
65-69		18.8	14.7	22.9
20-24	*2020*	14.4	12.1	16.6
25-29		21.8	19.4	24.2
30-34		28.0	25.3	30.7
35-39		33.0	29.9	36.3
40-44		35.7	31.8	40.3
45-49		36.2	31.4	42.2
50-54		35.8	30.0	43.1
55-59		34.7	27.7	43.1
60-64		33.6	26.1	43.5
65-69		28.0	20.4	37.2
20-24	*2030*	18.2	15.4	21.0
25-29		24.7	22.0	27.5
30-34		29.2	26.3	32.0
35-39		33.6	30.3	37.1
40-44		36.1	32.1	40.9
45-49		36.9	31.7	43.4
50-54		36.5	30.0	45.1
55-59		35.5	28.0	46.1
60-64		34.6	26.8	46.3
65-69		33.6	25.6	45.3
20-24	*2040*	19.1	16.1	22.0
25-29		26.4	23.4	29.5
30-34		30.2	27.3	33.2
35-39		34.0	30.7	37.6
40-44		36.2	32.1	40.9
45-49		36.9	31.7	43.3
50-54		36.5	30.1	45.0
55-59		35.6	28.1	46.4
60-64		35.0	27.1	47.1
65-69		34.5	26.6	46.8

Table 38. Forecasted percentage prevalence of obesity to 2040 in Urban India (Women)

Age	Year	Proportion	Lower Bound	Upper Bound
20-24	2010	2.7	2.0	3.3
25-29		5.5	4.5	6.5
30-34		8.8	7.5	10.1
35-39		11.7	10.1	13.2
40-44		15.0	12.7	17.2
45-49		15.0	12.9	17.1
50-54		6.8	4.5	9.1
55-59		6.2	4.3	8.1
60-64		4.0	1.9	6.2
65-69		7.8	4.7	11.0
20-24	2020	4.2	3.2	5.3
25-29		6.9	5.6	8.2
30-34		10.4	8.8	12.2
35-39		14.7	12.0	17.2
40-44		18.8	14.7	22.3
45-49		20.9	15.7	25.5
50-54		22.6	15.7	28.7
55-59		21.4	13.3	28.4
60-64		14.4	5.1	23.3
65-69		9.9	2.8	16.6
20-24	2030	5.3	4.0	6.6
25-29		8.9	7.1	10.6
30-34		12.6	10.6	14.8
35-39		16.6	13.7	19.5
40-44		20.7	16.4	24.7
45-49		24.1	17.9	29.9
50-54		26.2	17.6	33.1
55-59		26.2	15.6	34.9
60-64		24.4	12.5	34.1
65-69		20.4	8.2	29.9
20-24	2040	5.6	4.2	7.0
25-29		10.0	8.0	12.1
30-34		14.5	12.1	17.0
35-39		18.6	15.5	21.9
40-44		22.4	17.9	26.8
45-49		25.6	19.2	31.5
50-54		27.6	19.0	35.3
55-59		28.6	17.1	38.1
60-64		26.9	13.7	37.1
65-69		23.5	9.4	33.9

Table 39. Forecasted percentage prevalence of overweight to 2040 in Rural India (Men)

Age	*Year*	*Proportion*	*Lower Bound*	*Upper Bound*
20-24	2010	5.1	3.9	6.3
25-29		9.2	7.0	11.3
30-34		11.7	9.1	14.3
35-39		12.8	10.3	15.2
40-44		13.3	10.4	16.0
45-49		13.5	10.4	16.5
50-54		8.7	7.0	10.4
55-59		5.1	3.8	6.4
60-64		4.1	2.9	5.4
65-69		4.8	3.4	6.2
20-24	2020	10.6	8.1	13.1
25-29		15.3	11.9	19.1
30-34		18.2	14.0	22.5
35-39		21.1	16.5	25.8
40-44		22.4	17.6	27.5
45-49		22.0	16.9	27.3
50-54		21.5	16.3	26.7
55-59		21.5	16.4	26.9
60-64		18.0	13.7	22.4
65-69		14.0	10.2	17.6
20-24	2030	13.5	10.3	16.6
25-29		17.9	14.0	22.5
30-34		21.5	16.4	27.0
35-39		24.4	18.4	30.7
40-44		26.1	19.5	32.8
45-49		26.9	20.5	33.7
50-54		27.0	20.8	34.0
55-59		27.1	20.4	34.1
60-64		26.5	19.7	33.2
65-69		25.4	19.2	31.7
20-24	2040	14.1	10.8	17.5
25-29		19.4	15.1	24.5
30-34		23.1	17.6	29.3
35-39		25.8	19.5	32.8
40-44		27.9	20.9	35.4
45-49		28.9	21.5	36.6
50-54		29.4	21.7	37.3
55-59		30.3	22.7	38.5
60-64		30.6	23.5	38.6
65-69		29.7	22.6	37.1

Table 40. Forecasted percentage prevalence of obesity to 2040 in Rural India (Men)

Age	*Year*	*Proportion*	*Lower Bound*	*Upper Bound*
20-24	*2010*	0.8	0.4	1.1
25-29		1.3	0.7	1.9
30-34		1.6	1.1	2.2
35-39		2.4	1.5	3.2
40-44		2.1	1.4	2.9
45-49		2.4	1.6	3.2
50-54		2.5	1.5	3.5
55-59		0.5	0.1	1.0
60-64		0.9	0.3	1.5
65-69		1.0	0.3	1.7
20-24	*2020*	1.5	0.8	2.2
25-29		2.8	1.3	4.3
30-34		3.8	1.9	5.8
35-39		5.2	2.8	7.8
40-44		5.6	3.3	8.2
45-49		5.9	3.5	8.3
50-54		5.0	2.8	7.5
55-59		4.4	2.4	6.8
60-64		3.2	1.6	5.1
65-69		1.1	0.1	2.1
20-24	*2030*	1.9	1.0	2.8
25-29		3.7	1.7	5.7
30-34		5.6	2.7	8.3
35-39		7.5	4.0	11.1
40-44		8.6	4.8	12.5
45-49		9.4	5.5	13.9
50-54		9.0	5.0	13.0
55-59		8.1	4.3	12.0
60-64		6.0	2.8	9.8
65-69		4.5	1.8	7.7
20-24	*2040*	2.0	1.0	2.9
25-29		4.1	2.0	6.5
30-34		6.5	3.2	9.7
35-39		8.7	4.6	12.8
40-44		10.5	5.8	15.2
45-49		11.8	6.7	16.9
50-54		11.7	6.5	17.1
55-59		11.2	6.0	16.9
60-64		9.3	4.4	14.0
65-69		7.1	3.0	11.5

Table 41. Forecasted percentage prevalence of overweight to 2040 in Urban India (Men)

Age	*Year*	*Proportion*	*Lower Bound*	*Upper Bound*
20-24	*2010*	10.5	8.8	12.2
25-29		17.0	14.6	19.2
30-34		21.5	18.9	24.3
35-39		26.0	21.9	30.2
40-44		27.2	24.1	30.3
45-49		28.3	25.4	31.2
50-54		20.0	16.4	23.6
55-59		11.8	9.1	14.5
60-64		9.6	6.6	12.6
65-69		11.0	7.9	14.2
20-24	*2020*	17.9	15.0	20.8
25-29		24.8	21.4	28.9
30-34		31.0	26.6	36.1
35-39		35.7	30.3	40.7
40-44		38.7	33.0	44.7
45-49		40.9	34.5	47.6
50-54		38.9	32.4	45.6
55-59		36.6	30.4	43.0
60-64		30.1	24.2	36.5
65-69		23.3	17.8	28.9
20-24	*2030*	22.6	18.9	26.4
25-29		28.8	24.7	33.6
30-34		34.0	29.2	39.6
35-39		38.2	32.6	44.5
40-44		41.7	34.9	49.1
45-49		43.9	36.2	52.0
50-54		42.6	34.7	51.3
55-59		41.0	33.4	49.9
60-64		37.2	29.9	45.5
65-69		32.8	26.1	39.9
20-24	*2040*	23.8	19.9	27.7
25-29		31.1	26.5	36.2
30-34		36.1	30.9	42.1
35-39		39.5	33.8	46.1
40-44		42.2	35.5	49.8
45-49		44.1	36.5	52.9
50-54		43.4	35.0	53.2
55-59		41.8	33.5	51.7
60-64		38.6	30.6	48.0
65-69		34.6	27.5	42.9

Table 42. Forecasted percentage prevalence of obesity to 2040 in Urban India (Men)

Age	*Year*	*Proportion*	*Lower Bound*	*Upper Bound*
20-24	*2010*	1.9	1.2	2.6
25-29		3.2	2.3	4.0
30-34		5.0	3.1	6.9
35-39		5.2	3.8	6.4
40-44		6.0	4.9	7.1
45-49		6.1	4.2	7.9
50-54		5.7	3.8	7.7
55-59		1.2	0.2	2.2
60-64		2.1	0.8	3.4
65-69		2.3	0.9	3.8
20-24	*2020*	4.0	2.4	5.5
25-29		5.4	3.4	7.6
30-34		6.3	3.8	8.8
35-39		7.7	4.7	11.0
40-44		8.9	4.7	13.2
45-49		8.4	3.9	13.0
50-54		8.5	4.0	12.8
55-59		8.1	3.3	12.7
60-64		6.9	3.0	11.1
65-69		2.78	0.3	5.5
20-24	*2030*	5.0	3.1	6.9
25-29		7.2	4.5	10.0
30-34		9.1	5.6	12.6
35-39		10.5	6.2	14.9
40-44		11.0	5.6	16.7
45-49		11.5	5.1	17.9
50-54		11.8	4.0	19.6
55-59		11.0	3.0	18.6
60-64		10.3	3.0	17.2
65-69		9.1	2.4	15.3
20-24	*2040*	5.3	3.2	7.3
25-29		8.2	5.1	11.4
30-34		10.7	6.6	14.9
35-39		12.4	7.4	17.3
40-44		13.7	7.4	19.9
45-49		14.1	6.5	21.8
50-54		13.9	4.7	22.9
55-59		13.8	4.0	22.7
60-64		13.2	3.2	22.7
65-69		11.6	2.4	20.0

Table 43. Forecasted percentage prevalence of overweight and obesity to 2040 in India (Men) using South Asian BMI cut-offs*

Weight	*Residence*	*Year*	*20-34*			*35-54*			*55-69*			*All*		
			Point est.	*Lower*	*Upper*	*Point est.*	*Lower*	*Upper*	*Point est.*	*Lower*	*Upper*	*Point est.*	*Lower*	*Upper*
Overweight	*Rural*	*2010*	17.2	15.3	18.7	20.1	17.7	22.3	7.8	6.7	9.2	16.8	15.3	18.1
		2020	27.5	24.6	30.4	32.9	28.0	37.7	22.3	17.8	26.8	28.5	24.9	32.8
		2030	30.9	27.8	34.3	36.2	29.9	42.3	28.3	22.2	34.5	32.2	27.7	37.8
		2040	32.6	29.3	36.1	36.7	30.5	43.2	29.1	23.2	35.7	33.1	28.5	39.0
Obese	*Rural*	*2010*	3.4	2.7	4.1	6.6	5.3	7.7	2.1	1.5	2.7	4.5	3.8	5.0
		2020	7.2	5.5	8.4	13.6	11.6	16.1	10.7	8.5	12.2	10.6	8.9	11.9
		2030	9.5	7.2	11.1	20.1	16.6	23.6	20.6	16.6	24.5	16.6	13.5	19.0
		2040	10.9	8.3	12.7	24.1	19.7	28.1	26.4	21.0	31.4	20.7	16.8	24.1
Overweight	*Urban*	*2010*	27.9	25.5	29.4	33.0	31.0	34.6	17.4	14.3	20.9	28.2	26.7	29.2
		2020	35.5	33.4	38.4	35.9	31.1	38.8	22.7	17.4	26.2	33.5	29.9	36.1
		2030	40.6	38.0	43.8	35.0	30.0	38.6	22.0	17.4	26.1	34.4	30.9	37.5
		2040	43.1	40.2	46.3	34.1	29.2	37.9	21.4	17.2	25.6	34.0	30.6	37.4
Obese	*Urban*	*2010*	7.8	6.4	8.8	15.6	13.6	17.1	4.7	3.5	6.6	10.4	9.2	11.2
		2020	10.5	8.5	12.0	27.3	23.2	31.5	28.4	21.3	33.4	20.7	17.1	23.7
		2030	13.2	10.8	15.2	32.0	25.7	37.8	43.1	35.2	50.0	27.3	22.2	32.0
		2040	15.0	12.2	17.3	35.0	28.0	41.2	47.2	38.0	54.7	31.1	25.1	36.2

*South Asian BMI cut-offs use a BMI between 18.50kg/m^2 - 22.99kg/m^2 to denote normal weight; BMI between 23.00kg/m^2 - 27.49kg/m^2 to denote overweight; and BMI greater than or equal to 27.50kg/m^2

Table 44. Forecasted percentage prevalence of overweight and obesity to 2040 in India (Women) using South Asian BMI cut-offs*

Weight	*Residence*	*Year*	*20-34*			*35-54*			*55-69*			*All*		
			Point est.	*Lower*	*Upper*	*Point est.*	*Lower*	*Upper*	*Point est.*	*Lower*	*Upper*	*Point est.*	*Lower*	*Upper*
Overweight	*Rural*	*2010*	14.8	13.2	16.1	20.9	19.4	23.0	10.6	9.4	11.9	16.5	15.5	17.5
		2020	26.5	23.2	30.0	31.5	28.7	36.4	23.6	20.7	27.4	27.9	25.1	32.2
		2030	29.3	25.9	33.6	35.5	31.4	41.4	27.7	24.0	33.3	31.6	27.8	36.9
		2040	30.7	27.2	35.4	36.1	31.9	42.4	28.7	24.9	34.7	32.6	28.6	38.2
Obese	*Rural*	*2010*	4.3	3.2	5.0	9.3	7.6	10.7	6.1	5.0	7.0	6.6	5.7	7.1
		2020	7.3	6.2	9.4	14.4	12.7	16.7	14.3	11.8	16.6	11.8	10.2	13.6
		2030	9.6	8.2	12.4	20.1	17.0	24.1	21.9	18.1	26.6	17.1	14.5	20.6
		2040	11.0	9.3	14.1	24.1	20.4	29.3	26.6	21.6	31.7	20.8	17.6	25.4
Overweight	*Urban*	*2010*	25.3	23.8	26.4	34.3	32.9	35.8	24.1	21.0	26.9	28.6	27.6	29.7
		2020	31.5	28.7	33.3	34.3	31.8	36.5	25.6	22.0	29.4	31.7	28.8	33.5
		2030	35.8	32.8	38.0	34.9	32.1	37.2	25.2	21.7	29.9	33.2	30.3	35.5
		2040	37.8	34.5	40.0	35.2	32.5	37.7	25.0	21.6	29.9	33.7	30.7	36.1
Obese	*Urban*	*2010*	12.2	11.3	13.5	25.2	23.3	26.6	13.8	11.2	15.8	17.7	16.8	18.6
		2020	15.2	13.0	16.6	32.2	29.3	35.5	39.5	34.5	44.6	26.7	24.5	29.4
		2030	19.1	16.2	21.1	35.0	32.0	39.0	49.7	43.1	55.6	32.3	29.2	35.6
		2040	21.5	18.3	23.8	37.8	34.3	42.0	51.7	44.9	57.8	35.7	32.2	39.3

*South Asian BMI cut-offs use a BMI between 18.50kg/m^2 - 22.99kg/m^2 to denote normal weight; BMI between 23.00kg/m^2 - 27.49kg/m^2 to denote overweight; and BMI greater than or equal to 27.50kg/m^2