REGIONAL INEQUALITIES IN HEALTH IN THE UK: THE CONTRIBUTION OF INDIVIDUAL-LEVEL CHARACTERISTICS AND THE ROLE OF SMALL AREA ENVIRONMENT

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ABSTRACT

Background: Regional health inequalities in the UK pose a significant public health challenge, marked by considerable disparities in health outcomes across different geographical areas. Understanding these geographic differences is complex, influenced by various lifestyle factors and health indicators at both individual and environmental levels, with limited information available to guide intervention development.

Objective: This study investigates the underlying sources of regional disparities in chronic kidney disease (CKD) and hypertension in the UK and examines the contribution of neighbourhood environments to these disparities.

Methods: Using a nationally representative dataset from the Understanding Society data, individual-level biomarker data was linked to neighbourhood-level data from the English Indices of Deprivation at the Lower Layer Super Output Area (LSOA) level. The London region served as a reference group due to its generally better health outcomes. Initially, ordinary least squares regression and Oaxaca-Blinder decomposition were employed, later supplemented by unconditional quantile regression analysis to assess regional differentials in the biomarkers and quantify contribution of neighbourhood characteristics.

Results: Significant regional disparities were found across the UK, primarily driven by differences in observed regional characteristics. Education appeared as a crucial factor in health disparities. Concentration was given to the lower tail (25th quantile) of estimated glomerular filtration rates and the upper tail (90th quantile) of systolic blood pressure, indicating higher risks for CKD and hypertension respectively. Neighbourhood-level characteristics were significant drivers of these regional inequalities. Socioeconomic status and demographics are associated with coastal disparities in the East of England region.

Conclusion: The findings suggest that individual-level characteristics and neighbourhood environments contribute to regional health disparities in the UK. Addressing CKD and hypertension requires integrated approaches that combine individual interventions with a focus on the neighbourhood context. However, methods used in this study only show associations and do not establish causality, limiting specific intervention recommendations for local authorities.

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ABBREVIATIONS

BHPS – The British Household Panel Survey

BMI – Body Mass Index

CKD – Chronic Kidney Disease

DNA – Deoxyribonucleic Acid

eGFR – Estimated Glomerular Filtration Rate

EID – English Indices of Deprivation

EQ-5D – EuroQol- 5 Dimension

ESRC – Economic and Social Economic Research

EU – European Union

GB – Great Britain

GOR – Government Office Regions

GP – General Practitioner

GPS – General Population Sample

HDL – High-Density Lipoprotein

IF – Influence Function

ISER – Institute for Social Research Council

LSOA – Lower Layer Super Output Area

LWF – Living Wage Foundation

NHS – National Health Service

NICE – National Institute for Health and Care Excellence

NRES – National Research Ethics Service

NVQ – National Vocational Qualification

OB – Oaxaca-Blinder

OECD – Organisation for Economic Co-operation and Development

OHID – Office for Health Improvement and Disparities

OLS – Ordinary Least Squares

ONS – Office for National Statistics

RIF – Recentred Influence Function

SBP – Systolic Blood Pressure

SEP – Socioeconomic Position

SES – Socioeconomic Status

SO_2 – Sodium Dioxide

TED – Treatment Effect Deviation

UK – United Kingdom

UKHLS – United Kingdom Household Longitudinal Study

UQR – Unconditional Quantile Regression

WHO – World Health Organisation

This thesis is dedicated to

Jehovah El Shaddai – God Almighty

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STATEMENT OF AUTHORSHIP

I certify that the thesis I have presented for examination for the award of PhD degree in Health Economics of the University of East Anglia is solely my own work.

The following conference presentations have been made based on sections of this thesis:

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Ilori G, Shepstone L, Khondoker M, and Turner D. Coastal versus inland disparities in chronic kidney disease and hypertension in East of England. NIHR ARC East of England Early Career Symposium, Cambridge, March 2025.

CHAPTER 1

BACKGROUND

1.0 INTRODUCTION

In the UK, people living in the least deprived areas of the country live around 20 years longer in good health than people in the most deprived areas (Connolly et al., 2017). Even though steady improvements in the population's health have been evident over recent decades, preventable inequalities in health persist within and between regions in the UK (Shelton, 2009; Plumper et al., 2018; Davillas and Jones, 2020). Knowledge of factors contributing to these differences and how they contribute to them is required to tackle these regional health disparities. This thesis examines regional inequalities in health, using the exemplars of chronic kidney disease (CKD) and hypertension and the potential role of the neighbourhood environment over the individual-level characteristics in the UK.

Regional inequalities are vast; therefore, exemplars are used in this research to illustrate key differences in selected conditions. The reason for focussing on these conditions is due to the fact that CKD is a common and costly health issue, affecting one in ten people in the UK and costing the NHS an estimated £1.4 billion annually (Caskey et al., 2018; NHS Kidney Care, 2017). Hypertension, a key risk factor for cardiovascular disease, is also a leading cause of other chronic conditions. High blood pressure affects one in four adults, costing the NHS £2.1 billion annually (ONS, 2023). A better understanding of the underlying sources of the regional inequalities in these diseases will have the potential to assist resource allocation and area-based policies to improve the population’s health status. I am unaware of any work that has focused on regional inequalities in CKD and hypertension in the UK or England and has considered the contribution of individual-level characteristics and the small area environment together.

The thesis is organised into six chapters. The first chapter presents a general background on regional health inequalities, chronic kidney disease, and hypertension, establishes the gap in knowledge being addressed, and presents the rationale behind this work. Chapter One ends by specifying the research questions to be investigated in this thesis. Chapter Two discusses the statistical and health economic methods used for the analyses in this study. Chapter Three provides empirical results for what lies behind the observed regional differences in health in the UK. While Chapter Four examines regional disparities in chronic kidney disease (CKD) and hypertension across England. Chapter Five narrows the focus to coastal versus inland disparities within the East of England. This shift is driven by evidence suggesting that coastal areas may experience distinct health challenges due to factors such as socioeconomic deprivation, reduced healthcare access, and environmental exposures. By comparing coastal and inland populations, this research aims to provide a more granular understanding of geographic health inequalities and inform targeted public health interventions. The final chapter discusses the main findings, thesis contribution, recommendations for future work, and concluding remarks.

1.1 WHAT ARE REGIONAL INEQUALITIES IN HEALTH?

Regional inequalities in health are defined as the differences in health outcomes between groups of people living in different regions within a country (Public Health England, 2017). Regional health disparities pose a significant and urgent challenge for policymakers, particularly because they disproportionately affect populations with the poorest health outcomes (Sen, 1997). These disparities contribute to widening social inequalities, increased healthcare costs, and higher burdens on public health services (Sen et al., 2004). The urgency arises from the need to prevent further deterioration in health equity and address underlying socioeconomic and environmental determinants. Policymakers are especially concerned as persistent disparities undermine efforts to achieve national health targets, economic productivity, and social cohesion. Despite steady growth and better health outcomes over the years, distinct health discrepancies persist between regions in the United Kingdom (Shelton, 2009; Plumper et al., 2018; Davillas and Jones, 2020). The recent government reform agenda “The Levelling Up white paper” (2022) shows the UK has severe and longstanding geographical health inequalities. In the Marmot review, Marmot et al. (2010) argue that health inequalities are pervasive, affecting everyone, not just the most disadvantaged. By addressing the determinants of health, it may be possible to reduce these inequalities and improve health outcomes for the entire population.

An NHS Scotland policy report states that health inequalities contradict the principle of social justice because many are avoidable (NHS Scotland, 2016). However, while some disparities can be reduced through targeted interventions, others may persist due to structural, geographic, or biological factors, requiring long-term policy commitments to mitigate their impact. A recent report on Wales by the Office for National Statistics (2020) found people aged 65 years and over living in the most deprived areas of Wales had lower life expectancy than those in the least deprived areas. This difference was 4.4 years for males and 4.9 years for females. Public Health England (2019) reported that people in the least deprived parts of England live on average, 19 years in good health compared to people in the country’s poorest areas. Health inequalities cut across various social and demographic indicators, including socioeconomic status, occupation, geographical location, and protected characteristics in the Equality Act 2010 (NHS England, 2017).

In order to study whether there are regional health inequalities, a method of measuring and comparing health between groups or areas is needed. Previous studies conducted in the UK and elsewhere have acknowledged regional variation in the health of their respective population using different health indicators. White et al. (2011) used self-reported health status indicators to investigate neighbourhood deprivation and regional inequalities in self-reported health among Canadians. They concluded that neighbourhood deprivation significantly predicted fair/poor health in all geographic regions. Franzini and Giannoni (2010) used self-reported health indicators to examine the determinants of health disparities between Italian regions. They found that residents in areas with more poverty, unemployment, and income inequality are more likely to report poor health. At the same time, Vallejo-Torres and Morris (2010) used smoking, obesity, and health-related measures (EQ-5D) as health indicators to investigate the contribution of smoking and obesity to income-related inequality in health in England. The result showed significant income-related health inequalities in England, and the extent of the disparity varied by area. One limitation of these studies is the reliance on self-reported outcome variables, which may introduce bias. Differences in regional access to healthcare, variations in diagnostic practices, treatment availability, and individual perceptions of health can all influence self-reported data, potentially leading to inconsistencies and measurement errors (Bound et al., 2001). However, this research uses biomarker measures which is free from free of reporting bias.

1.2 BIOMARKERS AS OBJECTIVE MEASURES OF CHRONIC KIDNEY DISEASE AND HYPERTENSION

The term biomarker, or biological marker, refers to a broad range of objective measures which capture what is happening at the cellular level at a given moment or an indicator of normal biological processes, pathogenic processes, or pharmacologic responses to a therapeutic intervention (Strimbu and Tavel, 2010). They are typically measured on a continuous scale associated with increasing or decreasing risk depending on a biomarker of a disease state (Rosero-Bixby and Dow, 2012). Using biomarkers to assess risks for outcomes directly can help overcome the lack of good health information while also providing an immediate assessment of objective health disparities for individuals and groups. Cardiovascular, metabolic, and other biomarkers have been shown to be predictors of morbidity and mortality when used alone or alongside self-reported health measures (Lee et al., 2015; Carrieri and Jones, 2017).

1.3 EXISTING LITERATURE

The literature review aims to identify studies that examine self-reported health measures, biomarker measures, chronic kidney disease and hypertension as outcome variables driven by statistical methods.

Regional health inequalities have attracted increasing interest over the last decade. Several kinds of research have been undertaken using different health indicators and measurements to identify the determinants of health inequalities within and across regions in the United Kingdom and internationally. However, these indicators are classified into inequalities in self-reported health, biomarkers, CKD, and hypertension.

1.4 HEALTH INEQUALITIES: SELF-REPORTED HEALTH MEASURES

Research on regional health disparities consistently highlights the impact of socioeconomic, environmental, and geographic factors on health outcomes. Across multiple studies, poorer health tends to be concentrated in disadvantaged regions, with variations observed across different countries and health measures. **Table 1.1** shows the description summary of key findings of previous studies.

A key theme is the north-south health divide, particularly evident in England. Ellis and Fry (2010) found that northern regions reported poorer health outcomes compared to the Midlands and London, with the East of England and southern regions showing the best outcomes. Similarly, Plümper et al. (2018) identified significant spatial disparities in premature mortality in Great Britain, reinforcing the link between geographic location and health inequality.

Socioeconomic status (SES) emerges as a major determinant across multiple studies. Vallejo-Torres and Morris (2010) demonstrated that obesity—both a health outcome and risk factor—is predominantly concentrated among lower-income populations in England. Costa-Font and Gil (2008) found that obesity-related inequalities in Spain were strongly linked to income disparities. Similarly, Franzini and Gionnoni (2010) showed that Italians living in regions with higher poverty and unemployment were more likely to report poor health, a pattern also observed in China by Fan et al. (2019).

Environmental factors also play a crucial role. Burgoine et al. (2011) found that walkability and food availability significantly influenced BMI in Northeast England. In Spain, Raftopoulou (2017) linked obesity risk to social environmental factors such as green space availability and crime levels. Di Paola et al. (2018) further noted that BMI disparities in Spain were primarily driven by women, suggesting gendered dimensions to geographic health inequalities.

Table 1.1 Summary of key findings

Study	Country	Health Measure	Key Finding
Ellis & Fry (2010)	England	Life expectancy, obesity, mortality	Northern regions fare worse than Midlands & London; best outcomes in South & East England
Vallejo-Torres & Morris (2010)	England	Obesity (self-reported)	Higher obesity rates among low-income populations
Raftopoulou (2017)	Spain	BMI	Lack of green spaces & crime linked to higher BMI, especially for women
Di Paola et al. (2018)	Spain	BMI	South-to-north BMI differences mainly driven by women
Costa-Font & Gil (2008)	Spain	Obesity	Strong income-related disparities in obesity
Burgoine et al. (2011)	England	BMI, obesogenic environment	Walkability & food access significantly associated with BMI
Franzini & Gionnoni (2010)	Italy	Self-reported health	Poorer health in regions with high poverty & unemployment
Fan et al. (2019)	China	Self-reported health	Residents in less developed regions have poorer health
Riva et al. (2008)	England	Self-reported health	Rural residents report better health than urban dwellers
Plümper et al. (2018)	Great Britain	Premature mortality	Significant spatial disparities in health outcomes
Skapinakis et al. (2005)	Wales	Mental health	Social deprivation explains mental health disparities
Wilson et al. (2009)	Scotland/Canada	BMI, chronic conditions, hospitalisation	Socioeconomic gradients in health outcomes; Glasgow’s high-SES areas resemble Hamilton’s low-SES areas

Rural versus urban disparities also emerge in the literature. Riva et al. (2008) found that rural residents in England were less likely to report poor health compared to urban dwellers, contrasting with findings from Wilson et al. (2009), who observed socioeconomic gradients in health status across urban neighbourhoods in Glasgow (Scotland) and Hamilton (Canada). Lastly, Skapinakis et al. (2005) explored mental health disparities in Wales, showing that regional social deprivation was a key factor contributing to mental health inequalities.

1.5 HEALTH INEQUALITIES: BIOMARKER STUDIES

A sizeable body of literature has used biomarker data to analyse regional and socioeconomic inequalities in health in the UK and internationally. This literature aims to have a health measure free of reporting bias. Carieri and Jones (2017) examine the income-health relationship from 2003 to 2012. They used total cholesterol, glycated haemoglobin, fibrinogen, and ferritin as the outcome variables. Using the recentred influence function method, they found a non-linear relationship between income and health and a strong gradient for income at the highest quantiles of the biomarker's distributions. Lee et al. (2015) explored education, gender, and state-level disparities in the health of older Indians in 2010. The health outcomes include C-reactive protein, a marker of inflammation, and haemoglobin, a marker of anaemia. Using ordinary least squares and Oaxaca-Blinder decomposition, they found substantial regional disparities in haemoglobin between women and those with no formal education who had lower levels. For C-reactive protein, they discovered that the oldest individuals are more at risk of inflammation than those living in urban areas. Also, Jurges et al. (2013) found a positive relationship between schooling and biomarkers of cardiovascular diseases (C-reactive protein and fibrinogen). Muennig et al. (2007) examined the differences between socioeconomic groups in C-reactive protein and cholesterol homocysteine associated with cardiovascular diseases. They found a positive effect of income and education on good cholesterol and a slightly significant impact on fibrinogen. On the contrary, Ploubidis et al. (2014) found a negative impact of early-life socioeconomic position on fibrinogen levels later in life.

Davillas and Jones (2020) studied regional inequalities in adiposity in England from 2010 to 2011. Multilevel analysis and Shapley decomposition results found that neighbourhoods with disadvantaged environments may influence an individual's adiposity levels, especially at the higher tails of its distribution. Chaparro et al. (2018) examined Britain's neighbourhood deprivation and health biomarkers using forced expiratory volume in 1s, systolic blood pressure, BMI, and C-reactive protein. They found that residents of poor neighbourhoods had worse health outcomes. Davillas et al. (2017) found that socioeconomic inequalities in inflammation followed a heterogeneous pattern by age (C-reactive protein and fibrinogen). Bird et al. (2010) studied neighbourhood socioeconomic status and biological wear and tear in US adults from 1988 to 1994. Using hierarchical linear models, they found that being male, older, having lower income, and having less education were independently associated with worse allostatic load (cumulative burden on the body resulting from chronic stress). After accounting for the individual socioeconomic position, Ribeiro et al. (2019) examine the association between neighbourhood deprivation and allostatic load. They found that participants in the most deprived quintile had a higher allostatic load than those in the least deprived quintile. Dowd and Goldman (2006) tested the influence of stress biomarkers on the relationship between socioeconomic status and health. They found that chronic stress is not very different across socioeconomic groups. Midouhas et al. (2019) investigate neighbourhood-level air pollution, green space, and inflammation in adults. They found neighbourhood-level nitrogen dioxide predicted later fibrinogen levels but not C-reactive protein.

1.6 CHRONIC KIDNEY DISEASE

Chronic kidney disease is a condition characterised by the gradual loss of kidney function over time (Nation Kidney Foundation, 2023). It typically develops slowly and may progress over several years, eventually leading to kidney failure. Chronic kidney disease is a growing concern in England, and it is projected that up to a million individuals have the condition but are unaware (Kerr et al., 2012). CKD reduces an individual's quality of life, eventually leading to premature morbidity and mortality. Kidney function is assessed by estimating the kidney's glomerular filtration rate. The estimated glomerular filtration rate (eGFR) measures levels of kidney function and indicates how well the kidneys filter wastes and extra fluid from the body. The eGFR levels of 90mL and above signify normal or increased kidney function, while lower eGFR levels indicate risks of kidney disease (Kidney Research UK., 2023). Kidney Research UK (2018) reported that people from lower socioeconomic regions are more likely to develop CKD. However, recognizing the cause of these differences can be challenging given the regional disparities, different lifestyles, and other health influences at the individual and environmental levels. Also, understanding the contribution of the neighbourhood environment to chronic kidney disease is crucial for effective policy strategies.

Limited studies have provided evidence regarding inequalities in CKD prevalence internationally and across different regions of England. Chan et al. (2014) address health disparities in chronic kidney disease in Taiwan. Using ordinary least squares regression, they found that areas with higher percentages of education status or elderly had higher CKD prevalence. Contrastingly, Brown and Elliot (2021) and Nicholas et al. (2015) studied the social determinants of health, focusing on chronic kidney disease in the US. They found that chronic kidney disease disproportionally affects populations with relatively poor social determinants. Hossain et al. (2012) investigated the social deprivation and prevalence of chronic kidney disease in the UK. Using the kernel density estimation, they found an increased burden of CKD in deprived areas. Also, Phillips et al. (2023) examined inequalities in managing diabetic kidney disease in UK primary care. They found that there are inequalities in the management of diabetic kidney disease in the UK.

1.7 HYPERTENSION

According to WHO (2023), hypertension or high blood pressure is a condition that affects the blood vessels. Hypertension is a cardiovascular risk factor that exhibits regional variations across England. Blood pressure is recorded with systolic blood pressure (the force at which the heart pumps blood around the body) and diastolic pressure (the resistance to the blood flow in the blood vessels between heartbeats when blood is pumped around the heart). In this thesis, the systolic blood pressure is considered. A normal blood pressure reading is around 120mmHg. A systolic blood pressure of 140mmHg or higher indicates high blood pressure (NICE, 2022).

Public Health England (2017) reported that people from the most deprived areas in England are 30% more likely to have hypertension than those in the least deprived areas. Epidemiological studies have revealed variations in hypertension prevalence among different regions of England. Factors such as socioeconomic status, ethnicity, lifestyle behaviours, and access to healthcare services have been found to contribute to these disparities (De Gaudemaris et al., 2002; Siven et al., 2015). However, the role of the neighbourhood environment has yet to be explored based on my knowledge. Therefore, addressing regional disparities in hypertension requires understanding the causes for these variations and the role the individual-level and environmental factors have to play.

De Gaudemaris et al. (2002) studied the socioeconomic inequalities in hypertension prevalence and care in a French population. Using logistic regression and variance analysis, they found that hypertension was higher among participants of lower occupational categories. Siven et al. (2015) investigate the social, lifestyle and demographic inequalities in hypertension care in Finland. Similar to the French population earlier, they found that hypertension disparities exist, and it is more prevalent in people of lower socioeconomic status. Also, Scholes et al. (2020) used bivariate probit regression modelling to explore the income-based inequalities in hypertension using the English population. They found that participants in low-income households have a higher probability of being hypertensive. Matheson et al. (2008) examine the neighbourhood chronic stress and gender inequalities in hypertension among Canadian adults. Using a multilevel analysis, they found that neighbourhood deprivation was significantly associated with hypertension. Comparable results from other countries were found through the literature (e.g. Fateh et al., 2014; Christiani et al., 2015).

A crucial link has been established between hypertension and CKD. Kidney Research UK (2023) explains that hypertension is an important cause and consequence of CKD, creating a vicious cycle of hypertension and progressive kidney damage. Damaged kidneys can cause high blood pressure, which can, in turn, cause further kidney damage. NHS Kidney Care (2017) stated that CKD is usually caused by other conditions that strain the kidneys, which can also strain the small blood vessels and stop the kidneys from working correctly. Public Health England (2017) reported that hypertension is a significant risk factor for the development of CKD and has been suggested to be the second leading cause of kidney failure after diabetes.

1.8 HEALTH INEQUALITIES: COASTAL VS NON-COASTAL

Regional disparities highlight broad health inequalities across the UK, but they may mask important intra-regional differences, particularly between coastal and inland areas. Coastal communities often experience greater socioeconomic deprivation and healthcare access challenges (Asthana and Gibson, 2021), all of which contribute to higher disease risk. Unlike broader regional comparisons, a coastal versus inland disparities focus allows for a more targeted understanding of localised health inequalities, ensuring that policy interventions address the unique vulnerabilities of coastal populations. By applying the Oaxaca-Blinder decomposition method, the key factors driving coastal disparities can be identified, offering deeper insights into the structural determinants of health inequalities in these areas.

Coastal communities are regions that border the sea or ocean and often have distinctive geographical, economic, social, and environmental characteristics. Recently, the Health report of the Chief Medical Officer in England (2021) highlights the health disparities between England's coastal and inland regions. The report specifically showed that a high proportion of poor health conditions in England are concentrated in coastal communities. Evidence have suggested that there are higher deprivation, unemployment, poor education, housing problems, and flooding in coastal communities than inland communities (ONS, 2021).

The literature presents conflicting evidence on health disparities between coastal and inland communities. Some studies suggest that coastal populations experience better health outcomes, potentially due to environmental benefits such as increased physical activity and lower air pollution (Wanezaki et al., 2016; White et al., 2014). Conversely, other research indicates that inland regions generally have better health outcomes on average, with coastal communities facing higher rates of socioeconomic deprivation and limited healthcare access (ONS, 2021; Bird, 2021). For example, Wheeler et al. (2012) investigated whether living by the coast improves health and well-being. After accounting for the population's local age and socioeconomic profiles, they found that coastal populations have better health than non-coastal populations. However, Asthana and Gibson (2021), in their work on the analysis of coastal health outcomes, found that there is an excess of many long-term conditions compared with the inland areas with similar demographics and deprivation.

From the literature reviewed above, it is evident that work has been done on regional and socioeconomic health inequalities. However, most of the work is either compared between the North-South divide, urban and rural areas, regions in England or elsewhere. Also, the biomarker data are selective, and only a few studies account for chronic kidney disease and hypertension, which are mainly US population. It is not clear what the underlying sources of health inequalities across different regions of the United Kingdom are. Most studies examine either individual-level characteristics or neighbourhood factors in relation to regional health inequalities (Di Paola et al., 2018; Chaparro et al., 2018), often overlooking how these factors interact. This limited approach makes it difficult to disentangle the relative contributions of personal circumstances (e.g., income, lifestyle) and broader environmental influences (e.g., healthcare access, deprivation). A decomposition approach, which systematically splits these effects, provides a clearer understanding of the drivers of health disparities and helps identify targeted policy interventions.

Therefore, this research uses Oaxaca-Blinder decomposition analysis to quantify the contributions of individual and neighbourhood characteristics in explaining regional differences between people in London and those in the other regions of the UK.

1.9 RESEARCH AIM

This study aims to investigate regional health disparities and their association with individual and neighbourhood characteristics in adults in the UK.

1.9.1 RESEARCH QUESTIONS

1. Are there regional health disparities in the UK with respect to health outcomes?
2. What lies behind the observed regional differences in health?
3. Does the neighbourhood environment contribute to chronic kidney disease and hypertension in England?
4. What are the underlying sources of chronic kidney diseases and hypertension disparities between coastal and non-coastal areas in the East of England region?

CHAPTER 2

DATA AND METHODS

The previous chapter sets this thesis in context by discussing chronic kidney disease and hypertension biomarkers as measures of health to compare across regions in the UK and the rationale for this thesis. This chapter discusses the dataset used in conducting the analyses presented in this thesis, including data sources, data collection, data description, ethics and data access, the variables of interest (outcomes and covariates, including a rationale for inclusion), and statistical methods.

2.1 THE DATA

This thesis employs the United Kingdom Household Longitudinal Study (UKHLS) data, also known as the Understanding Society data, to examine geographical inequalities in health in the UK. The Economic and Social Research Council (ESRC) initiated the Understanding Society data collection, and the Institute for Social and Economic Research (ISER) led the study at the University of Essex. The UKHLS is a nationally representative panel survey covering 40,000 households across the United Kingdom (England, Wales, Scotland, and Northern Ireland). It is designed to be representative across key demographic, socioeconomic, and geographical variables, including age, sex, income, education, and housing status. This ensures that findings on health inequalities reflect broader population patterns and variations across different social and regional groups. The overall purpose of the Understanding Society is to provide high-quality longitudinal data about subjects such as health, work, education, income, family, and social life to help understand the long-term effects of social and economic change, as well as policy interventions designed to impact upon the general well-being of the UK population. Hence the data is ideal for the kind of analyses explored in this thesis.

The UKHLS data collection began in January 2009, with households selected following a multi-stage clustered sample design (Knies, 2015). The British Household Panel Survey (BHPS) was incorporated into the UKHLS in wave 2 to expand its longitudinal scope. The BHPS, which began in 1991, is an annual panel survey of individuals living in private households in the UK, with face-to-face interviews conducted each year for all household members aged 16 and over. In wave 2 of the UKHLS sample and wave 3 of the BHPS sample (2010–2012), a nurse visit was introduced, including health assessments and biomarker data collection (e.g., blood pressure, cholesterol, and other key health indicators). With consent, blood samples were frozen for future analysis and DNA extracted. A part of the blood samples was analysed to produce a set of biomarkers, which are characteristics that objectively measure indicators of normal biological processes, pathogenic processes, or pharmacologic responses to a therapeutic intervention. **Figure 2.1** illustrate the integration of BHPS into UKHLS and the timeline of health data collection.

This thesis uses the General Population Sample (GPS), a subsample of the UK Household Longitudinal Study (UKHLS), as shown in **Figure 2.2**. The GPS consists of a clustered and stratified probability sample of approximately 24,000 households in Great Britain and a simple random sample of 2,000 households in Northern Ireland, with the latter selected at twice the probability of the Great Britain sample. In Wave 2 of UKHLS, a nurse assessment was conducted on a subset of the GPS sample, with 10,175 participants consenting to provide a blood sample. BHPS respondents joined Understanding Society in Wave 2 for interviews, but their biomarker data was collected separately in Wave 3 (2011–2012). In Wave 3, a similar health survey was carried out on a subset of the former BHPS sample, with 3,342 adults providing blood samples. These subsamples allow for in-depth biomarker analysis within the broader UKHLS framework. Please see Benzeval et al. (2014) for a detailed discussion on the nurse assessment and the biomarker data.

Figure 2.1 Illustration of the integration of BHPS into UKHLS and the timeline of health data collection

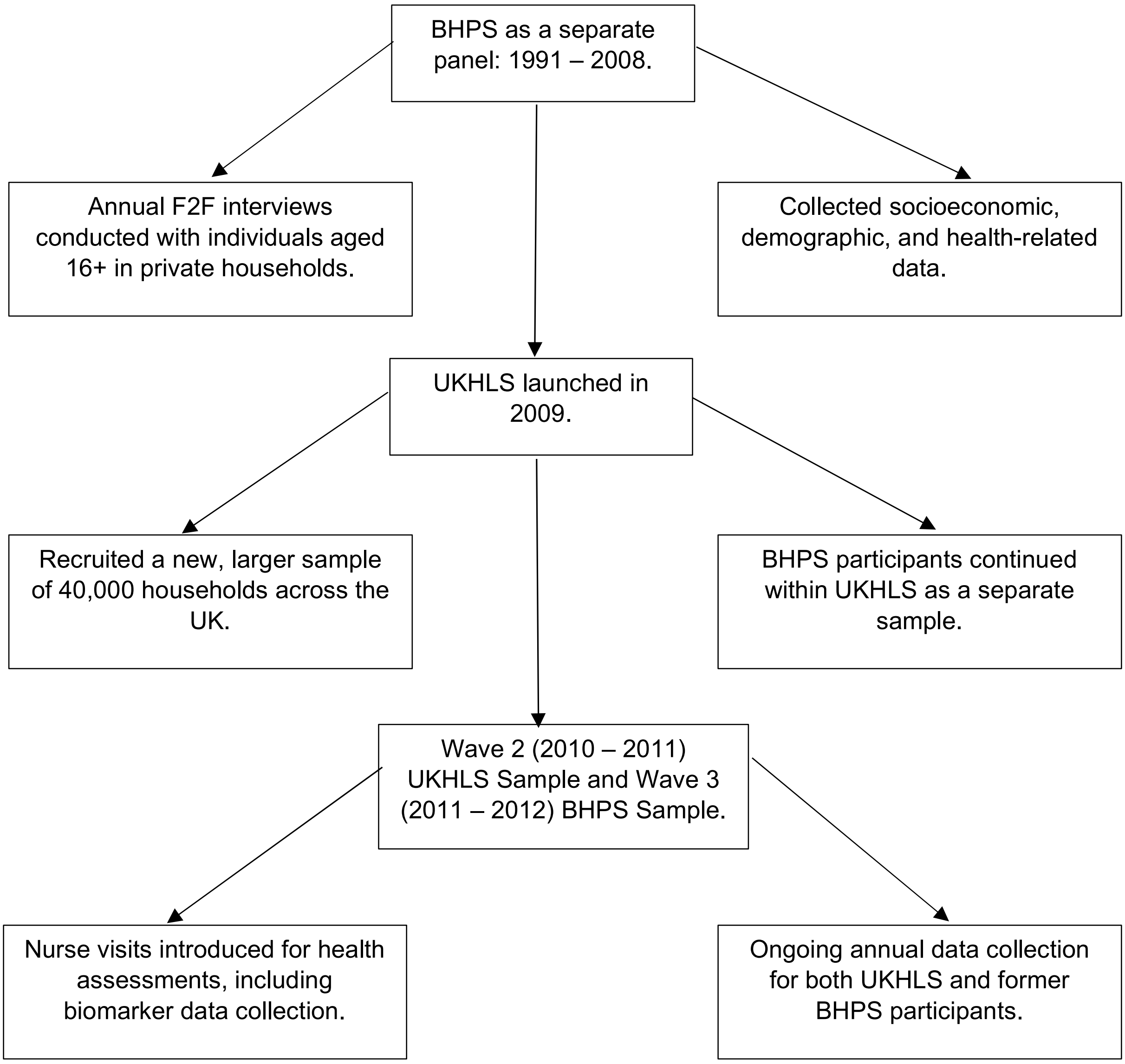
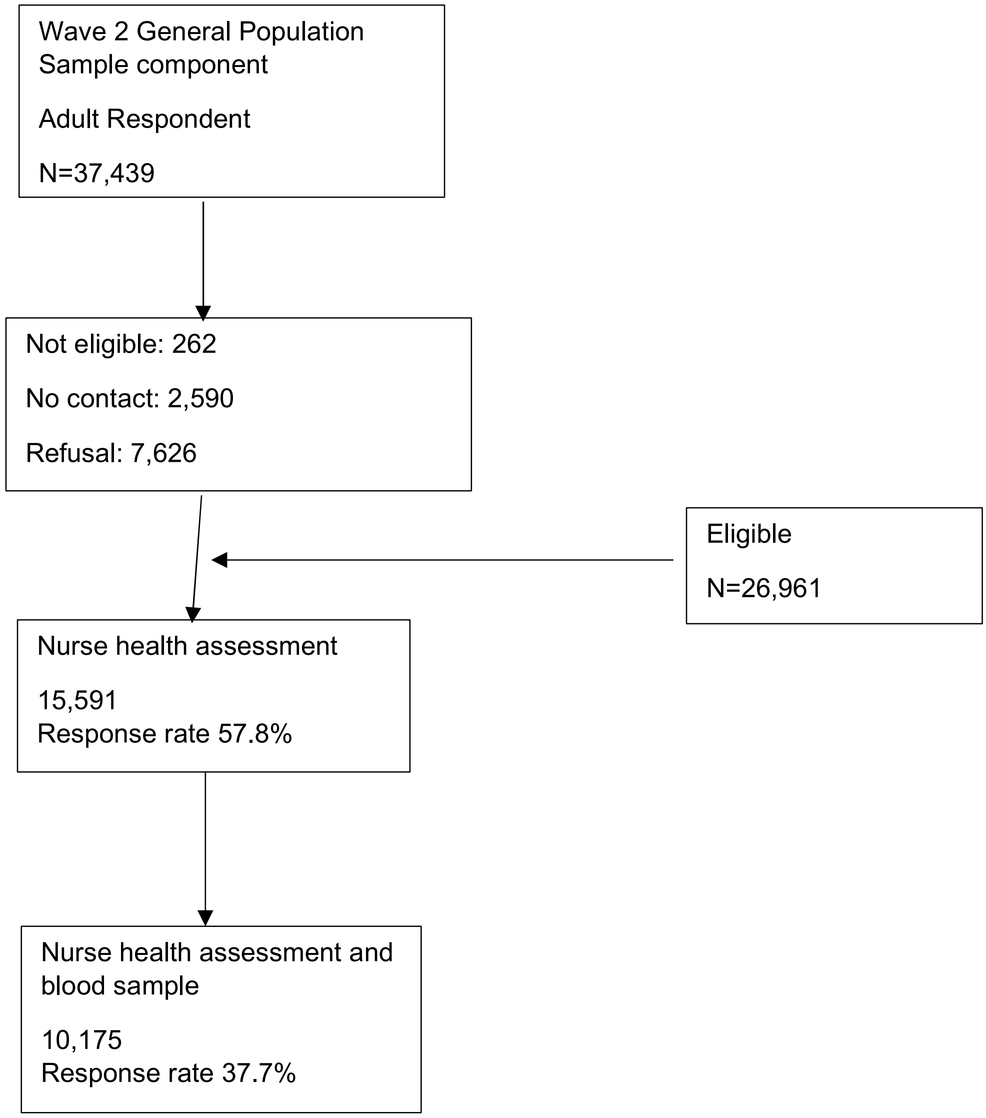


Figure 1.2 Flow diagram of participation in the nurse health assessment general population sample component



Adapted from McFall et al. (2014) Understanding Society: Waves 2 and 3 Nurse Health Assessment, 2010-2012

2.1.1 SURVEY PARTICIPANTS AND SELECTION CRITERIA FOR THE NURSE-COLLECTED AND BLOOD-BASED BIOMARKER DATA

The eligibility criteria for participation in the survey include completing the main interview survey in English, being 16 or older, and not being pregnant for women. Inclusion was open only to participants in England, Wales, and Scotland, as nurse recruitment proved difficult in Northern Ireland. Blood sample collections were further restricted to those with no blood clots or bleeding disorders and no history of fits for the health measures and biomarker data. Nurse visits were conducted over two years, starting in May 2010. The National Centre for Social Research undertook the nurse assessment, which trained registered nurses on data collection and study protocols. A nurse visited study participants who fulfilled the eligibility criteria five months after the main interview to collect a blood sample and complete health measures. All participants received a £10 voucher upon completing the nurse visit as a gesture of appreciation for participating.

2.1.2 ETHICS AND DATA ACCESS/REGULATION

During the visit, the nurses explained the protocol for health measures and blood sample collection. They sought informed verbal consent from participants to participate in each study wave, and written consent was obtained for blood sample collection. Participants were enrolled after consent was provided. Participants could decline any procedure or measurement at any time. The UKHLS wave 2 was granted ethical approval through a letter from the University of Essex Ethics Committee dated 6 July 2007, while details of ethical approval for early BHPS waves, including wave 3, are not available due to differences in ethical review processes and record-keeping practices at the time.

The nurse-led health data collection, including biomarker sampling, was approved by the National Research Ethics Service (NRES) under approval number 10/H0604/2. These approvals ensure that the study complies with ethical guidelines for research involving human participants, including informed consent, data confidentiality, and participant well-being. UKHLS is available through the UK Data Archive under the end user licence (University of Essex, 2014).

2.1.3 APPLICATION FOR SPECIAL LICENSE TO CENSUS 2011 LOWER LAYER SUPER OUTPUT AREA DATA FOR UKHLS WAVE 2 AND 3

As part of this thesis research on regional health inequalities in the UK, an application was submitted for Special Licence Access to the Census 2011 Lower Layer Super Output Areas (LSOA) data linked to Waves 2 and 3 of the Understanding Society. The primary justification for this application was the need for nationally representative data covering all age groups and geographic regions. Additionally, access to LSOA-level identifiers was essential for linking neighbourhood-level characteristics, including deprivation indicators, with biomarker data collected in UKHLS nurse visits during Waves 2 and 3. This linkage enables a more granular analysis of how small-area socioeconomic factors contribute to observed disparities in regional health conditions. Given the scope of my research, I determined that no alternative UK datasets would sufficiently address my specific research aims. The unique combination of UKHLS biomarker data and neighbourhood deprivation measures made the dataset crucial for my study.

The application process for the Special License Data involved submitting a detailed research proposal outlining:

1. The necessity of accessing LSOA-level identifiers for linking with UKHLS Wave 2 and 3 biomarker data.

2. A comprehensive data security and storage plan in line with UK Data Service regulations.
3. Justification for why alternative data sources would not meet the research objectives.

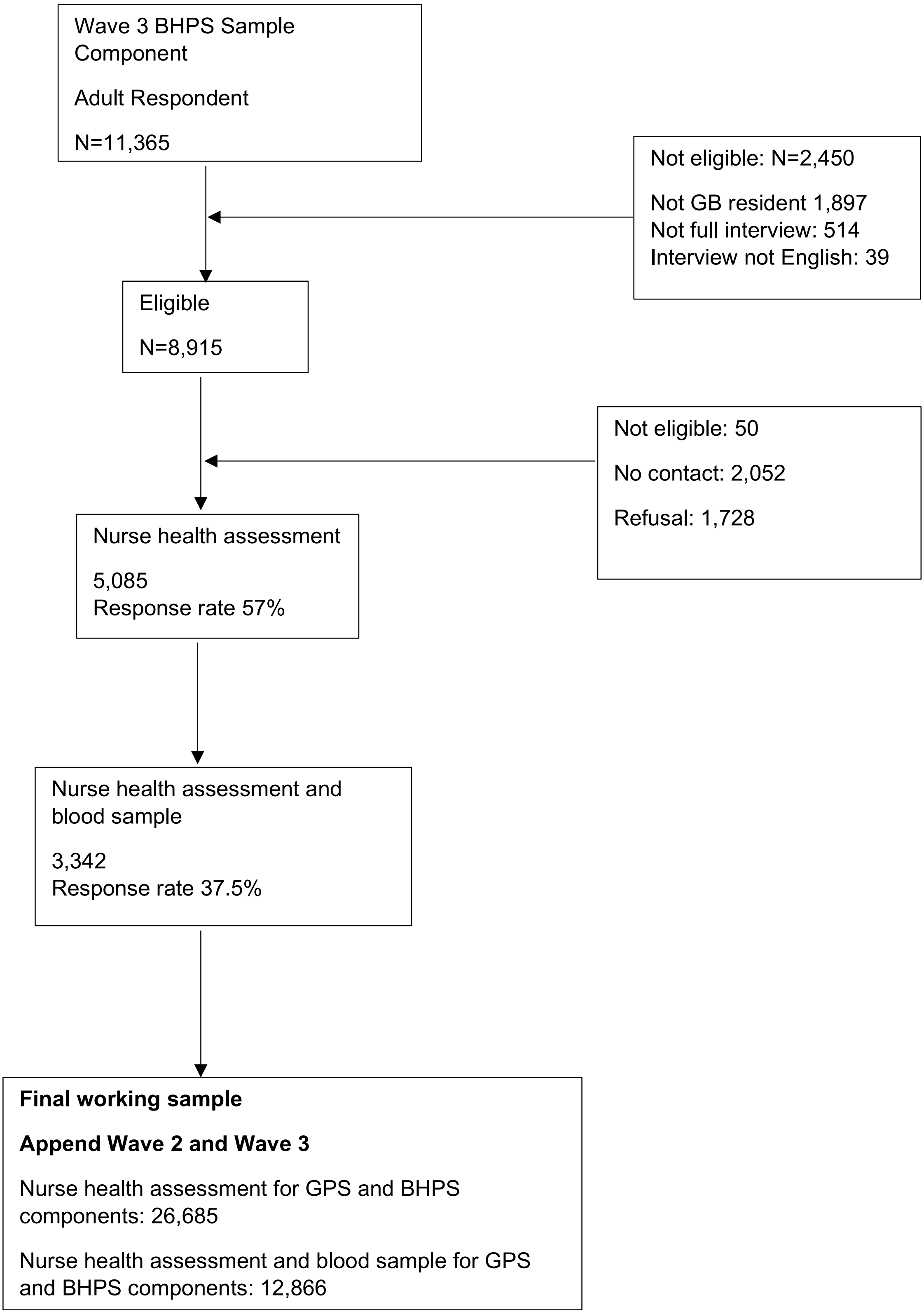
Following submission, the application underwent a two-month review period before receiving approval. The approval process included an assessment of the research rationale, methodology, and security protocols to ensure that the requested data would be handled responsibly and for legitimate research purposes. This data was available solely for England because each nation uses a different measurement system for the LSOA data and, therefore, cannot be linked. Hence, the reason for concentrating only on England in Chapter 4.

Given the sensitive nature of Special License data, there was strict adherence to data security and confidentiality protocols as outlined in the Microdata Handling and Security Guidelines: Guide to Good Practice (UK Data Service, 2024).

2.2 STUDY DESIGN

This study follows a cross-sectional design since the second wave of UKHLS and third wave of BHPS are merged and analysed. The pool data from the merged surveys has a potential sample size of 36,963 participants, of which 20,685 completed the nurse health assessment. Also, 12,866 provided blood and had at least one biomarker extracted. Therefore, the final working sample size **(Fig. 2.3)** differed for each outcome indicator. Sample weights are provided by UKHLS to adjust for survey design, non-response, and attrition, ensuring that the results are representative of the UK population. These weights account for key demographic and socioeconomic factors, including age, sex, ethnicity, and geographic distribution. Given the focus on health inequalities, appropriate reweighting is applied to each subset analysed to maintain representativeness within specific groups, such as the GPS and former BHPS samples used in the health assessments. Further details on the weighting methodology can be found in Benzeval et al. (2014).

Figure 2.2 Flow diagram of participation in the nurse health assessment BHPS component



Adapted from McFall et al. (2014) Understanding Society: Waves 2 and 3 Nurse Health Assessment, 2010-2012

2.2.1 SAMPLE WEIGHTING AND REPRESENTATION

To ensure the sample is representative of the UK population, various weightings are applied based on key demographic and methodological factors. These weightings account for differences in selection probabilities, survey non-response, and attrition over time. Specifically, the weights incorporate variables such as:

- **Age and sex:** To align the sample distribution with UK population demographics.
- **Geographical region:** To account for variations across different areas.
- **Household structure:** Adjusting for differences in household composition.
- **Ethnicity and socioeconomic status:** Ensuring representation across diverse population subgroups.

The weighting process involved calibration to known population benchmarks, using external sources such as census data and administrative records. Specifically, the study employs:

- **UKHLS nurse visits weights:** Adjusted for non-response in biomedical data collection.
- **UKHLS blood person weights:** Applied to ensure representation in blood-based biomarker analysis.

The derivation and application of these weights follow the methodology outlined in Understanding Society User Guide (University of Essex, ISER, 2022) and related technical reports (Lynn, 2009; Kaminska & Lynn, 2019).

2.2.2 STRATIFICATION IN GENERAL POPULATION SAMPLE

The GPS used in this thesis is a clustered and stratified probability sample drawn from approximately 24,000 households. The stratification was based on:

- **Geographical regions:** Ensuring coverage across urban and rural areas.
- **Socioeconomic indicators:** Balancing representation across different income and employment groups.
- **Household composition:** Ensuring diverse family and living arrangements are included.

By incorporating these stratification criteria, the GPS ensures a robust, nationally representative sample, minimizing selection bias and improving the generalisability of findings. Again, this information is provided in the UKHLS, Waves 1-12, 2009-2022. User Guide (University of Essex, ISER, 2022).

2.3 OUTCOME VARIABLES

The outcome variables in this thesis are categorised into nurse-measured indicators and blood-based biomarkers.

2.3.1 NURSE-MEASURED INDICATORS

Table 2.1 presents the summary statistics of both the nurse measured and biomarker indicators. Discussion of the nurse measured indicators used in this thesis are explained below.

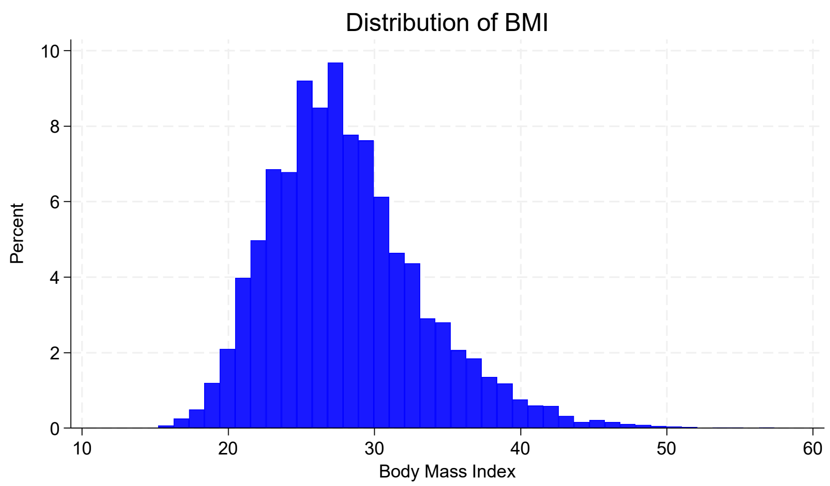
Table 2.1 Summary statistics of health outcomes

Variables	Observations	Mean	Standard Deviation
Body Mass Index	25,970	28.01	5.46
Systolic blood pressure	21,929	126.12	16.69
Cholesterol ratio	17,178	3.78	1.39
eGFR	17,237	94.77	25.51

BODY MASS INDEX

Body mass index (BMI) is defined as an individual's weight (kilograms) divided by the square of their height (in meters). BMI was calculated from heights and weights measured by a nurse. Height was measured with a portable stadiometer, and weight was measured with a Tanita BF 522 floor scale with participants wearing neither socks nor shoes. Only one measurement to the nearest millimetre and 0.1kg was taken. Participants who weighed more than 130kg were asked for their estimated weights because the scales were inaccurate above this level. BMI was categorized as follows: underweight (BMI <18.5 kg/m²), normal weight (BMI 18.5 – 24.9 kg/m²), overweight (BMI ≥25 kg/m²), and obese (BMI ≥30 kg/m²), with higher or lower values potentially indicating poor health (NHS Inform, 2023). **Figure 2.4** shows the distribution of BMI across the sample population. The distribution appears right skewed, meaning there are more individuals with higher BMI values extending towards the upper range. Most of the population falls between BMI 20 and 35, with a peak around 28.

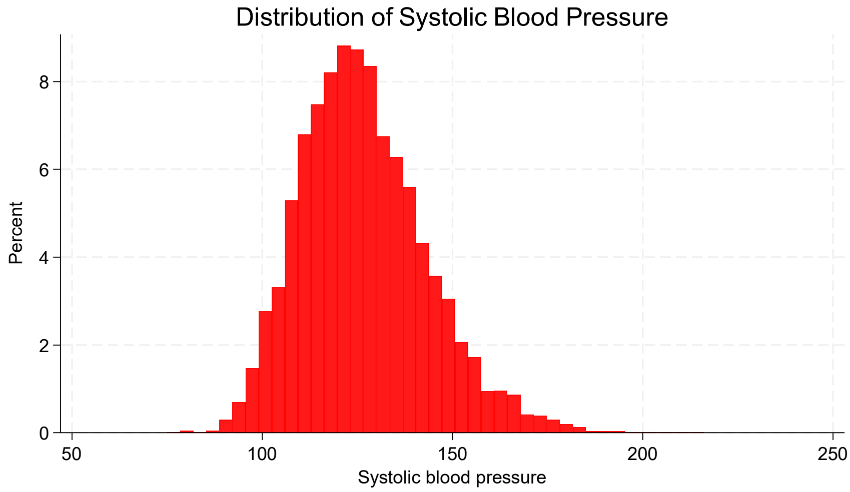
Figure 2.3 BMI distribution



SYSTOLIC BLOOD PRESSURE

This is the maximum pressure in an artery when the heart pumps blood. The systolic blood pressure was measured using a portable blood pressure monitor, the Omron HEM 907 (McFall et al., 2014), with three cuff sizes. Assessment was conducted on the right arm, with the participant sitting in a comfortable chair and their arm supported to bring the elbow to the heart level. Feet were placed flat on the floor. Nurses took readings three times. However, the second and third averages were used for this analysis, believing that the first reading could impose an upward bias base on factors such as participant anxiety or acclimatisation to the measurement process (Davillas and Pudney, 2020). According to Haider et al. (2003), systolic blood pressure is more predictive of health risks than diastolic blood pressure. Blood pressure of 130mmHg and above is a risk factor for cardiovascular disease (McFall et al., 2014; Carey et al., 2018). **Figure 2.5** presents the distribution of systolic blood pressure across the sample population. The histogram appears to be normal (bell-shaped)**,** suggesting that systolic blood pressure follows a normal distribution within the population, with a concentration around the mean of 126.

Figure 2.4 Systolic blood pressure distribution



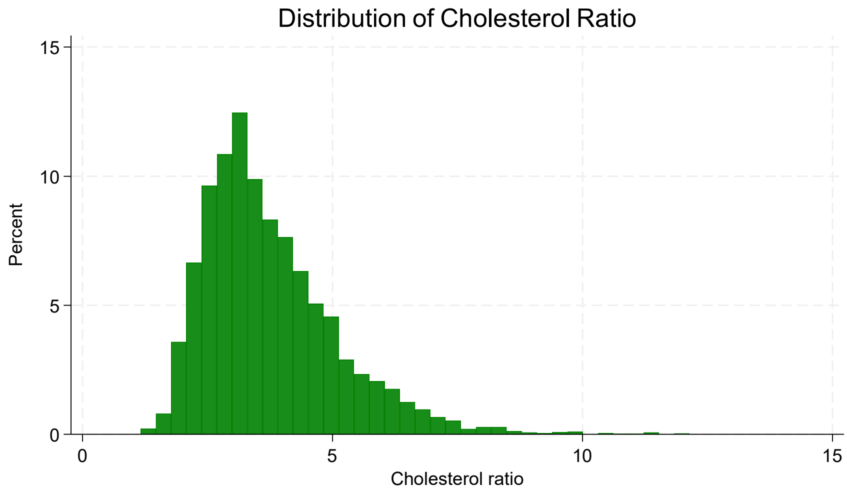
2.2.2 BLOOD-BASED BIOMARKERS

Discussion of the blood-based biomarkers used in this thesis are explained below.

CHOLESTEROL RATIO

This is the ratio between total cholesterol and high-density lipoprotein (HDL) cholesterol measured in the blood. Total cholesterol and HDL-cholesterol were measured from blood serum using enzymatic methods with a Roche Modular P analyser (McFall et al., 2004) calibrated to the Centre for Disease Control guidelines. Ratios of 6 and above indicate a higher risk of heart disease (NHS UK, 2022). **Figure 2.6** illustrate the distribution of cholesterol ratio across the sample population. The distribution is right-skewed (positively skewed)**,** meaning most individuals have lower cholesterol ratios, while a smaller portion has very high values. The peak of the histogram occurs around the mean of 3.8.

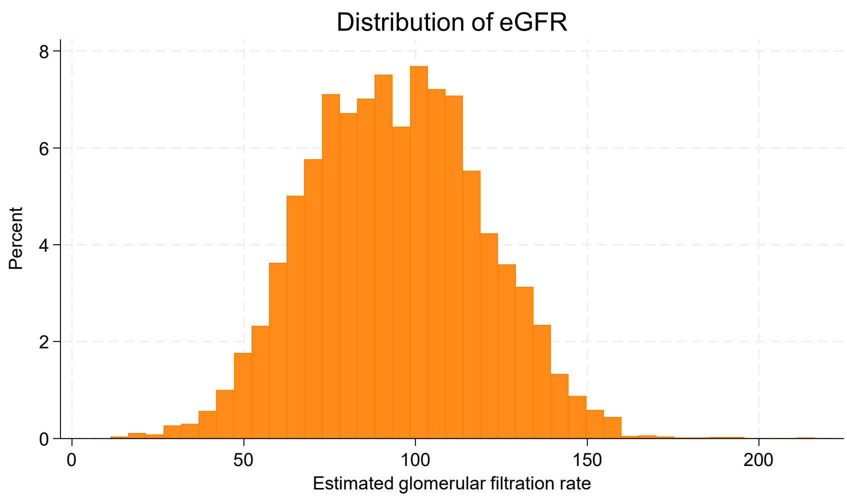
Figure 2.5 Cholesterol ratio distribution



ESTIMATED GLOMERULAR FILTRATION RATE

This is calculated from the serum creatinine concentration. Creatinine was measured from serum samples using an enzymatic method on the Roche P module analyser (McFall et al., 2004). The eGFR shows how much blood the kidneys clean in one minute, measured in millimetres. The equation for calculating eGFR, as provided by Levey et al. (2009), incorporates serum creatinine, age, sex, and race to estimate kidney function. Levels of eGFR below 89mL indicate potential risk of chronic kidney disease (Davillas and Pudney, 2020). **Figure 2.7** shows the distribution of eGFR across the sample population. The distribution appears normal (bell-shaped), centred around an eGFR value of 95. There is some skewness on the right, indicating that a small proportion of individuals have very high eGFR values above 150-200.

Figure 2.6 eGFR distribution



2.4 COVARIATES

2.4.1 INDIVIDUAL-LEVEL CHARACTERISTICS

A set of detailed individual-level characteristics typically associated with chronic health conditions following the literature (Flint et al., 2014; Davillas et al., 2016; Carrieri and Jones, 2017; Raftopoulou, 2017; Davillas et al., 2017) were included in this study.

Demographic characteristics include age (measured in years at the time of assessment), sex, and marital status. Sex is recorded as male or female. Marital status is captured in four categories: single, married/cohabiting, separated/divorced, and widowed. Socioeconomic status variables include household income (deflated using 2010 - 2011 retail price index (RPI), equivalised[1] using the Organisation for Economic Co-operation and Development (OECD) modified scale and log-transformed), education (no qualification, O-level, A-level and degree), job status (unemployed, self-employed, paid employment, and retired) and house ownership (renting, or homeowner). Lifestyle characteristics include physical activity (no activity, or some form of activity), smoking status (never smoked, ex-smoker, and smoker), alcohol consumption defined as (never taken alcohol, frequent in-take, and rare in-take), weekly fruit consumption (never consume fruit, 1-3 days weekly fruit consumption, 4-6 days weekly fruit consumption, and daily fruit consumption) and number of fruit and vegetables eaten daily.

[1] The modified OECD equivalence scale is the standard scale for the Statistical Office of the European Union (Eurostat). It adjusts household income to reflect the different resource needs of single adults, any additional adults in the household, and children in various age groups.

2.4.2 REGIONAL LEVEL INDICATORS

To examine regional inequalities in the biomarker data, eleven binary indicators representing the government office regions (GORs) for Great Britain (nurse recruitment proved difficult in Northern Ireland) are included: Northeast, Northwest, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, Southeast, Southwest, Wales, and Scotland.

2.4.3 NEIGHBOURHOOD-LEVEL DATA AND VARIABLES

To obtain neighbourhood-level data, UKHLS Wave 2 and 3 data (2010–2012) were linked at the Lower Layer Super Output Area (LSOA) level with selected sub-domains of the 2010 English Indices of Deprivation (EID2010). LSOAs are statistical lower-layer geography used in England to measure relative deprivation in small areas. Each LSOA comprises, on average, 1,500 residents and 650 households. Following established methodology (Flouri et al., 2013) and considering the availability of linked data, the LSOAs of UKHLS Wave 2 and 3 participants were used to define neighbourhood regions. **Table 2.2** presents the summary of the neighbourhood-level variables used in my analysis.

Table 2.2. Summary of Neighbourhood-level variables

Variables	Description	Interpretation
Crime Level	Rate of recorded crime (violence, burglary, theft, criminal damage)	Higher values indicate increased crime rates
Air Quality	Concentration of sulphur dioxide relative to WHO safe limits	Higher values indicate increased pollution
GP Distance	Mean road distance (km) to the nearest GP	Increase distance suggests lower healthcare accessibility
Income Deprivation	Proportion of population experiencing income-related deprivation	Higher values indicate increase deprivation
Skill Deprivation	Proportion of adults with low/no qualifications	Higher values indicate lower educational attainment

NEIGHBOURHOOD CRIME LEVELS

Neighbourhood crime rates were measured using the EID2010 Crime Domain Index, which captures the rate of recorded crime in an area for violence, burglary, theft, and criminal damage (Lad, 2011). These crime types reflect the risk of personal and material victimisation at a small area level. Prior research suggests that higher crime rates are linked to increased stress and poor physical health outcomes (Putrik et al., 2019) and may contribute to an elevated risk of cardiovascular disease (Kahn et al., 1998). Crime levels were operationalised as a binary variable (least crime vs. most crime) following the approach of Davillas and Jones (2020).

AIR QUALITY

Air quality was assessed using the EID2010 Sulphur Dioxide (SO_2) Indicator, which measures the average concentration of pollutants at the LSOA level, divided by WHO-recommended safe guideline levels (WHO, 2021). Higher values indicate poorer air quality at the small-area level. SO_2 has been widely used in air quality assessments (Katsouyanni, 2003; Chaparro et al., 2018; Davillas & Jones, 2020). Previous studies have linked air pollution exposure to respiratory symptoms, cardiovascular disease, and increased mortality (Holgate, 2017; An et al., 2018), as well as reductions in outdoor physical activity (An et al., 2018).

HEALTHCARE ACCESS

A proxy for neighbourhood geographical barriers to healthcare was included using the EID2010 road distance to the nearest General Practitioner (GP). This variable captures the mean road distance (in km) from an LSOA to the closest GP. Access to GPs is a critical determinant of participation in NHS Health Checks, introduced in 2009, which assess cardiovascular risk and promote disease prevention (Dalton et al., 2011; Burgess et al., 2015). Proximity to a GP can influence an individual's likelihood of attending such screenings.

INCOME DEPRIVATION

Neighbourhood income deprivation was measured using the EID2010 Income Deprivation Index, which quantifies the proportion of the population in an LSOA experiencing income-related deprivation. This includes families claiming income support, income-based jobseeker’s allowance, or pension credit. Income deprivation has been associated with increased prevalence of cardiovascular diseases and other adverse health conditions (Baker, 2019). The index is a ratio-scale variable, where higher values indicate a greater proportion of income-deprived residents in an LSOA.

SKILL DEPRIVATION

The EID2010 Skill Deprivation Sub-Domain was used to assess educational attainment at the LSOA level. This variable represents the proportion of adults with no qualifications or qualifications below National Vocational Qualification (NVQ) Level 2 (McLennan et al., 2011). Prior research indicates that lower skill levels are linked to poorer self-assessed health, increased psychological distress, functional health limitations, and multiple health problems (Jokela, 2015). Like the Income Deprivation Index, this is a ratio-scale variable, where higher values indicate a greater proportion of individuals with low qualifications in an LSOA.

2.5 STATISTICAL METHODS

This section provides an overview of the three main statistical methods used in this thesis.

2.5.1 ORDINARY LEAST SQUARE REGRESSION

Ordinary least squares (OLS) estimates parameters of a linear relationship between an outcome and one or more independent variables. The method minimizes the sum of squared distances between the observed and the predicted values from the linear model. The OLS estimator is consistent if the independent variables are uncorrelated with the error term. It is optimal for linear unbiased estimators when the errors are homoscedastic and serially uncorrelated. Under these conditions, the OLS method provides minimum-variance mean-unbiased estimation when the errors have finite variances. Under the added assumption that the errors are normally distributed, OLS is the maximum likelihood estimator. Previous researchers have used OLS when investigating regional and socioeconomic disparities in health (Lee et al., 2015; Carrieri and Jones, 2017).

The initial analyses used linear regression models with biomarkers as dependent variables and OLS to estimate regression coefficients. The linear regression models were constructed as a function of the covariates:

$$Bio_i = X_i'B + \varepsilon_i \tag{1}$$

where Bio_i is any of the outcome variables. X_i is a matrix of regressor variables, i.e., the independent variables; B is the associated parameter vector, and ε_i are unobserved error terms in the model.

The analysis accounts for sample weights, which are provided by UKHLS for researchers to incorporate at their discretion. Based on the data user guide and training I attended; I included weighting to ensure that the results are representative of the UK population. Specifically, sample weights were applied as [pw=indnsus_xw] for nurse-measured health outcomes and [pw=indbdub_xw] for blood-collected health outcomes. These weights were included at the end of my STATA code. For example: “reg bmi ib(7).region if sample_bmi ~= . [pw=indnsus_xw], vce(robust)"

The F-test was conducted to determine whether there were significant differences in the predictors across regions. Specifically, the test was applied to assess whether the inclusion of regional dummy variables significantly improved the model fit, indicating potential regional-level variation in the relationships between predictors and health outcomes.

2.5.2 OAXACA-BLINDER DECOMPOSITION METHOD

Decomposition approaches are used to examine distributional variations in the dependent variable between groups or time points. In this research context, the decomposition method is widely used to analyse regional disparities in health outcomes by dividing them into explained and unexplained components. The explained component accounts for differences due to observable factors such as socioeconomic status, neighbourhood-level factors, and demographic characteristics, while the unexplained component reflects disparities arising from unmeasured or structural factors, including discrimination or systemic inequalities. This method, originally developed in labour economics, has been increasingly applied in health inequalities research to identify key determinants of regional health gaps and quantify their contributions (Lee et al., 2015; Carrieri and Jones, 2017; Di Paola et al., 2018).

The standard Oaxaca-Blinder (OB) decomposition (Blinder 1973; Oaxaca 1973) explains the mean differences in the outcome variable between two groups. This statistical analysis decomposes the differences into a part explained by the group differences in the predictors (explained or the observed effect) and a part that captures the effects of differences in the estimated coefficients and unobserved variables (unexplained or coefficient effect). Originally, the OB decomposition was used to study labour market outcomes by groups such as sex, race, and so on. The method decomposes mean differences in log wages based on linear regression models in a counterfactual manner i.e., it estimates what wages would be if one group had the same characteristics as another, helping to isolate the sources of wage disparities. (Blinder 1973; Oaxaca 1973). Decomposition analysis is important for drawing policy implications because it helps to identify the extent to which health disparities are driven by factors that can be addressed through policy interventions. By distinguishing between explained disparities such as differences in income, education, or healthcare access and unexplained disparities, which may be linked to systemic biases or discrimination, policymakers can design targeted strategies to reduce health inequalities. For example, if the analysis finds that regional health disparities are largely explained by differences in educational attainment, policymakers might focus on improving access to quality education or implementing health education programs to address long-term health inequalities (Doorslaer and Koolman, 2004).

Oaxaca-Blinder decomposition analysis was conducted to quantify the contributions of individual and neighbourhood characteristics in explaining regional differences between people in London and those in the other eight regions of England. In addition, a coastal analysis was performed for the East of England region to examine how health disparities in coastal areas compare to inland regions. While OLS analysis reveals the association between the health outcomes (eGFR, systolic blood pressure, BMI, and cholesterol ratio) and its risk factors, the decomposition analysis allows us to estimate the association between the health outcomes disparities and their contributing causes, helping to identify specific factors that could reduce regional health inequalities. For example, if the analysis reveals that differences in educational attainment significantly contribute to health disparities, policymakers could implement targeted interventions such as health education programs or improved access to schooling in disadvantaged regions to mitigate these gaps.

The two-fold decomposition based on the pooled linear parameter estimates was adopted (Oaxaca and Ransom, 1994; Jann, 2008). The decomposition equation is given as:

$$\overline{Bio}_{R1} - \overline{Bio}_{R2} = \{E(X_{R1}) - E(X_{R2})\}'\beta_{R2} + E(X_{R1})'(\beta_{R1} - \beta_{R2}) + E(\mu_{R1}) - E(\mu_{R2}) \quad (2)$$

$$\overline{Bio}_{R1} - \overline{Bio}_{R2} = \{E(X_{R1}) - E(X_{R2})\}'\beta_{R2} + E(X_{R1})'(\beta_{R1} - \beta_{R2})$$

Where:

- $\overline{Bio}_{R1}$ and $\overline{Bio}_{R2}$ represent the mean biomarker outcomes for participants in Region 1 (London, the reference region) and Region 2 (any other region in Great Britain or England), respectively.
- $E(X_{R1})$ and $E(X_{R2})$ are the expected values of the observed variables for each region.
- β represents the estimated regression coefficient for each group.

The equation consists of two components:

1. Explained component (observed factors)

$$\{E(X_{R1}) - E(X_{R2})\}'\beta_{R2}$$

This term captures the part of the health outcome disparity that is due to differences in observed characteristics between regions, such as socioeconomic status and neighbourhood-level factors. It helps quantify how much of the regional health gap can be attributed to measurable individual and neighbourhood factors.

2. Unexplained component (Coefficient effect)

$$E(X_{R1})'(\beta_{R1} - \beta_{R2})$$

It represents the portion of the outcome differential that remains after accounting for differences in observable characteristics between groups. This component captures disparities due to differences in coefficients (returns to characteristics) and other unmeasured factors.

The percentage of the outcome difference explained by each covariate can be calculated by dividing the explained difference by the total difference:

$$\frac{\{E(X_{GOR1})-E(X_{GOR2})\}'\beta^{*}}{\overline{Bio}_{R1}-\overline{Bio}_{R2}} \tag{3}$$

Given that most health issues are concentrated in the lower or upper tails of the outcome distribution, this analysis will extend beyond the mean of the Oaxaca-Blinder decomposition, focusing specifically on disease areas. The explained and the unexplained parts will be decomposed into contributions of each covariate at each quantile, allowing for the consideration of the entire distribution (Firpo et al., 2009).

2.5.3 CONDITIONAL QUANTILE REGRESSION

A quantile regression estimates the effect of the explanatory variables on the dependent variable at different points of the dependent variable's conditional distribution (Eide and Showalter, 1998). Conditional quantile regression was originally introduced as a robust technique which allows for estimation where the typical assumption of non-linearity of the relationship might not be strictly satisfied (Koenker and Basset, 1978). Unlike OLS, quantile regression is not limited to estimating the mean of the dependent variable, and it can be employed to explain the determinants of the dependent variable at any point of the distribution of the dependent variable. The formula for conditional quantile regression is similar to that of OLS regression but instead focuses on estimating the conditional quantile of the dependent variable:

$$y_i = x_i'\beta_\theta + \mu_{\theta i},\ Quant_\theta(y_i|x_i) = x_i'\beta_\theta, \tag{4}$$

Where $Quant_\theta(y_i|x_i)$ denotes the conditional quantile of y_i, conditional on the regressor vector x_i, β_θ is the vector of coefficients to be estimated, which depends on the quantile of y_i and $\mu_{\theta i}$ represents the error term.

The objective is to estimate the coefficient β_θ such that the quantile of the conditional distribution of y given x is accurately predicted. As described by Koenker and Basset (1978), the estimation is done by minimizing the quantile loss function:

$$\underset{\beta \epsilon R^K}{Min} [\textstyle\sum_{\{i:y_i \geq X_i\beta\}} \theta|y_i - X_i\beta| + \sum_{\{i:y_i < X_i\beta\}} (1-\theta)|y_i - X_i\beta|] \tag{5}$$

Where θ is the quantile of interest, y_i is the observed outcome, X_i is the vector of explanatory variables, and β is the vector of coefficients. The coefficient vector β will differ depending on the quantile being estimated.

A standard conditional quantile regression may generate results that are often not generalisable in a policy or population setting (Borah and Basu, 2013). However, the unconditional quantile regression method overcomes this as it produces more generalisable results and marginalises the effect over the distributions of the covariates in the model.

2.5.4 UNCONDITIONAL QUANTILE REGRESSION

Unconditional Quantile Regression (UQR) is a statistical method based on the Influence Function (IF), which measures how an individual observation affects a distributional statistic, such as a quantile. This thesis applies UQR to examine the entire distribution of eGFR and systolic blood pressure (SBP) levels, assessing potential regional differences at various quantiles of the distribution. To estimate the UQR, we use the Recentred Influence Function (RIF), which is derived by adding the statistic of interest (e.g., a specific quantile) to its corresponding IF. The RIF provides a transformed version of the outcome variable for each quantile, which can then be used in an OLS regression to assess how explanatory variables influence different points of the outcome distribution. The RIF of the biomarkers (eGFR and SBP) is estimated directly from the data:

1. First, the sample quantile q is computed.
2. Then, the density of the biomarker distribution at that quantile is estimated using kernel density methods.
3. Finally, for a given observed quantile q_τ , a RIF value is generated, which depends on whether an individual's biomarker level is below or above the quantile.

This approach allows for a detailed Oaxaca-Blinder decomposition, providing insights into the factors driving regional health disparities at different points in the outcome distribution.

$$RIF(Bio; q_\tau) = q_\tau + \frac{\tau - I[Bio \leq q_\tau]}{f_{Bio}(q_\tau)} \qquad (6$$

Where:

- q_τ is the observed quantile at level τ.
- τ is a probability value between 0 and 1, indicating the quantile being analysed.

- $1[Bio \leq q_\tau]$ is an indicator that equals one if the observed value of the biomarker is less than or equal to the observed quantile and zero otherwise.
- $f_{Bio}(q_\tau)$ is the estimated kernel density of the biomarker measured at the τth quantile.

To analyse regional disparities in the biomarkers, the Oaxaca-Blinder (OB) decomposition technique using the RIF regression in equation 1 as a basis for the decomposition (Oaxaca, 1973; Blinder, 1973; Jann, 2008; Carrieri and Jones, 2017; Di Paola et al., 2018) is used. Differences in estimated biomarker levels between regions at each quantile can, however, be decomposed as follows:

$$\Delta_{Bio}^{\tau} = [\widehat{RIF}(Bio_{R1}, q_{R1\tau}) - [\widehat{RIF}(Bio_{R2}, q_{R2\tau})]$$

$$\Delta_{Bio}^{\tau} = (\bar{X}_{R1}^{\tau} - \bar{X}_{R2}^{\tau})\beta_{R1}^{\tau} + \bar{X}_{R2}^{\tau}(\beta_{R1}^{\tau} - \beta_{R2}^{\tau}) \qquad (7)$$

Where:

- $\bar{X}_{R1}^{\tau}$ and $\bar{X}_{R2}^{\tau}$ are the observed quantile means of the independent variables[2] for the subsamples of the different regions in England.
- β_{R1}^{τ} and β_{R2}^{τ} are the coefficients of the unconditional quantile regression.

The first part $(\bar{X}_{R1}^{\tau} - \bar{X}_{R2}^{\tau})\beta_{R1}^{\tau}$, also termed the 'explained' part of Equation 3, are the quantile biomarkers differentials explained by differences in the observed characteristics between the regions. The second part $\bar{X}_{R2}^{\tau}(\beta_{R1}^{\tau} - \beta_{R2}^{\tau})$, which is termed the 'unexplained part', is the quantile biomarker differentials that are unexplained. It accounts for differences due to the potential effects of estimated coefficients or unobserved factors.

[2] For categorical regressors, the detailed decomposition results depend on the choice of the base category. A solution is to compute the decomposition based on "normalised" effects, i.e., effects that are expressed as deviation contrasts from the grand mean (Yun, 2005).

The explained and unexplained parts are further decomposed into a detailed decomposition where the contributions of individual variables at each quantile of the systolic blood pressure and eGFR distribution are shown. The detailed individual contributions of all the covariates of the explained part are obtained as follows:

$$(\bar{X}_{R1}^{\tau} - \bar{X}_{R2}^{\tau})\beta_{R1}^{\tau} = (\bar{X}_{1R1}^{\tau} - \bar{X}_{1R2}^{\tau})\beta_{1R1}^{\tau} + (\bar{X}_{2R1}^{\tau} - \bar{X}_{2R2}^{\tau})\beta_{2R1}^{\tau} + \dots \quad (8)$$

where $\bar{X}_{1R1}^{\tau}$ and $\bar{X}_{1R2}^{\tau}$... are the means of the single covariates and β_{1R1}^{τ} are the associated coefficients of the unconditional quantile regression estimated on the subsample of the different regions. The left-hand side represents the total explained component of the regional differences in the outcome variable. The right-hand side decomposes the total explained component into contributions from individual predictors.

Similarly, the detailed individual contributions of all the covariates to the unexplained part are given as follows:

$$\bar{X}_{R2}^{\tau}(\beta_{R1}^{\tau} - \beta_{R2}^{\tau}) = \bar{X}_{1R2}^{\tau}(\beta_{1R1}^{\tau} - \beta_{1R2}^{\tau}) + \bar{X}_{2R2}^{\tau}(\beta_{2R1}^{\tau} - \beta_{2R2}^{\tau}) + \dots \quad (9)$$

The RIF-unconditional quantile regression, as implemented in STATA by Fortin (2010), together with the OB decomposition developed by Jann (2008), is used to perform OB decomposition across regional disparities in eGFR and systolic blood pressure across the quantile distribution in the UK. Also, the analysis is adjusted using the UKHLS sample weights that account for key demographic and socioeconomic factors, including age, sex, ethnicity, and geography, making the sample representative of the UK population[3]

[3] Adjusting for sample weight is essential to produce unbiased, accurate, and generalisable results from the data. Also, ensuring that the findings truly reflect the characteristics and behaviours of the overall UK population.

CHAPTER 3

WHAT LIES BEHIND THE OBSERVED REGIONAL DIFFERENCES IN HEALTH IN THE UK?

3.0 BACKGROUND

Global health disparities are a significant and urgent challenge for policymakers, encompassing both inequalities between countries such as differences in healthcare access, disease burden, and life expectancy and disparities within countries, where factors like socioeconomic status, geographic location, and healthcare infrastructure contribute to uneven health outcomes (Sen, 1997). Despite continuous growth and outstanding health outcomes over the years, distinct health discrepancies persist between regions in the United Kingdom (Shelton, 2009; Plumper et al., 2018). The Marmot Review (Marmot et al., 2010) shows that health inequalities affect everyone, not just the most disadvantaged. While lower-income groups experience the greatest burden, even the most well-off are affected through wider societal consequences, such as increased healthcare costs, reduced economic productivity, and social instability. Moreover, evidence suggests a social gradient in health, meaning that health outcomes improve at every step up the socioeconomic ladder, but no group is entirely immune to disparities.

There is a growing body of evidence documenting regional health inequalities in the distribution of health and access to healthcare internationally and in the United Kingdom (UK) using different subjective and objective measures (Davillas and Jones, 2020; Vallejo-Torres and Morris, 2010). For example, Costa-Font (2008) used self-reported health status and disability indicators to explore socioeconomic determinants of health and disability in old age in Spain. Davillas and Jones (2020) used biomarker outcome measures (body mass index and waist circumference) to investigate regional inequalities in adiposity in England. Some limitations of these studies are that 1) self-reported indicators can be problematic because of reporting errors, which can result in heterogeneity in the thresholds (variation in outcomes between studies) (Lee et al., 2015); 2) Biomarker data are specific to particular conditions and do not account for most of the chronic conditions in the UK.

This study aims to investigate the following research questions:

- Are there regional inequalities in health in the UK?
- How does the level of health outcomes differ by government office regions (GORs)?
- What lies behind these differences in health outcomes across GORs in the UK?

Four biomarkers that are relevant to chronic conditions and life expectancy were considered:

- Nurse-measured: Body Mass Index and systolic blood pressure.
- Blood-based: Cholesterol ratio and eGFR.

Ordinary least squares (OLS) regression method and a standard Oaxaca-Blinder decomposition was estimated using the Understanding Society data to answer the research questions. Results show regional disparities in health in the UK and that socioeconomic status, such as job status and education, contribute to these regional differences. Lifestyle factors, such as alcohol intake is also associated with regional disparities in health in the UK. Policies focusing on education and creating employment for deprived regions may reduce health disparities in the UK.

3.1 DATA AND VARIABLES

The data used in this research is from the United Kingdom Household Longitudinal Study, a nationally representative panel survey of households in the United Kingdom. This analysis did not include Northern Ireland, as nurse recruitment proved difficult in this region.

3.1.1 OUTCOME VARIABLES

Information about the outcome variables is provided in Chapter 2.

3.1.2 COVARIATES

Following the literature, important covariates associated with critical health conditions have been included (Flint et al., 2014; Raftopoulou, 2017). These factors have been documented to vary within and between regions (Shelton, 2009; Di Paola and Raftopoulou, 2018).

Demographic characteristics include age as a continuous measure, sex, and marital status. Marital status is captured in four categories: single, married/cohabiting, separated/divorced, and widowed. Socioeconomic characteristics include household income, education (no qualification, O-level, A-level, or degree), and job status, which is captured as (employed and unemployed). Health-related lifestyle indicators include alcohol consumption, which is captured as 3-categories: never drank alcohol, rare consumption of alcohol and frequent consumption of alcohol. Physical activity is proxied by sports activities (active or otherwise), and the number of fruits and vegetables eaten daily were used to proxy healthy dietary habits (Davillas et al., 2016).

3.2 STATISTICAL ANALYSIS

A linear regression model using OLS for each biomarker health outcome was created.

$$Bio_i = X_i'B + \varepsilon_i \qquad (1)$$

Where the biomarker outcomes for individual i are modelled as a function of the explanatory variables. X_i is a matrix of regressor variables: age, sex, and regional dummies variable (i.e. binary indicators). B is the associated parameter vector, and ε_i are unobserved error terms in the model, assumed to be normally distributed. The F-test was used to assess statistical significance of the differences of the regional dummies. Where F-test is significant, it becomes compelling to investigate the sources of those differences.

3.2.1 OAXACA-BLINDER DECOMPOSITION ANALYSIS

Information about Oaxaca Blinder decomposition is provided in Chapter 2.

3.3 SAMPLE CHARACTERISTICS

Table 3.1 shows the descriptive statistics for the explanatory variables. On average, the age of individuals represented in the sample is around 51 years, with females having the highest level of representation (56%) compared to males. Also, 55% of the sample participants are married or cohabiting. For education, around 22% of individuals in the sample have a degree, and a higher percentage have both A-levels and O-levels of 33% and 31%, respectively. Furthermore, 54% of the sample participants are employed. The lifestyle characteristics of the sample participants show that, on average, individuals consume around three fruits or vegetables daily, 58% consume alcohol often, and 74% are physically active. A more substantial proportion of sample representation is found in the Southeast region (11%) and the Scotland region (29%).

Table 3.1 Descriptive statistics of explanatory variables

Characteristics	n (%) or Mean (SD)
Demographics	
Age (Mean, SD)	50.51 (17.92)
Sex	
Male	11,831 (43.86)
Female	15,146 (56.14)
Marital status	
Single	6,743 (25.27)
Married/cohabiting	14,693 (55.06)
Separated/divorced	3,167 (11.87)
Widowed	2,083 (7.81)
Socioeconomic status	
Log of household income (Mean, SD)	7.341 (0.62)
Education	
No education	3,763 (14.13)
O-level	8,278 (31.08)
A-level	8,826 (33.13)
Degree	5,770 (21.66)
Job-status	
Unemployed	12,142 (45.54)
Employed	14,523 (54.47)
Lifestyle factors	
Fruit and vegetables eaten daily (Mean, SD)	3.378 (1.58)
Physical activity	
Not Active	4,769 (26.02)
Active	13,557 (73.98)
Alcohol consumption	
Never drank alcohol	1,326 (8.17)
Rare consumption	5,451 (33.60)
Frequent consumption	9,448 (58.23)
Government Office Region	
Northeast	1,036 (3.84)
Northwest	2,449 (9.08)
Yorkshire and the Humber	1,832 (6.80)
East Midlands	1,787 (6.63)
West Midlands	1,741 (6.46)
East of England	2,099 (7.79)
London	1,504 (5.58)
Southeast	2,994 (11.11)
Southwest	2,092 (7.76)
Wales	1,494 (5.54)
Scotland	7,933 (29.42)

3.4 RESULTS

3.4.1 DETERMINANTS OF BODY MASS INDEX

Table 3.2 shows the Ordinary Least Squares (OLS) regression estimates of the BMI determinants using a multiple linear regression model. A linear relationship between age and BMI was found (see **Fig.3.1**). On average, the results shows that females have a lower BMI value than males, which is statistically significant. The unadjusted model of just the regions regressed on BMI, shows that on average, all regions have a statistically significantly higher BMI than London, except East of England and Southeast which are not statistically significant. A graphical representation of the results can be found in **Figure 3.2**. The F-test for the joint significance of the GORs for both models shows apparent regional differences in BMI.

Figure 3.1 Margin graph of body mass index with age

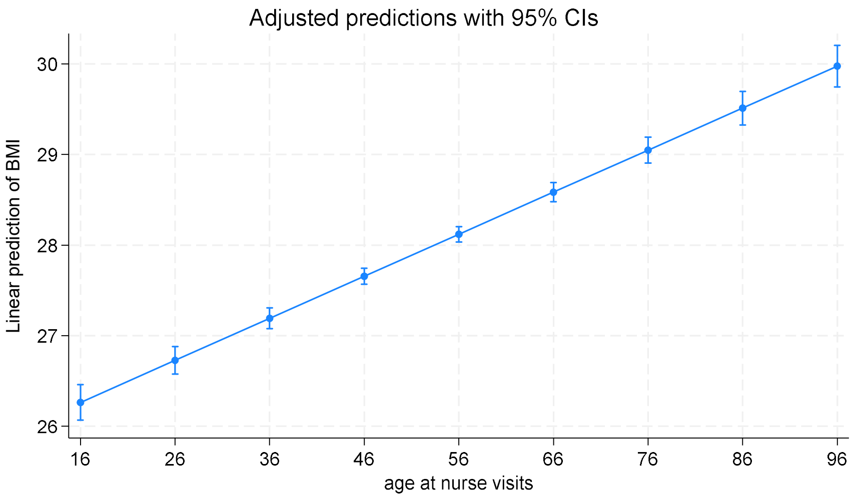


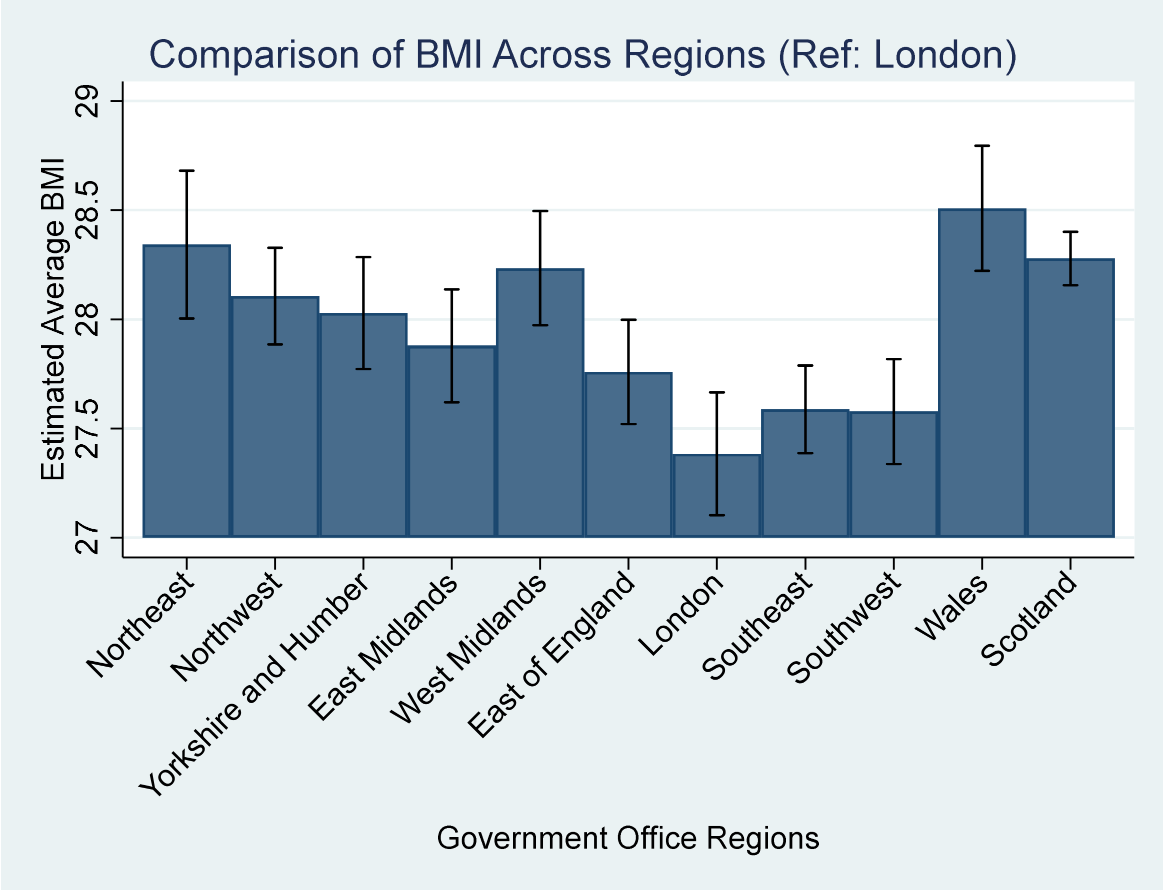
Table 3.2 Association between explanatory variables and Body Mass Index

Predictors	Coefficient (SE)	Coefficient (SE)
Region		
Northeast	0.95^{***} (0.26)	0.78^{**} (0.31)
Northwest	0.69^{***} (0.22)	0.47^{*} (0.26)
Yorkshire and the Humber	0.58^{**} (0.24)	0.26 (0.27)
East Midlands	0.67^{***} (0.24)	-0.03 (0.27)
West Midlands	0.72^{***} (0.23)	0.28 (0.28)
East of England	0.30 (0.22)	-0.06 (0.26)
Southeast	0.20 (0.20)	-0.24 (0.24)
Southwest	0.47^{**} (0.22)	-0.46^{*} (0.25)
Wales	1.19^{***} (0.28)	0.68^{*} (0.37)
Scotland	0.86^{***} (0.19)	0.35 (0.24)
Age		0.03^{***} (0.00)
Female		-0.29^{***} (0.11)
Marital status		
Married		1.47^{***} (0.15)
Divorced		0.99^{***} (0.20)
Widowed		0.38 (0.28)
Log household income		-0.49^{***} (0.09)
Highest qualification		
O-level and other		-0.49^{***} (0.18)
A-level and higher		-0.47^{**} (0.19)
Degree		-1.22^{***} (0.20)
Employed		0.89^{***} (0.13)
Alcohol consumption		
Frequent in-take		-0.87^{***} (0.23)
Rare in-take		0.35 (0.24)
Fruit and veg eaten/day		-0.05 (0.03)
Physical activity		-0.71^{***} (0.14)
Constant	27.12^{***} (0.17)	30.40^{***} (0.78)
Joint significance test (F-test)		
Regional dummies	F (10, 25,970) = 4.95 Prob > F =0.00	F (10,25,970) =5.02 Prob > F =0.00
Observations	25,970	25,970

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: London is the reference region. Sample is weighted using UKHLS nurse visits weights; SE – Standard errors.

Figure 3.2 Comparison of BMI across regions



3.4.2 OAXACA BLINDER DECOMPOSITION RESULTS

Table 3.3 presents the aggregated decomposition results of the regional differences in BMI. The decomposition result shows the differences in BMI values across regions of the UK. A negative (positive) difference means that the BMI value is higher (lower) in the GORs compared with the London region, i.e., London is the reference group. This region, known for better health outcomes, serves as a benchmark for comparison. Examining it helps illustrate how other regions might look if they shared similar characteristics. A higher BMI indicates an increased risk of obesity-related disease.

The decomposition analysis shows that all the regions except for Southwest have a higher BMI value compared to the London region. OLS results confirm these differences, with statistical significance in six out of ten regions. The differences are then decomposed into the explained and the unexplained parts. The explained part for all the regions is significant. However, not all the regions have a significant overall regional difference. For example, the decomposition analysis evidence that 80% (-0.51 units) and 86% (-0.66 units) of the aggregated regional BMI gap of Yorkshire and Humber and West Midlands region is due to the differences in the levels of covariates ($p<0.01$) respectively. However, the remaining 20% (-0.13 units) and 14% (-0.11 units) are unexplained. In cases where the explained or unexplained portion exceeds 100%, this may suggest that observed covariates (coefficient effect) alone would predict an even larger BMI gap than what is observed, implying counteracting effects from unmeasured factors or model limitations.

Table 3.3 Oaxaca - Blinder decomposition for regional differences in Body Mass Index

	Northeast	Northwest	Yorkshire & Humber	East Midland	West Midland	East of England	Southeast	Southwest	Wales	Scotland
London Mean	27.29***	27.29***	27.29***	27.29***	27.29***	27.29***	27.29***	27.29***	27.29***	27.29***
	(0.213)	(0.213)	(0.213)	(0.213)	(0.213)	(0.213)	(0.213)	(0.213)	(0.213)	(0.213)
Comparison GORs Mean	28.47***	28.07***	27.93***	27.72***	28.06***	27.69***	27.33***	27.22***	28.40***	27.98***
	(0.239)	(0.156)	(0.173)	(0.175)	(0.193)	(0.158)	(0.121)	(0.151)	(0.306)	(0.113)
Difference	-1.18***	-0.79***	-0.64**	-0.43	-0.77***	-0.41	-0.04	0.06	-1.11***	-0.70***
	(0.320)	(0.264)	(0.274)	(0.276)	(0.287)	(0.265)	(0.245)	(0.261)	(0.373)	(0.241)
Explained	-0.49***	-0.34***	-0.51***	-0.59***	-0.66***	-0.61***	-0.38***	-0.54***	-0.62***	-0.37***
	(0.132)	(0.100)	(0.112)	(0.116)	(0.118)	(0.107)	(0.0968)	(0.111)	(0.178)	(0.0854)
% Explained	41%	44%	80%	138%	86%	152%	981%	-839%	56%	54%
Unexplained	-0.70**	-0.45*	-0.13	0.16	-0.11	0.21	0.34	0.60**	-0.49	-0.32
	(0.329)	(0.271)	(0.280)	(0.282)	(0.288)	(0.266)	(0.239)	(0.264)	(0.366)	(0.243)
% Unexplained	59%	56%	20%	-38%	14%	-52%	-881%	939%	44%	46%
Observations	1,632	2,564	2,107	2,117	2,092	2,394	3,001	2,367	1,274	3,844

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: The sample is weighted using the UKHLS nurse visit weights

Tables 3.4 and 3.5 provide detailed estimates of the effects of the included covariates using the Oaxaca decomposition method. This approach separates the explained and unexplained components of the regional gap in BMI. Interpretation focuses on factors with negative parameters because, when divided by the aggregated differences (Table 3.4), the result is positive. This indicates that these factors contribute to widening the regional BMI gap. Understanding these contributions is crucial for policy interventions aimed at mitigating variables that exacerbate regional health disparities. The results suggest that education is the primary contributor to regional disparities, followed by age and household income.

Table 3.4 Contribution of individual variables on the explained part of BMI

Explained	Northeast	Northwest	Yorkshire & Humber	East Midland	West Midland	East of England	Southeast	Southwest	Wales	Scotland
Demographics										
Age	-0.07	-0.06*	-0.08**	-0.13**	-0.11**	-0.18***	-0.17***	-0.15***	-0.10	-0.08**
	(0.05)	(0.03)	(0.04)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.07)	(0.03)
Sex	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.01	-0.00	-0.00
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Marital status	-0.13**	-0.10**	-0.10**	-0.15***	-0.20***	-0.20***	-0.20***	-0.19***	-0.14**	-0.11***
	(0.05)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.04)
Socioeconomic status										
Household income	-0.10	-0.03	-0.15**	-0.09*	-0.09*	-0.05*	-0.00	-0.05	-0.22**	-0.14***
	(0.07)	(0.04)	(0.06)	(0.05)	(0.05)	(0.03)	(0.01)	(0.04)	(0.10)	(0.04)
Education	-0.22***	-0.16***	-0.18***	-0.23***	-0.23***	-0.15***	-0.10***	-0.16***	-0.29***	-0.12***
	(0.07)	(0.05)	(0.06)	(0.06)	(0.07)	(0.05)	(0.03)	(0.05)	(0.10)	(0.04)
Job-status	0.05	0.05*	0.04	0.03	0.06*	0.02	0.02	0.02	0.09*	0.03
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.05)	(0.02)
Lifestyle factors										
Alcohol intake	0.04	0.02	0.02	0.02	0.00	0.02	0.07*	0.03	0.06	0.07
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
Fruit and vegetables eaten/day	-0.00	0.01	0.00	0.00	0.01	-0.01	-0.00	-0.00	-0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Physical activity	-0.06	-0.07**	-0.06*	-0.04	-0.10**	-0.05*	0.01	-0.03	-0.01	-0.00
	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)	(0.03)	(0.03)	(0.01)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5 Contribution of individual variables on the unexplained part of BMI

Unexplained	Northeast	Northwest	Yorkshire & Humber	East Midland	West Midland	East of England	Southeast	Southwest	Wales	Scotland
Demographics										
Age	0.94	1.29	0.96	0.08	1.22	0.52	-0.06	1.05	0.91	1.34*
	(1.20)	(0.92)	(0.97)	(0.98)	(1.03)	(0.93)	(0.83)	(0.90)	(1.39)	(0.80)
Sex	0.67	0.32	0.18	0.70	0.49	0.97	1.06	1.04	0.43	0.26
	(0.95)	(0.76)	(0.82)	(0.81)	(0.82)	(0.77)	(0.70)	(0.75)	(1.07)	(0.70)
Marital status	-1.09	-1.09*	-0.06	-0.84	-1.39**	0.03	-1.06*	-1.50**	-0.76	-1.86**
	(0.71)	(0.64)	(0.85)	(0.66)	(0.69)	(0.84)	(0.61)	(0.62)	(1.30)	(0.73)
Socioeconomic status										
Household income	-2.98	-5.82*	2.36	-0.96	-0.27	-0.33	-3.76	-2.69	3.33	3.63
	(3.69)	(3.09)	(3.19)	(2.86)	(3.15)	(2.88)	(2.62)	(2.91)	(4.86)	(2.61)
Education	0.32	-0.93	-0.96	-1.04	-1.21*	-0.05	-1.09	-0.86	0.03	-0.56
	(0.96)	(0.71)	(0.73)	(0.72)	(0.72)	(0.78)	(0.69)	(0.70)	(0.96)	(0.69)
Job-status	0.38	0.41	0.48	-0.35	0.11	0.42	-0.12	0.62*	-0.18	-0.00
	(0.46)	(0.38)	(0.40)	(0.40)	(0.40)	(0.39)	(0.35)	(0.37)	(0.53)	(0.35)
Lifestyle factors										
Alcohol intake	1.44**	0.81	0.81	1.10	0.31	0.82	0.87	0.78	3.99***	0.30
	(0.65)	(0.59)	(0.61)	(0.89)	(0.90)	(0.59)	(0.58)	(0.60)	(1.36)	(0.69)
Fruit and vegetables eaten/day	0.20	0.52	0.33	0.69	0.14	0.45	0.62	0.76	-0.16	1.10**
	(0.58)	(0.52)	(0.58)	(0.54)	(0.58)	(0.55)	(0.48)	(0.52)	(0.79)	(0.47)
Physical activity	-1.37**	-0.44	-0.66	-0.66	-0.34	-0.82	-0.78	-0.78	-1.20	-1.16**
	(0.69)	(0.61)	(0.62)	(0.62)	(0.62)	(0.62)	(0.60)	(0.60)	(0.78)	(0.59)
Constant	0.79	4.49	-3.57	1.43	0.85	-1.81	4.66	2.18	-6.89	-3.37
	(4.07)	(3.43)	(3.65)	(3.42)	(3.52)	(3.30)	(3.01)	(3.34)	(4.96)	(3.08)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.4.3 DETERMINANTS OF SYSTOLIC BLOOD PRESSURE

The OLS regression for the systolic blood pressure results is presented in Table 3.6. Systolic blood pressure increases with age **(Fig 3.3)**. Also, on average, females have a lower systolic blood pressure than males ($p<0.01$). The results of the unadjusted model of only the regions show a higher and significant systolic blood pressure in all regions compared to London, except West Midlands, which has no significant difference compared to the London region **(Fig. 3.4)**. The F-test conducted for the joint significance for the government office region shows regional differences in systolic blood pressure ($p<0.01$).

Figure 3.3 Margin graph of systolic blood pressure with age

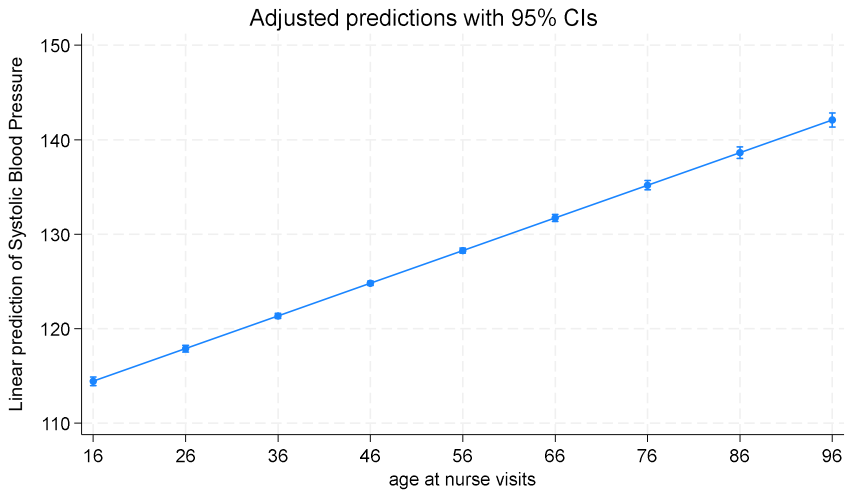
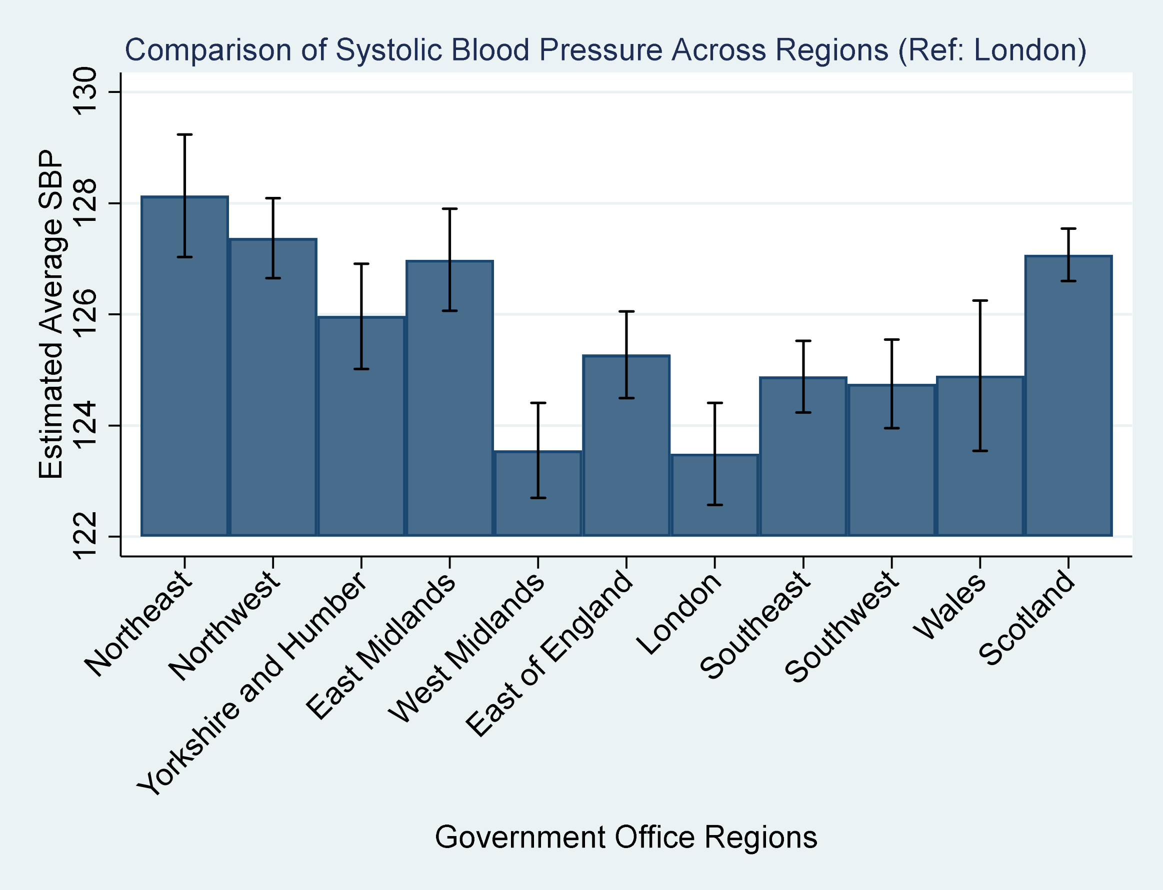


Table 3.6 Association between explanatory variables and Systolic blood pressure

	Coefficient (SE)	Coefficient (SE)
Region		
Northeast	5.55*** (0.85)	4.20*** (0.89)
Northwest	4.69*** (0.68)	3.65*** (0.67)
Yorkshire and the Humber	3.72*** (0.76)	2.12*** (0.73)
East midlands	4.96*** (0.75)	3.58*** (0.72)
West midlands	0.46 (0.72)	-0.99 (0.69)
East of England	3.39*** (0.69)	1.60** (0.68)
Southeast	2.61*** (0.65)	1.16* (0.63)
Southwest	3.08*** (0.68)	0.96 (0.68)
Wales	2.98*** (0.93)	1.29 (1.08)
Scotland	4.73*** (0.59)	3.85*** (0.61)
Age		0.34*** (0.01)
Female		-7.10*** (0.31)
Marital status		
Married		-1.48*** (0.39)
Divorced		-1.79*** (0.57)
Widowed		1.56* (0.83)
Log household income		-0.42 (0.26)
Highest qualification		
O-level and other		-0.81 (0.57)
A-level and higher		-1.55*** (0.58)
Degree		-3.36*** (0.62)
Employed		0.47 (0.35)
Alcohol consumption		
Frequent in-take		0.54 (0.65)
Rare in-take		-0.40 (0.66)
Fruit and veg eaten/day		0.00 (0.09)
Physical activity		-0.38 (0.39)
Constant	122.22*** (0.53)	116.70*** (2.08)
Joint significance test (F-test)		
Regional dummies	F (10, 21,929) = 13.56 Prob > F = 0.00	F (10, 21,929) = 13.94 Prob > F =0.00
Observations	21,929	21,929

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: London is the reference region. Sample is weighted using UKHLS nurse visits weights; SE – Standard errors.

Figure 3.4 Comparison of Systolic Blood Pressure across regions



3.4.4 OAXACA BLINDER DECOMPOSITION RESULTS

Table 3.7 presents the decomposition analysis for the aggregated regional differences in systolic blood pressure. **Tables** 3.8 and 3.9 present detailed contributions of covariates to the regional differences in systolic blood pressure. The systolic pressure values are higher for all regions than London. The aggregated decomposition analysis results show significant regional differences between London and nine geographical regions except West Midlands, whose results are not statistically significant. This difference is divided into the explained and the unexplained parts. The percentage contribution of the explained part is greater than the unexplained part for five regions.

This means that for those regions with greater percentage points, the overall regional disparities in systolic blood pressure are mainly due to the differences in the levels of observable characteristics. For example, the decomposition analysis shows that 53% (-1.84 units) and 55% (-1.32 units) of the overall regional mean SBP gap of the East of England and Southeast region are due to the differences in the levels of observable characteristics. The unexplained part for these regions contributed 47% and 45%, respectively.

The detailed decomposition shows that education contributes to regional differences in all regions as well as age. Other factors that contribute to regional disparities are household income and physical activities. However, these factors only contribute to regional inequalities in eight out of the ten regions of analysis. Also, marital status and alcohol consumption contribute towards a regional gap in the unexplained part.

Table 3.7 Oaxaca-Blinder decomposition for regional differences in Systolic blood pressure

	Northeast	Northwest	Yorkshire & Humber	East Midland	West Midland	East of England	Southeast	Southwest	Wales	Scotland
London Mean	122.86***	122.86***	122.86***	122.86***	122.86***	122.86***	122.86***	122.86***	122.86***	122.86***
	(0.60)	(0.60)	(0.60)	(0.60)	(0.60)	(0.60)	(0.60)	(0.60)	(0.60)	(0.60)
Comparison GORs Mean	128.02***	127.82***	126.19***	127.61***	123.24***	126.31***	125.23***	125.62***	126.30***	128.05***
	(0.78)	(0.48)	(0.56)	(0.57)	(0.51)	(0.48)	(0.41)	(0.49)	(1.03)	(0.36)
Difference	-5.16***	-4.97***	-3.34***	-4.75***	-0.38	-3.45***	-2.38***	-2.77***	-3.44***	-5.19***
	(0.99)	(0.77)	(0.82)	(0.83)	(0.79)	(0.77)	(0.72)	(0.78)	(1.20)	(0.70)
Explained	-0.74	-1.41***	-1.45***	-1.49***	-1.44***	-1.84***	-1.32***	-1.75***	-2.16***	-1.47***
	(0.54)	(0.44)	(0.47)	(0.46)	(0.45)	(0.42)	(0.40)	(0.45)	(0.73)	(0.40)
% Explained	14%	28%	43%	31%	379%	53%	55%	63%	63%	28%
Unexplained	-4.42***	-3.56***	-1.89**	-3.26***	1.06	-1.61**	-1.06*	-1.02	-1.28	-3.72***
	(0.91)	(0.68)	(0.74)	(0.75)	(0.71)	(0.69)	(0.63)	(0.70)	(1.08)	(0.62)
% Unexplained	86%	72%	57%	69%	-279%	47%	45%	37%	37%	72%
Observations	1386	2132	1703	1812	1815	2048	2609	2034	1068	3236

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: The sample is weighted using the UKHLS nurse visit weights

Table 3.8 Contribution of individual variables on the explained part of systolic blood pressure

Explained	Northeast	Northwest	Yorkshire & Humber	East Midland	West Midland	East of England	Southeast	Southwest	Wales	Scotland
Demographics										
Age	-0.42	-0.75**	-0.75**	-1.04***	-0.90***	-1.67***	-1.25***	-1.41***	-1.24**	-1.11***
	(0.40)	(0.32)	(0.34)	(0.34)	(0.31)	(0.36)	(0.32)	(0.35)	(0.52)	(0.34)
Sex	-0.18	-0.18	-0.15	0.06	-0.02	-0.05	-0.06	-0.10	-0.23	-0.05
	(0.22)	(0.18)	(0.18)	(0.20)	(0.20)	(0.18)	(0.17)	(0.18)	(0.31)	(0.14)
Marital status	0.15	-0.03	0.04	0.09	0.14	0.16	0.12	0.05	0.12	0.21**
	(0.14)	(0.10)	(0.11)	(0.14)	(0.15)	(0.16)	(0.12)	(0.13)	(0.22)	(0.09)
Socioeconomic status										
Household income	-0.05	-0.09	-0.24	-0.18	-0.15	-0.08	0.01	0.02	-0.34	-0.14*
	(0.18)	(0.11)	(0.18)	(0.13)	(0.12)	(0.08)	(0.01)	(0.11)	(0.25)	(0.08)
Education	-0.33*	-0.28**	-0.35**	-0.43**	-0.43***	-0.21	-0.25***	-0.34**	-0.51*	-0.36***
	(0.19)	(0.13)	(0.16)	(0.17)	(0.16)	(0.13)	(0.09)	(0.15)	(0.31)	(0.14)
Job-status	0.04	0.07	0.02	0.05	0.08	0.02	0.01	0.06	0.11	0.02
	(0.07)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.02)	(0.05)	(0.10)	(0.02)
Lifestyle factors										
Alcohol intake	0.11	-0.08	0.00	0.01	-0.03	0.01	0.01	0.01	-0.06	-0.04
	(0.08)	(0.09)	(0.08)	(0.09)	(0.07)	(0.06)	(0.10)	(0.09)	(0.10)	(0.08)
Fruit and vegetables eaten/day	-0.00	0.02	-0.00	-0.00	0.00	0.01	0.07	0.00	0.02	0.01
	(0.01)	(0.03)	(0.01)	(0.01)	(0.02)	(0.04)	(0.06)	(0.05)	(0.05)	(0.02)
Physical activity	-0.05	-0.07	-0.03	-0.04	-0.13*	-0.03	0.02	-0.02	-0.02	0.00
	(0.05)	(0.06)	(0.04)	(0.05)	(0.08)	(0.04)	(0.03)	(0.04)	(0.09)	(0.01)

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9 Contribution of individual variables on the unexplained part of systolic blood pressure

Unexplained	Northeast	Northwest	Yorkshire & Humber	East Midland	West Midland	East of England	Southeast	Southwest	Wales	Scotland
Demographics										
Age	-3.25	0.58	1.01	1.56	3.37	-0.39	-0.32	0.23	1.01	-2.51
	(3.45)	(2.57)	(2.79)	(2.95)	(2.84)	(2.69)	(2.38)	(2.62)	(4.14)	(2.13)
Sex	0.89	0.22	-0.33	0.82	0.99	0.09	0.31	0.18	1.89*	-0.63
	(0.90)	(0.69)	(0.74)	(0.79)	(0.75)	(0.70)	(0.66)	(0.71)	(1.04)	(0.64)
Marital status	-5.77*	-6.14**	-6.69**	-5.94**	-3.86	-6.13**	-6.53**	-7.02**	-3.97	-5.21*
	(2.98)	(2.93)	(2.82)	(2.87)	(3.58)	(2.82)	(2.78)	(2.80)	(3.35)	(3.03)
Socioeconomic status										
Household income	-10.37	-1.32	7.33	5.66	0.89	-0.57	-11.96	-12.61	10.42	3.36
	(12.91)	(8.72)	(9.94)	(8.40)	(7.79)	(8.37)	(7.66)	(8.33)	(10.32)	(7.57)
Education	-0.74	2.56	2.15	-1.65	2.02	-0.29	1.27	-1.26	-1.86	2.54*
	(1.54)	(1.58)	(1.65)	(1.21)	(1.59)	(1.12)	(1.63)	(1.17)	(1.84)	(1.40)
Job-status	0.98	0.16	1.04	-0.23	-0.31	0.95	0.56	0.04	-1.05	0.31
	(1.30)	(0.94)	(0.99)	(1.03)	(0.95)	(0.96)	(0.90)	(0.96)	(1.29)	(0.88)
Lifestyle factors										
Alcohol intake	-0.02	-4.66**	-1.44	-1.53	-3.40	-1.19	-1.49	-1.62	-2.98	-1.65
	(1.87)	(2.35)	(1.74)	(2.55)	(2.19)	(1.66)	(1.67)	(1.70)	(1.98)	(1.98)
Fruit and vegetables eaten/day	-0.55	-1.37	-0.08	-0.43	-2.08	-0.03	1.14	-0.25	3.33	-0.50
	(1.59)	(1.44)	(1.49)	(1.58)	(1.39)	(1.47)	(1.36)	(1.41)	(2.28)	(1.22)
Physical activity	-2.69	-0.66	-2.75*	-1.21	-0.85	-2.94**	-2.11	-2.01	0.91	-3.02**
	(1.81)	(1.41)	(1.48)	(1.46)	(1.38)	(1.39)	(1.40)	(1.43)	(2.12)	(1.30)
Constant	17.09	7.08	-2.14	-0.31	4.29	8.89	18.07**	23.28**	-8.99	3.59
	(12.86)	(9.12)	(10.46)	(9.42)	(9.29)	(9.05)	(8.38)	(9.14)	(11.36)	(8.30)

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.4.5 DETERMINANTS OF CHOLESTEROL RATIO

Table 3.10 presents the OLS regression result of the association between explanatory variables and cholesterol ratio. The cholesterol ratio decreases as age increases, although this is not statistically significant. Also, the results reveal that, on average, females have a lower cholesterol ratio than males ($p<0.01$). The results of the geographical regions for the unadjusted model show that all the regions have a higher and significant cholesterol ratio than the London region, except Northwest, Southeast and Wales, which have no significant difference. **Figure 3.5** provides a graphical representation of the comparison of cholesterol ratio across regions. The F-test result presented in the OLS table for both models shows a significant difference in cholesterol ratio levels across the government office regions in the UK.

Figure 3.5 Comparison of Cholesterol Ratio across regions

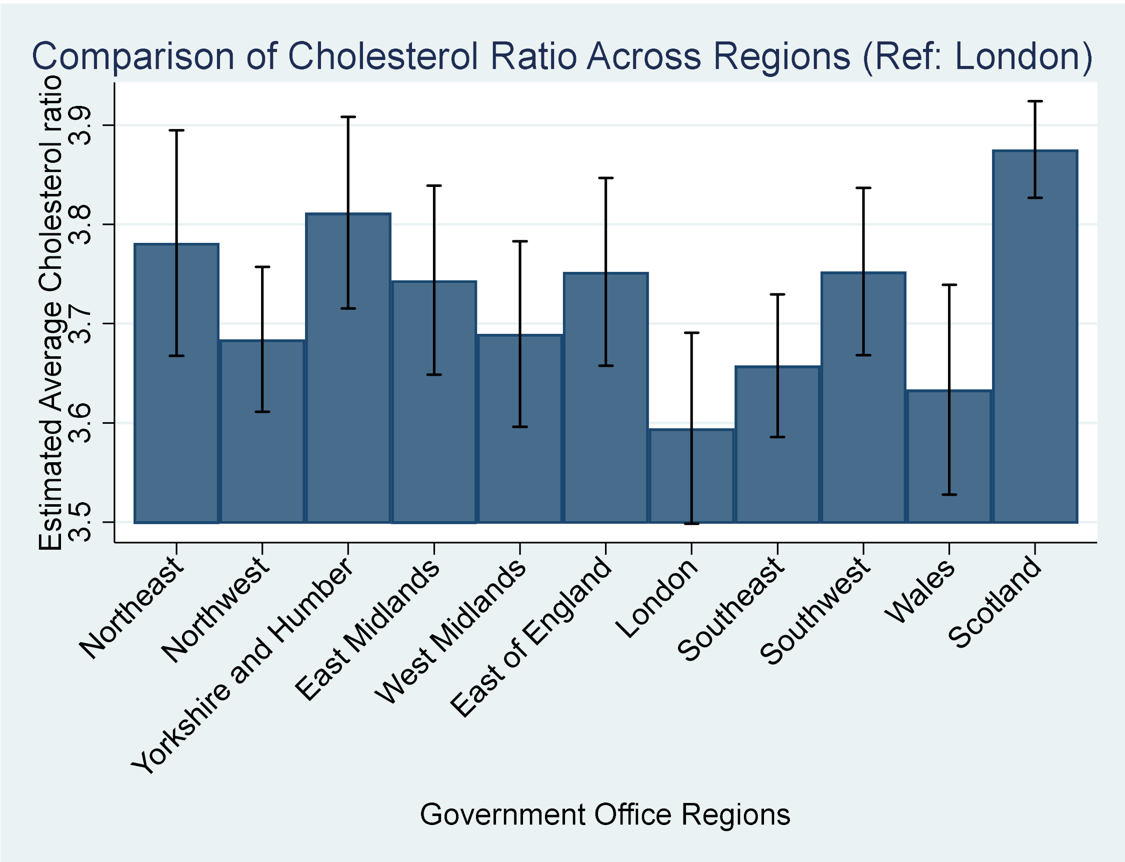


Table 3.10 Association between explanatory variables and Cholesterol ratio

	Coefficient (SE)	Coefficient (SE)
Region		
Northeast	0.21*** (0.08)	0.14 (0.09)
Northwest	0.10 (0.06)	0.07 (0.07)
Yorkshire and the Humber	0.24*** (0.07)	0.26*** (0.09)
East midlands	0.20*** (0.07)	0.12 (0.08)
West midlands	0.13* (0.07)	0.04 (0.08)
East of England	0.20*** (0.07)	0.14* (0.08)
Southeast	0.08 (0.06)	0.02 (0.07)
Southwest	0.19*** (0.07)	0.09 (0.08)
Wales	0.05 (0.08)	-0.08 (0.10)
Scotland	0.32*** (0.06)	0.33*** (0.07)
Age		-0.00 (0.00)
Female		-0.79*** (0.03)
Marital status		
Married		0.36*** (0.05)
Divorced		0.41*** (0.06)
Widowed		0.18** (0.09)
Log household income		-0.05 (0.03)
Highest qualification		
O-level and other		-0.10* (0.06)
A-level and higher		-0.19*** (0.06)
Degree		-0.24*** (0.07)
Employed		0.25*** (0.04)
Alcohol consumption		
Frequent in-take		-0.38*** (0.07)
Rare in-take		-0.10 (0.07)
Fruit and veg eaten/day		-0.01 (0.01)
Physical activity		-0.11*** (0.04)
Constant	3.57*** (0.05)	4.56*** (0.23)
Joint significance test (F-test)		
Regional dummies	F (10, 17,178) = 6.12 Prob > F = 0.00	F (10, 17,178) = 5.69 Prob > F = 0.00
Observations	17,178	17,178

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: London is the reference region. Sample is weighted using UKHLS blood person weights ; SE – Standard errors.

3.4.6 OAXACA BLINDER DECOMPOSITION RESULTS

Table 3.11 shows the OB decomposition analysis. **Tables** 3.12 and 3.13 present the detailed contribution of individual variables to the regional disparities in cholesterol ratio for both the explained and unexplained parts of the analysis. The mean values for the cholesterol ratio for all the regions are higher than that of the London region. A higher cholesterol ratio increases the risk of heart disease. The aggregated OB decomposition analysis shows that six regions significantly differ in the cholesterol ratio. Both the explained and unexplained parts cause this difference. Four regions (Yorkshire and Humber, East Midlands, West Midlands, and Scotland) are statistically significant for the explained part, while three are statistically significant for the unexplained part. Also, the unexplained part has a greater percentage contribution to the regional disparities compared to the explained part.

Table 3.11 Oaxaca-Blinder decomposition for regional differences in Cholesterol ratio

	Northeast	Northwest	Yorkshire & Humber	East Midland	West Midland	East of England	Southeast	Southwest	Wales	Scotland
London Mean	3.57***	3.57***	3.57***	3.57***	3.57***	3.57***	3.57***	3.57***	3.57***	3.57***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Comparison GORs Mean	3.79***	3.69***	3.86***	3.77***	3.70***	3.78***	3.66***	3.74***	3.56***	3.90***
	(0.07)	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)	(0.04)	(0.05)	(0.09)	(0.04)
Difference	-0.21**	-0.12	-0.29***	-0.19**	-0.12	-0.20**	-0.08	-0.17**	0.01	-0.33***
	(0.09)	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.11)	(0.07)
Explained	-0.07	-0.02	-0.07*	-0.07**	-0.11***	-0.05	-0.02	-0.06	-0.13**	0.04
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.06)	(0.04)
% Explained	33%	17%	24%	37%	92%	25%	25%	35%	-130%	12%
Unexplained	-0.14	-0.10	-0.22**	-0.12	-0.01	-0.15**	-0.06	-0.11	0.14	-0.37***
	(0.09)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.11)	(0.07)
% Unexplained	67%	83%	76%	63%	8%	75%	75%	65%	140%	112%
Observations	958	1518	1287	1286	1255	1432	1828	1458	752	2406

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: The sample is weighted using the UKHLS blood person weights

The detailed decomposition presented in Table 3.12 shows that education contributes to regional differences in all four regions that are statistically significant in the aggregated results (Table 3.11). Also, household income contributed to the observed regional differences in the Yorkshire and Humber region. The unexplained part in Table 3.13 shows that marital status and household income contribute to regional disparities in the unexplained part of the analysis.

Table 3.12 Contribution of individual variables on the explained part of cholesterol ratio

Explained	Northeast	Northwest	Yorkshire & Humber	East Midland	West Midland	East of England	Southeast	Southwest	Wales	Scotland
Demographics										
Age	-0.03*	-0.02	-0.01	-0.01	-0.00	-0.02	-0.01	-0.02	-0.01	-0.00
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)
Sex	-0.00	0.01	0.00	-0.01	-0.02	-0.02	-0.01	-0.01	-0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
Marital status	-0.01	-0.01	-0.02	-0.03	-0.05**	-0.01	-0.02	-0.02	-0.03	-0.04***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
Socioeconomic status										
Household income	-0.01	-0.00	-0.05**	-0.01	-0.01	-0.01	-0.00	-0.01	-0.03	0.00
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)
Education	-0.04	-0.01	-0.04**	-0.03	-0.03	-0.02	-0.01	-0.01	-0.08**	0.02
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.04)	(0.01)
Job-status	0.02*	0.01	0.02*	0.02	0.01	0.01	0.01	0.00	0.02	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lifestyle factors										
Alcohol intake	0.01	0.01	0.02*	0.01	0.00	0.02*	0.01	0.01	0.02	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Fruit and vegetables eaten/day	0.00	-0.00	-0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.00
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Physical activity	-0.01	-0.01	0.00	-0.01	-0.01	-0.01	-0.00	-0.01	-0.02	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.13 Contribution of individual variables on the unexplained part of cholesterol ratio

Unexplained	Northeast	Northwest	Yorkshire & Humber	East Midland	West Midland	East of England	Southeast	Southwest	Wales	Scotland
Demographics										
Age	-0.39	0.31	0.44	0.31	0.59*	0.17	0.27	0.18	0.94**	0.34
	(0.36)	(0.27)	(0.32)	(0.29)	(0.31)	(0.28)	(0.26)	(0.29)	(0.47)	(0.23)
Sex	0.09	0.02	0.11	0.04	0.16*	0.14	0.16*	0.16*	0.14	0.18**
	(0.10)	(0.09)	(0.10)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.11)	(0.08)
Marital status	-0.28	-0.49	-0.33	-0.04	-0.59	-0.30	-0.35	-0.37	0.24	-0.60
	(0.41)	(0.39)	(0.43)	(0.47)	(0.40)	(0.40)	(0.42)	(0.40)	(0.46)	(0.40)
Socioeconomic status										
Household income	-1.38	-1.27	2.85**	-0.45	-0.38	0.29	-0.04	-0.50	0.74	-1.18
	(1.24)	(0.94)	(1.25)	(0.87)	(0.91)	(0.91)	(0.84)	(0.85)	(1.11)	(0.78)
Education	-0.63**	-0.46*	-0.57**	-0.47*	-0.43*	-0.52*	-0.26	-0.44	-0.00	-0.42*
	(0.26)	(0.25)	(0.25)	(0.25)	(0.24)	(0.28)	(0.27)	(0.27)	(0.32)	(0.24)
Job-status	-0.13	0.18*	0.00	-0.02	0.12	0.11	-0.06	0.11	0.09	-0.15*
	(0.13)	(0.09)	(0.12)	(0.10)	(0.11)	(0.10)	(0.09)	(0.10)	(0.12)	(0.09)
Lifestyle factors										
Alcohol intake	0.40	0.08	0.22	0.15	-0.39	0.09	0.04	0.11	-0.25	0.07
	(0.34)	(0.20)	(0.31)	(0.21)	(0.26)	(0.28)	(0.24)	(0.25)	(0.34)	(0.20)
Fruit and vegetables eaten/day	0.11	-0.03	-0.19	-0.10	-0.07	-0.10	-0.07	-0.05	0.02	-0.29**
	(0.16)	(0.14)	(0.17)	(0.15)	(0.15)	(0.15)	(0.14)	(0.16)	(0.20)	(0.15)
Physical activity	-0.18	0.03	-0.27*	-0.00	0.02	-0.02	0.13	0.08	0.11	-0.20
	(0.15)	(0.14)	(0.15)	(0.15)	(0.14)	(0.15)	(0.14)	(0.15)	(0.19)	(0.13)
Constant	2.25*	1.55	-2.46*	0.46	0.96	-0.01	0.12	0.62	-1.90	1.88**
	(1.34)	(1.09)	(1.39)	(1.17)	(1.09)	(1.09)	(1.07)	(1.04)	(1.48)	(0.96)

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.4.7 DETERMINANTS OF ESTIMATED GLOMERULAR FILTRATION RATE

The OLS regression results for the estimated glomerular filtration rate result are presented in Table 3.14. The result shows a statistically significant impact of age on the eGFR (p<0.01). **Figure** 3.6 shows the gradual decline in the eGFR as a person gets older. On average, females have a significantly higher eGFR than males, holding other variables constant. The result of the unadjusted model of only regions shows that all the regions have a significantly lower eGFR compared to the London region except Northwest and Wales, which have no significant difference compared to the London region (Fig.3.7). The F-test for the joint significance of both models of the GORs shows differences in eGFR levels across regions in the UK.

Figure 3.6 Margin graph of estimated glomerular filtration rate with age

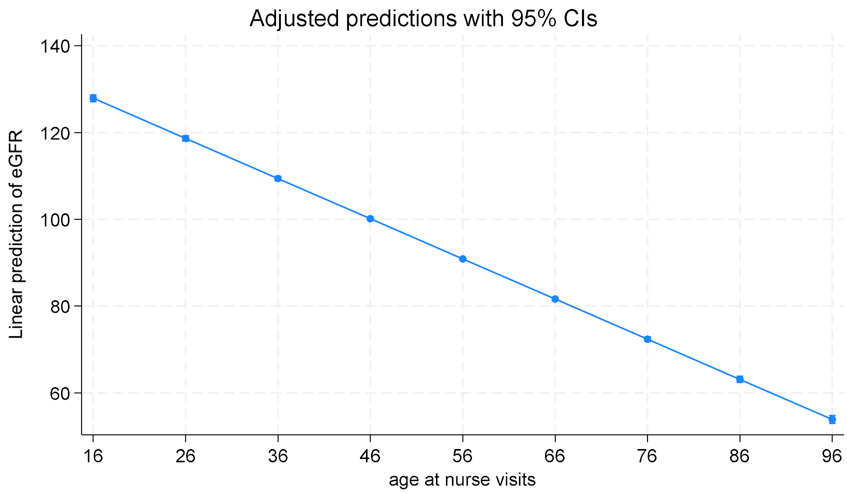
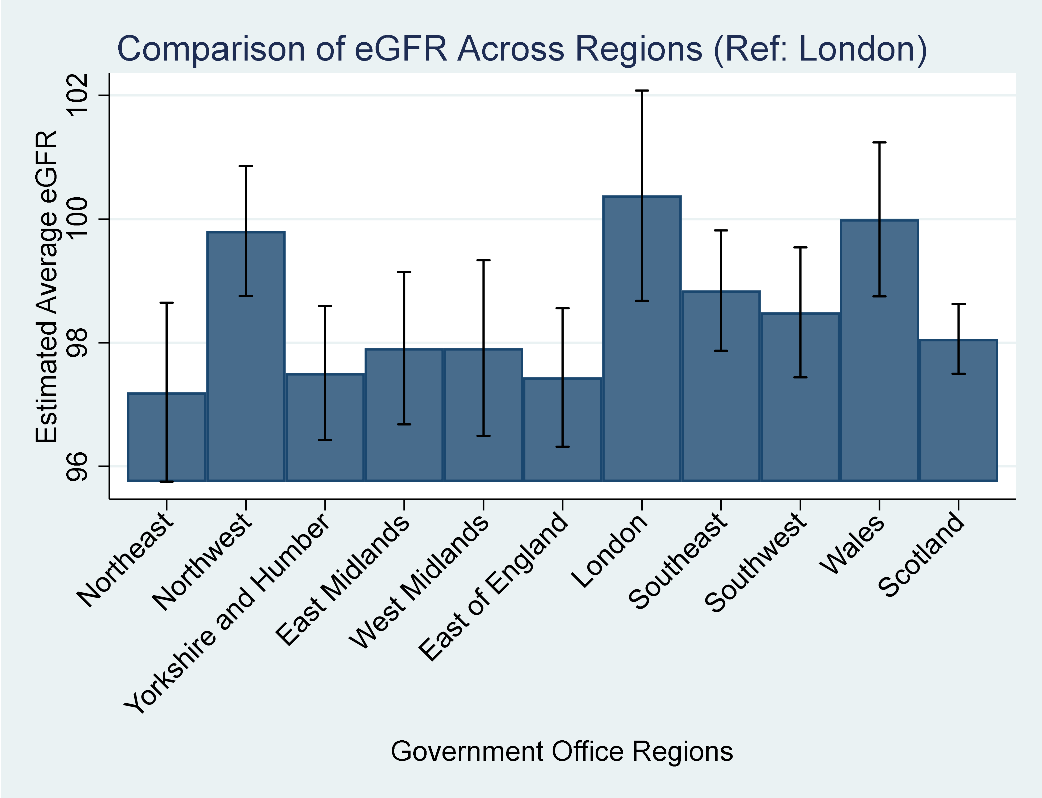


Table 3.14 Association between explanatory variables and eGFR

	Coefficient (SE)	Coefficient (SE)
Northeast	-6.40*** (1.81)	-1.33 (1.37)
Northwest	-4.53*** (1.61)	0.17 (1.23)
Yorkshire and the Humber	-6.74*** (1.64)	-2.22* (1.24)
east midlands	-7.29*** (1.69)	-2.04 (1.29)
West Midlands	-6.27*** (1.76)	-2.13 (1.39)
East of England	-8.30*** (1.63)	-2.52** (1.24)
Southeast	-5.90*** (1.57)	-0.42 (1.20)
Southwest	-7.31*** (1.61)	-0.46 (1.23)
Wales	-6.01*** (1.82)	1.96 (1.53)
Scotland	-6.59*** (1.43)	-0.96 (1.16)
Age		-0.92*** (0.02)
Female		23.83*** (0.43)
Marital status		
Married		0.01 (0.64)
Divorced		1.12 (0.83)
Widowed		-4.05*** (1.14)
Log household income		-0.49 (0.41)
Highest qualification		
O-level and other		0.47 (0.70)
A-level and higher		-0.23 (0.72)
Degree		1.82** (0.83)
Employed		-3.14*** (0.56)
Alcohol consumption		
Frequent in-take		0.01 (0.97)
Rare in-take		-0.52 (1.02)
Fruit and veg eaten/day		0.33** (0.14)
Physical activity		0.06 (0.55)
Constant	104.70*** (1.35)	134.42*** (3.27)
Joint significance test (F-test)		
Regional dummies	F (10, 17,237) = 3.38	F (10, 17,237) = 2.74
	Prob > F = 0.00	Prob > F = 0.00
Observations	17,237	17,237

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: London is the reference region. Sample is weighted using UKHLS blood person weights; SE – Standard errors.

Figure 3.7 Comparison of eGFR Across Regions



3.4.8 OAXACA BLINDER DECOMPOSITION RESULTS

Table 3.15 shows the aggregated decomposition analysis of individual variables to the regional disparities in eGFR. The mean values for the eGFR for all the regions are lower than those for the London region. A lower eGFR signifies greater risk of kidney disease. The decomposition analysis results show significant regional differences exist between London and all the regions. This difference is driven by the explained part, i.e., the differences in the level of the observed characteristics. For instance, the decomposition analysis evidence that 95% (5.02 units) and 93% (5.35 units) of the regional eGFR differences of the Southeast and Southwest regions respectively are due to the differences in the levels of covariates ($p<0.01$), respectively. However, the remaining 5% (0.25 units) and 7% (0.39 units) are unexplained and not statistically significant.

Table 3.15 Oaxaca-Blinder decomposition for regional differences in estimated glomerular filtration rate

	Northeast	Northwest	Yorkshire & Humber	East Midland	West Midland	East of England	Southeast	Southwest	Wales	Scotland
London Mean	103.17***	103.17***	103.17***	103.17***	103.17***	103.17***	103.17***	103.17***	103.17***	103.17***
	(1.51)	(1.51)	(1.51)	(1.51)	(1.51)	(1.51)	(1.51)	(1.51)	(1.51)	(1.51)
Comparison GORs Mean	98.28***	99.40***	96.15***	96.98***	96.31***	95.38***	97.91***	97.43***	98.35***	99.47***
	(1.33)	(0.99)	(1.04)	(1.15)	(1.25)	(0.97)	(0.85)	(0.96)	(2.07)	(0.67)
Difference	4.89**	3.77**	7.02***	6.20***	6.86***	7.79***	5.26***	5.74***	4.82*	3.70**
	(2.02)	(1.81)	(1.84)	(1.90)	(1.96)	(1.80)	(1.74)	(1.79)	(2.56)	(1.65)
Explained	3.10*	4.18***	4.70***	3.93***	5.13***	5.18***	5.02***	5.35***	6.61***	2.77**
	(1.62)	(1.38)	(1.44)	(1.48)	(1.51)	(1.37)	(1.32)	(1.38)	(2.21)	(1.18)
% Explained	63%	111%	67%	63%	75%	66%	95%	93%	137%	75%
Unexplained	1.79	-0.41	2.33*	2.27*	1.73	2.61**	0.25	0.39	-1.79	0.93
	(1.39)	(1.21)	(1.21)	(1.28)	(1.38)	(1.18)	(1.16)	(1.16)	(1.58)	(1.14)
% Unexplained	37%	-11%	33%	37%	25%	34%	5%	7%	-37%	25%
Observations	964	1525	1290	1289	1260	1438	1833	1462	757	2418

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: The sample is weighted using the UKHLS blood person weights

The detailed decomposition is presented in Tables 3.16 and 3.17. Interpretation is focused on coefficients with positive parameters because when they are divided by the result of the overall differences (table 3.15), the result is positive, which means it increases the regional gap in eGFR. The result shows that age and education contribute to the observed regional differences in the eGFR levels for all the regions represented.

Table 3.16 Contribution of individual variables on the explained part of the eGFR

Explained	Northeast	Northwest	Yorkshire & Humber	East Midland	West Midland	East of England	Southeast	Southwest	Wales	Scotland
Demographics										
Age	3.45***	4.38***	4.82***	3.85***	4.11***	5.06***	4.58***	4.96***	6.46***	3.00***
	(1.31)	(1.11)	(1.13)	(1.19)	(1.17)	(1.17)	(1.08)	(1.14)	(1.86)	(0.97)
Sex	0.07	-0.26	-0.02	0.46	0.64	0.73	0.48	0.50	0.31	-0.20
	(0.98)	(0.75)	(0.83)	(0.83)	(0.87)	(0.82)	(0.74)	(0.81)	(1.21)	(0.68)
Marital status	0.03	0.21	0.01	0.22	-0.08	-0.28	-0.04	-0.09	0.45	-0.08
	(0.31)	(0.25)	(0.30)	(0.28)	(0.36)	(0.29)	(0.27)	(0.28)	(0.48)	(0.12)
Socioeconomic status										
Household income	-0.59	-0.46*	-0.36	-0.33	-0.30	-0.23	-0.07	-0.16	-0.74*	-0.02
	(0.38)	(0.25)	(0.28)	(0.29)	(0.19)	(0.15)	(0.12)	(0.18)	(0.43)	(0.14)
Education	0.45	0.53*	0.29	0.09	0.71**	0.12	0.16	0.34	0.43	0.35**
	(0.36)	(0.27)	(0.29)	(0.34)	(0.33)	(0.22)	(0.14)	(0.26)	(0.48)	(0.17)
Job-status	-0.21	-0.24	-0.19	-0.20	-0.08	-0.10	-0.18	-0.09	-0.21	-0.22
	(0.18)	(0.17)	(0.18)	(0.15)	(0.11)	(0.12)	(0.14)	(0.10)	(0.25)	(0.13)
Lifestyle factors										
Alcohol intake	0.09	0.11	0.21	-0.02	0.19	0.16	0.30*	0.13	0.27	-0.08
	(0.12)	(0.10)	(0.14)	(0.08)	(0.15)	(0.14)	(0.18)	(0.12)	(0.23)	(0.08)
Fruit and vegetables eaten/day	-0.00	0.01	0.02	-0.04	0.00	-0.22	-0.18	-0.19	-0.28	0.01
	(0.08)	(0.06)	(0.07)	(0.07)	(0.05)	(0.14)	(0.13)	(0.15)	(0.22)	(0.02)
Physical activity	-0.19	-0.11	-0.08	-0.11	-0.07	-0.05	-0.03	-0.05	-0.09	0.01
	(0.24)	(0.14)	(0.13)	(0.13)	(0.16)	(0.08)	(0.04)	(0.09)	(0.20)	(0.02)

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.17 Contribution of individual variables on the unexplained part of the eGFR

Unexplained	Northeast	Northwest	Yorkshire & Humber	East Midland	West Midland	East of England	Southeast	Southwest	Wales	Scotland
Demographics										
Age	-1.76	-2.78	-0.90	-1.36	-3.77	-0.63	2.72	0.47	-9.91	-1.04
	(5.42)	(4.93)	(5.07)	(5.09)	(5.82)	(4.99)	(4.95)	(5.00)	(6.16)	(4.39)
Sex	0.63	3.40**	1.99	2.23	1.18	1.53	1.96	1.36	0.71	2.25*
	(1.48)	(1.35)	(1.37)	(1.37)	(1.42)	(1.31)	(1.29)	(1.31)	(1.58)	(1.25)
Marital status	2.60	-2.27	-1.11	3.47	1.98	-1.21	1.59	-0.50	9.49	0.81
	(7.05)	(7.23)	(7.29)	(7.04)	(7.23)	(7.07)	(7.05)	(7.41)	(7.15)	(7.22)
Socioeconomic status										
Household income	-9.53	-1.95	-25.72*	-22.85	-6.78	-6.96	8.53	-25.52	-10.21	-23.51*
	(17.90)	(14.56)	(14.96)	(17.83)	(15.51)	(13.64)	(13.63)	(16.25)	(16.64)	(12.85)
Education	5.17	-1.39	3.27	5.08	6.14*	1.15	-0.48	3.41	2.33	3.53
	(3.50)	(3.46)	(3.39)	(3.44)	(3.66)	(3.26)	(3.82)	(3.32)	(3.48)	(3.25)
Job-status	0.33	-0.90	-0.86	1.00	-2.18	-1.47	1.35	0.16	-2.80	1.37
	(1.99)	(1.76)	(1.72)	(1.87)	(1.96)	(1.80)	(1.83)	(1.85)	(1.89)	(1.72)
Lifestyle factors										
Alcohol intake	-5.36	-4.96	-4.04	-10.25**	-2.10	-1.96	1.46	-5.80	-4.75	-5.27
	(4.02)	(3.93)	(3.98)	(5.02)	(4.74)	(4.32)	(4.98)	(3.97)	(5.48)	(3.88)
Fruit and vegetables eaten/day	0.79	1.19	0.96	0.73	2.52	1.16	1.10	2.23	-0.93	2.72
	(2.63)	(2.47)	(2.53)	(2.61)	(2.89)	(2.63)	(2.54)	(2.60)	(3.28)	(2.31)
Physical activity	-0.46	-1.24	-1.36	-0.81	-1.75	-1.75	-1.15	-1.77	-2.91	-3.53
	(2.96)	(2.89)	(2.90)	(2.95)	(3.02)	(2.96)	(2.92)	(2.95)	(3.12)	(2.87)
Constant	9.38	10.49	30.09*	25.03	6.51	12.75	-16.84	26.37	17.20	23.60
	(20.34)	(17.77)	(17.77)	(20.44)	(19.33)	(16.91)	(17.35)	(19.30)	(19.35)	(16.03)

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5 DISCUSSION

Using data from a large nationally representative sample of adults across the UK, this chapter explores individual-level characteristics' contribution to regional inequalities in health.

The OLS regressions showed that as age increases, health outcomes decline. This is unsurprising. Literature such as Glassock and Winearls (2009), Diehr et al. (2013) and Mohebi et al. (2020) found that health variables decline on average with advancing age. The results also show that males have higher systolic blood pressure and cholesterol ratio. This finding is in line with previous literature that finds that males are at greater risk of high blood pressure than women (Reckelhoff, 2001; Maranon and Reckelhoff, 2013).

The study finds that, with respect to the four biomarkers considered in this study, London has better health outcomes than the other regions of the UK. This result is consistent with earlier evidence by the Office for National Statistics (2020) and NHS England (2019), which found that the London region has made progress in reducing risks associated with worse health measures, and there is evidence of improved life expectancy higher than that of the UK. The F-test for the overall test of the difference between the government office regions shows evident regional disparities existing with the four biomarkers across the UK after adjusting for age and sex alongside other variables in the OLS regression.

The Oaxaca-Blinder decomposition analysis conducted for all the biomarkers indicates what may contribute to the differences across regions in the UK. The findings suggest regional differences for all the biomarkers (BMI, systolic blood pressure, cholesterol ratio and eGFR). However, not all the biomarkers showed statistically significant regional differences compared to London for all the regions. For example, the BMI and cholesterol ratios were statistically significantly different in six regions, while systolic blood pressure was significantly different for nine regions. These regional differences are driven mainly by the unexplained variance across the regions, i.e., the unexplained part contributes a higher percentage of the differences. These differences are due to differential coefficient effects. This finding contrasts with that of Di Paola and Raftopoulou (2018), who used BMI as their health measure and some of the explanatory factors considered in this study. They found that the explained part contributes the most to the regional differences in Spain. Unlike the other biomarkers, the result of the eGFR reveals that the explained part of the decomposition analysis drives regional differences.

The detailed decomposition results show education as the main factor contributing to regional disparities in BMI, systolic blood pressure, cholesterol ratio and eGFR. This is consistent with the evidence from Kings Fund (2023), which suggests that education is associated with poorer physical health. Fiscella and Williams (2004) suggest that people of lower educational levels experience worse health outcomes than their colleagues with higher educational attainment. Education has been shown to positively contribute to health disparities in the literature (Ergin and Kunst, 2015; Di Paola and Raftopoulou, 2018). Also, the results show that age and household income contribute to the regional disparities in all the health outcomes considered. This finding suggests that differences in socio-demographic factors increase regional differences across regions in the UK. For the unexplained part, the findings indicate that differences in the model coefficient for marital status and alcohol consumption impact the regional gap in systolic blood pressure. This may imply that the benefits or drawbacks of marital status and complex interactions between alcohol consumption and other unobserved factors are not fully captured in the model. This could include unobserved social support, the social environment, mental health, stress levels, or behavioural differences associated with marital status and alcohol use that differently impact health. In contrast, differences in the coefficient of demographics and household income impact the regional disparities in cholesterol ratio.

Overall, the results suggest that regional health disparities could, in part, be addressed by improving education, as it influences long-term health outcomes through increased awareness, access to resources, and healthier lifestyle choices (Di Paola and Raftopoulou, 2018; Bird et al., 2010). However, education may also act as a proxy for other underlying factors, such as socioeconomic conditions and healthcare access, which contribute to disparities. In addition to long-term educational investments, more immediate interventions such as targeted health information campaigns and community-based health programs could help mitigate regional disparities in the short term. These findings align with the new government plan by the Department for Education (2022), which prioritizes increasing educational resources in underperforming areas to support long-term equity while complementing broader public health strategies.

Finally, positive lifestyle practices play a crucial role in reducing regional health disparities, as research suggests that behaviours such as diet, physical activity, and smoking significantly impact health outcomes (Davillas and Jones, 2020). Studies have shown that regions with higher engagement in healthy behaviours tend to experience lower levels of preventable diseases and better overall health indicators (Marmot, 2010; WHO, 2021). Implementing policies that promote healthier lifestyles such as public health campaigns, improved access to nutritious food, and incentives for physical activity could help narrow regional health gaps and improve overall well-being in society.

3.6 SUMMARY

This chapter uses the UKHLS data with the Oaxaca-Blinder decomposition analysis to explore what lies behind regional disparities in health in the UK. The findings show that socioeconomic status, such as education and household income, contribute to these regional differences. Lifestyle factors, such as alcohol intake, also lie behind regional disparities in health in the UK. The results suggest that policies aimed at supporting and empowering communities in deprived regions to make informed health choices could help reduce regional health disparities in the UK. Rather than imposing top-down initiatives, a collaborative approach working with local communities to co-develop health education programs and resources may be more effective in fostering sustainable, positive lifestyle changes.

The next chapter seeks to fill some gaps in research by attempting to understand the contribution of the small area environment to regional disparities by focusing on the estimated glomerular filtration rate, a marker for chronic kidney disease and systolic blood pressure a marker for hypertension. Also, the chapter introduces the unconditional quantile regression model with the Oaxaca blinder decomposition. This will overcome the limitation based on the mean and show potential differential associations at the lower tail of the distribution where chronic kidney diseases are concentrated as well as the upper tail of the distribution where hypertension is located.

CHAPTER 4

REGIONAL DISPARITIES IN CHRONIC KIDNEY DISEASE AND HYPERTENSION IN ENGLAND: A DECOMPOSITION ANALYSIS OF THE CONTRIBUTION OF THE NEIGHBOURHOOD ENVIRONMENT

4.0 BACKGROUND

Chronic kidney disease (CKD) and hypertension affect millions of people worldwide, and substantial human and financial costs result from both diseases (Atkins, 2005; Cheung et al., 2019; Aitken et al., 2014; Nguyen et al., 2018). Hypertension is a condition characterised by a persistent elevation in arterial pressure (NHS England, 2022). Hypertension is a major cardiovascular disease resulting from chronic blood pressure. It increases the amount of work on the heart by inducing structural and functional changes in the heart's muscular tissue (Tackling and Borhade, 2022). The National Institute for Health and Care Excellence (NICE) defines high blood pressure as a systolic blood pressure of 140mmHg or higher. Kidney Research UK (2023) suggests hypertension is both an important cause and consequence of CKD. Damaged kidneys can cause high blood pressure, which, in turn, causes further kidney damage. In England, CKD and hypertension do not affect everyone. Kidney Research UK (2018) have reported that people from lower socioeconomic areas are more likely to develop CKD. Public Health England (2017) reported that people from the most deprived areas in England are 30% more likely to suffer hypertension than those in the least deprived areas. However, understanding the cause behind these differences can be challenging given regional disparities, different neighbourhood-level characteristics, and other health influences at the individual and environmental levels.

Few studies have provided evidence regarding regional inequalities in CKD and hypertension. Chan et al. (2014) address health disparities in chronic kidney disease in Taiwan. Using ordinary least squares regression, they found areas with higher percentages of higher education status or elderly had higher CKD prevalence. Also, De Gaudemaris et al. (2002) and Siven et al. (2015) revealed disparities in hypertension prevalence among different regions of England. There is a paucity of information to facilitate the understanding and support intervention development as studies that focus on regional disparities in these diseases do not account for the contribution of the neighbourhood environment, nor were they conducted within a British population.

Therefore, this chapter investigates regional disparities in chronic kidney disease (CKD) and hypertension in England. One of the aims of this thesis is to explore regional disparities in CKD and hypertension in England and examine the relative role of neighbourhood-level factors over individual-level characteristics using a nationally representative dataset of 14,043[4] from the United Kingdom Household Longitudinal Study (UKHLS) across the government office regions. The UKHLS data were linked to neighbourhood-level data from the English deprivation indices at the Lower Layer Super Output Area (LSOA) level (More information in Chapter 2). Previous research has examined the influence of the neighbourhood environment on health (Diez Roux and Mair, 2010; Chaparro et al., 2018), with a consistent finding being that individuals in deprived neighbourhoods experience worse health outcomes than those in less disadvantaged areas.

In England, government office regions (GORs) are the country's highest tier of sub-national division and were established across England in 1994 (ONS, 2023). It comprises nine regions (Northeast, Northwest, Yorkshire and Humber, East Midlands,

[4] The dataset in this chapter is smaller because of the exclusion of Wales and Scotland.

West Midlands, East of England, London, Southeast, and Southwest). The regions are the primary level for delivering a wide range of government policies and programs. Therefore, GORs are used in this research to examine inequalities in CKD and hypertension at the aggregated regional level, which are relevant to the regional local authorities for policy prescribing.

4.1 DATA AND VARIABLES

This section provides the health outcome, individual-level, and small area-level characteristics used for the analysis.

4.1.1 OUTCOME

Information of the definition and measurement of eGFR and systolic blood pressure used in this chapter can be found in Chapter 2.

4.1.2 INDIVIDUAL-LEVEL CHARACTERISTICS

Based on the previous literature, the following contributors for model estimation were considered. Demographic characteristics include age categories (16-29, 30-39, 40-64, 65-74 and 75 years and over) and sex. Socioeconomic characteristics include the log of household income (equivalised using the OECD modified scale), job status (unemployed or employed), house ownership (renting or owning a home), and education (no education, O-level, A-level, or degree). Also included are lifestyle characteristics: weekly fruit intake (never consumed fruit, 1-3 days weekly fruit intake, 4-6 days weekly fruit intake, and daily fruit intake), physical activity (no activity, or some form of activity) and smoking status (never smoked, ex-smoker, and smoker).

4.1.3 NEIGHBOURHOOD-LEVEL HEALTH CHARACTERISTICS

The United Kingdom Household Longitudinal Study (UKHLS) wave 2 and 3 data (2010-2012) were linked at the Lower Layer Super Output Area (LSOA) level with selected sub-domains of the 2010 English Indices of Deprivation (EID2010). A set of small-area-level factors is employed as proxies for the neighbourhood-level environment.

Crime levels[5] (least crime-deprived neighbourhoods[6]or most crime-deprived neighbourhoods[7]), sulphur dioxide (SO_2) concentration used to proxy air pollution, road distance to a General Practitioner (GP), income deprivation and skill deprivation.

4.2 STATISTICAL ANALYSIS

Ordinary Least Squares (OLS) regression was initially used to estimate the regression coefficients (Appendix: Table A1 and A10), followed by an Oaxaca-Blinder decomposition analysis. While traditional Oaxaca-Blinder decomposition focuses on the means, the distributional Oaxaca-Blinder decomposition aims to understand differences across the entire distribution of the outcome variable. As mentioned in Chapter Two, focusing only on average regional gaps may miss significant differences that could occur at other points of the eGFR distribution (especially at the left tail, corresponding to risks of chronic kidney disease or at the right tail, where the risks of hypertension are concentrated). The RIF Oaxaca-Blinder decomposition provides a nuanced understanding of the eGFR regional differences across the entire distribution, highlighting how gaps can vary at different points. By identifying where gaps are

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[5] Information of how the neigbourhood-level data is measured is provided in Chapter 2.
[6] Least deprived neighbourhood refers to areas with the lowest levels of crime and associated negative impacts on community wellbeing.
[7] Most deprived neighbourhoods are areas with high level of crime and its associated negative effects, leading to a lower quality of life and greater challenges in maintaining community safety and well-being.

largest and what contributes to them, policymakers can design targeted interventions to address disparities more effectively.

Therefore, this chapter employs the Unconditional Quantile Regression (UQR) method proposed by Firpo et al. (2009). Detailed information of this method is provided in Chapter 2.

4.2.1 SAMPLE CHARACTERISTICS

Table 4.1 presents the summary statistics of both dependent and explanatory variables used in this analysis. Means (and standard deviation) are reported for continuous variables and frequency (with percentages) for categorical variables. The average eGFR levels are around 95mL. An estimated rate of over 90 is considered normal for most adults (Kidney Research UK, 2023). The average systolic blood pressure values fall within the elevated blood pressure (120-129 mm Hg) range (Carey et al., 2018). Most of the sample participants were aged 40-64 (47%) and were female (56%). The Southeast GOR has the highest percentage of individuals in the sample (17%). Regarding neighbourhood-level characteristics, 33% of individuals live in areas with higher criminal activity. On average, the air quality of areas is 0.05 ppm (parts per million) with a standard deviation of 0.03. On average, the road distance to a general practitioner (GP) is 1.7 kilometres (approximately one mile). For socioeconomic status variables, 54% of the sample are employed, 75% own a house, and 22% have an education up to a degree level. The lifestyle characteristics show that nearly half of the participants consume fruits daily (49%). In addition, 74% of the sample engage in physical activity, while 47% have never smoked.

Table 4.1 Descriptive statistics - Dependent and Independent variables

Variables	Mean (SD)	Frequency (%)
Dependent variables		
eGFR (N=8,610)	95.12 (25.70)	
Systolic blood pressure (N=11,499)	125.89 (16.83)	
Independent variables		
Demographics		
Age group		
16-29		1,964 (13.99)
30-39		2,086 (14.85)
40-64		6,600 (46.10)
65-74		2,078 (14.80)
75+		1,315 (9.36)
Sex		
Male		6,153 (43.82)
Female		7,890 (56.19)
Government office regions		
Northeast		842 (5.10)
Northwest		1,944 (13.84)
Yorkshire and Humber		1,461 (10.40)
East Midlands		1,406 (10.01)
West Midlands		1,407 (10.02)
East of England		1,688 (12.02)
London		1,248 (8.89)
Southeast		2,369 (16.87)
Southwest		1,678 (11.95)
Neighbourhood-level characteristics		
Crime levels		
Less deprived areas		9,361 (66.66)
Higher deprived areas		4,682 (33.34)
Air quality	0.05 (0.03)	
Road distance to a GP/km	1.68 (1.61)	
Income deprivation	216.99 (167.83)	
Skills deprivation	21.32 (19.04)	
Socioeconomic status		
Log of household income	7.32 (0.64)	
Job-status		
Unemployed		6,454 (46.54)
Employed		7,415 (53.47)
House ownership		
Rent		3,456 (25.03)
Own a home		10,353 (74.97)
Education		
No qualification		2,059 (14.81)
Degree		3,119 (22.44)
A-level		4,251 (30.59)
O-level		4,470 (32.16)
Lifestyle characteristics		
Weekly fruit intake		
Never		953 (6.79)
1-3 days		3,727 (26.55)
4-6 days		2,518 (17.93)
Every day		6,842 (48.73)
Physical activity		
No activity		3,703 (26.39)
Some activity		10,330 (73.61)
Smoking status		
Never smoked		5,762 (46.98)
Ex-smoker		3,892 (31.73)
Smoker		2,612 (21.30)
Sample size		**14,043**

4.3 RESULTS

Below are the RIF-OB decomposition results and interpretation, followed by the graphical (**Figure 4.1**) and **Table 4.3** representations of the contribution of covariates across quantiles of the biomarkers distributions.

4.3.2 OAXACA-BLINDER DECOMPOSITION ANALYSIS OF eGFR DIFFERENTIALS

Table 4.2 presents the aggregated RIF decomposition results for different quantiles of the unconditional distribution of the eGFR. The decomposition result shows the differences in eGFR measures across the different geographical regions in England. A positive difference means that the eGFR value is higher in the London region compared to the other areas; this means that London has a better eGFR value. We are primarily interested in the lower tail of the distribution (Q25), where the risk of CKD is concentrated. Also, the table includes the explained and unexplained parts. The explained part shows the differences in RIF contributed by the observed differences in the covariates on the eGFR, while the unexplained part shows the differences due to the coefficient effect. **Figure 4.1** presents the contribution of covariates across eGFR regional differentials for all the regions. The focus is on the positive values (covariates) on the y-axis (vertical axis) when the x-axis (horizontal axis) is at zero as they increase the regional gaps in these regions.

Table 4 Oaxaca-Blinder decomposition of the regional differentials across quantiles of the estimated glomerular filtration rate (mL).

London vs Northeast

	Q25	%	Q50	%	Q75	%	Q90	%
London	84.74^{***}		103.1^{***}		124.3^{***}		143.1^{***}	
	(1.93)		(1.81)		(2.21)		(2.94)	
Northeast	80.07^{***}		97.37^{***}		115.3^{***}		129.6^{***}	
	(1.81)		(1.81)		(1.97)		(2.62)	
Difference	4.67^{*}		5.71^{**}		8.997^{***}		13.51^{***}	
	(2.65)		(2.56)		(2.96)		(3.94)	
Explained	9.27^{***}	198	6.35^{*}	111	0.26	3	3.79	28
	(3.52)		(3.73)		(4.52)		(6.31)	
Unexplained	-4.60	-98	-0.64	-11	8.74^{*}	97	9.72	72
	(3.66)		(3.86)		(4.90)		(7.07)	

London vs Northwest

	Q25	%	Q50	%	Q75	%	Q90	%
London	84.74^{***}		103.1^{***}		124.3^{***}		143.1^{***}	
	(1.93)		(1.81)		(2.21)		(2.94)	
Northwest	81.73^{***}		100.8^{***}		118.5^{***}		133.2^{***}	
	(1.34)		(1.32)		(1.44)		(1.65)	
Difference	3.02		2.29		5.78^{**}		9.96^{***}	
	(2.35)		(2.24)		(2.64)		(3.37)	
Explained	6.39^{***}	212	5.95^{***}	260	2.84	49	7.46^{***}	75
	(2.20)		(2.25)		(2.37)		(2.73)	
Unexplained	-3.37	-112	-3.67	-160	2.94	51	2.50	25
	(2.55)		(2.47)		(3.07)		(4.15)	

London vs Yorkshire and Humber

	Q25	%	Q50	%	Q75	%	Q90	%
London	84.74^{***}		103.1^{***}		124.3^{***}		143.1^{***}	
	(1.93)		(1.81)		(2.21)		(2.94)	
Yorkshire & Humber	77.51^{***}		95.72^{***}		113.1^{***}		130.6^{***}	
	(1.32)		(1.49)		(1.56)		(1.97)	
Difference	7.23^{***}		7.36^{***}		11.23^{***}		12.53^{***}	
	(2.34)		(2.34)		(2.71)		(3.54)	
Explained	8.29^{***}	115	5.36^{*}	73	2.92	26	10.33^{**}	82
	(2.57)		(2.93)		(3.14)		(4.35)	
Unexplained	-1.06	-15	1.10	27	8.31^{**}	74	2.20	18
	(2.96)		(3.24)		(3.74)		(5.47)	

London vs East Midlands

	Q25	%	Q50	%	Q75	%	Q90	%
London	84.74^{***}		103.1^{***}		124.3^{***}		143.1^{***}	
	(1.93)		(1.81)		(2.21)		(2.94)	
East Midlands	80.01^{***}		97.86^{***}		115.5^{***}		133.2^{***}	
	(1.56)		(1.47)		(1.84)		(2.61)	
Difference	4.73^{*}		5.22^{**}		8.80^{***}		9.97^{**}	
	(2.48)		(2.33)		(2.88)		(3.93)	
Explained	5.30^{*}	112	6.31^{**}	121	7.90^{*}	90	12.45^{*}	125
	(3.14)		(2.10)		(4.05)		(6.38)	
Unexplained	-0.57	-12	-1.09	-21	0.90	10	-2.49	-25
	(3.45)		(3.32)		(4.55)		(7.54)	

London vs West Midlands

	Q25	%	Q50	%	Q75	%	Q90	%
London	84.74^{***}		103.1^{***}		124.3^{***}		143.1^{***}	
	(1.93)		(1.80)		(2.21)		(2.94)	
West Midlands	79.06^{***}		95.56^{***}		113.5^{***}		132.5^{***}	
	(1.48)		(1.51)		(1.64)		(2.49)	
Difference	5.69^{**}		7.52^{***}		10.77^{***}		10.67^{***}	
	(2.43)		(2.36)		(2.76)		(3.85)	
Explained	6.47^{**}	114	5.38^{*}	72	6.70^{**}	62	10.52^{**}	99
	(2.99)		(2.95)		(3.17)		(5.03)	
Unexplained	-0.78	-14	2.14	28	4.08	38	0.15	1
	(3.37)		(3.11)		(3.56)		(6.30)	

London vs East of England

	Q25	%	Q50	%	Q75	%	Q90	%
London	84.74***		103.1***		124.3***		143.1***	
	(1.93)		(1.80)		(2.21)		(2.94)	
East of England	78.39***		95.08***		113.3***		128.9***	
	(1.37)		(1.36)		(1.62)		(1.96)	
Difference	6.35***		8.00***		11.01***		14.21***	
	(2.36)		(2.26)		(2.74)		(3.53)	
Explained	9.57***	151	4.45	56	6.28*	57	7.24	51
	(2.80)		(2.73)		(3.66)		(4.57)	
Unexplained	-3.22	-51	3.55	44	4.73	43	6.98	49
	(3.01)		(2.95)		(4.16)		(5.69)	

London vs Southeast

	Q25	%	Q50	%	Q75	%	Q90	%
London	84.74***		103.1***		124.3***		143.1***	
	(1.93)		(1.80)		(2.21)		(2.94)	
Southeast	78.74***		98.29***		115.7***		132.7***	
	(1.14)		(1.25)		(1.38)		(1.79)	
Difference	6.00***		4.79**		8.58***		10.43***	
	(2.24)		(2.19)		(2.61)		(3.44)	
Explained	4.66*	78	8.01***	167	11.93***	139	12.84**	123
	(2.44)		(2.78)		(3.49)		(5.48)	
Unexplained	1.35	22	-3.23	-67	-3.34	-39	-2.41	-23
	(2.88)		(2.92)		(4.04)		(6.47)	

London vs Southwest

	Q25	%	Q50	%	Q75	%	Q90	%
London	84.74***		103.1***		124.3***		143.1***	
	(1.93)		(1.80)		(2.21)		(2.94)	
Southwest	80.96***		97.98***		116.1***		130.5***	
	(1.23)		(1.40)		(1.48)		(1.81)	
Difference	3.78*		5.09**		8.24***		12.64***	
	(2.29)		(2.29)		(2.66)		(3.45)	
Explained	6.20***	164	6.15**	121	6.67**	81	5.13	41
	(2.38)		(2.91)		(3.05)		(3.85)	
Unexplained	-2.41	-64	-1.06	-21	1.57	19	7.51	59
	(2.70)		(3.23)		(3.59)		(4.99)	

Note: Estimation is weighted using UKHLS blood person sample weight.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Northeast

London has a higher eGFR value than the Northeast region, with a regional difference of around 4.7 units (Q25). This difference is mainly evident in the explained part, where up to 198% (9.27 units) of the overall London and Northeast eGFR gap is due to the differences in the levels of observable characteristics. Figure 4.1 (Northeast) shows that the neighbourhood-level characteristics is the main contributor to this regional gap. Skill deprivation is the highest individual contributor, followed by road distance to a GP and crime area levels.

Figure 4.1 Contribution of covariates across regional differentials – eGFR

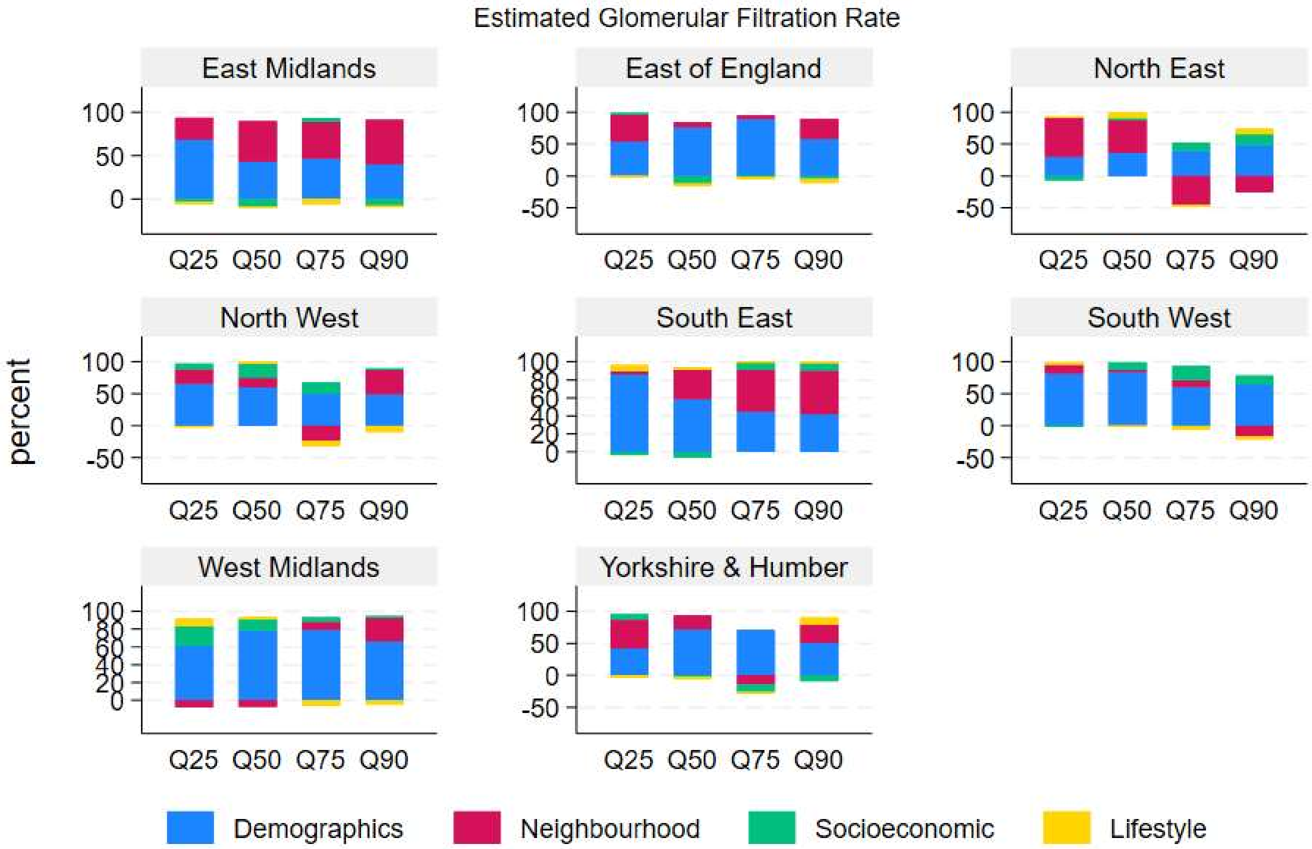

Table 5 Contribution of covariates across regional differentials – eGFR

Northeast

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	30.5	36.4	39.6	48.6
Neighbourhood factors	61.3	50.4	44.8	-25.6
Socioeconomic status	-6.7	3.9	12.2	17.0
Lifestyle	1.5	9.3	-3.4	8.8

Northwest

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	65.5	59.8	50.1	49.3
Neighbourhood factors	22.8	15.4	-23.9	37.7
Socioeconomic status	8.6	21.3	17.9	2.8
Lifestyle	-3.1	3.5	-8.1	-10.2

Yorkshire and Humber

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	41.7	71.5	70.9	50.9
Neighbourhood factors	45.5	22.2	-14.6	28.5
Socioeconomic status	8.7	-2.6	-11.8	-9.3
Lifestyle	-4.1	-3.7	-2.7	11.3

East Midlands

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	68.4	43.1	46.7	39.7
Neighbourhood factors	25.4	46.4	42.0	51.4
Socioeconomic status	-3.3	-9.0	4.9	-7.9
Lifestyle	-2.9	-1.5	-6.4	-1.0

West Midlands

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	61.1	78.4	79.2	66.5
Neighbourhood factors	-7.9	-7.4	9.6	26.6
Socioeconomic status	22.2	14.1	4.8	1.9
Lifestyle	8.8	0.1	-6.4	-5.0

East of England

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	53.9	76.2	89.3	58.4
Neighbourhood factors	43.4	7.8	5.1	31.0
Socioeconomic status	1.4	-11.4	-1.7	-4.2
Lifestyle	-1.3	-4.6	-3.9	-6.4

Southeast

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	86.1	58.7	44.7	41.9
Neighbourhood factors	3.5	32.6	46.4	48.5
Socioeconomic status	-3.6	-6.2	7.8	7.9
Lifestyle	6.8	2.5	1.1	1.7

Southwest

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	81.7	84.2	60.6	64.0
Neighbourhood factors	13.5	3.2	11.0	-16.7
Socioeconomic status	-0.9	11.5	21.8	14.6
Lifestyle	3.9	-1.1	-6.6	-4.7

Northwest

The results show no overall statistical difference in the eGFR levels between the Northwest region and London (Q25), even though the explained part is significant ($p<0.01$). The detailed figure for the Northwest presents the neighbourhood factors as the second highest contributor to the regional disparities in this area.

Yorkshire and Humber

The Yorkshire and Humber's aggregated OB decomposition estimates show that regional difference exists in eGFR measures in this region ($p<0.01$). The cause for this difference is attributed to the explained part, where up to 115% (8.29 units) of the overall regional disparities are due to the difference in the levels of observable covariates. Moving on to the Yorkshire and Humber figure (**Figure. 4.1**), the result reveals that the neighbourhood-level factor is the highest contributor to explaining the regional disparities in this area. Skill deprivation was the highest individual contributor, followed by air quality and income deprivation.

East Midlands

The result of the decomposition analysis shows that there is a significant regional gap between London and the East Midlands. Evidence suggests that 112% (5.3 units) of the overall regional differences are attributed to differences in the explained part. The figure for the contribution of covariates across regional differentials for the East Midlands panel shows that demographics is the highest contributor to regional differences while neighbourhood factor is the second highest contributor. Crime levels, road distance to a GP, and skill deprivation positively contribute to these disparities.

West Midlands

The West Midlands OB decomposition analysis shows a lower eGFR value than the London region, with a regional difference of 5.69. The result shows that 114% (6.47 units) of the aggregated regional eGFR differences in the Q25 are due to the differences in the explained part. The contribution of covariates across regional differential for the West Midlands panel shows that neighbourhood characteristics negatively contribute to the regional disparities in this area. From the figure, demographics (age and sex) are the highest contributor to the regional differences in this area, while socioeconomic status is the second largest contributor.

East of England

The decomposition analysis shows a significant regional gap between London and the East of England region. The explained part reveals that up to 151% (9.57 units) of the overall regional differences are due to the differences in observable characteristics. The contribution of covariates across regional differentials for the East of England panel shows that demographics is the highest contributor to regional disparities in this area. Neighbourhood-level factors follow them. Crime levels, income deprivation, and skill deprivation contribute to these disparities.

Southeast

The aggregated OB decomposition estimates show that London has a higher eGFR value than the Southeast region, with a regional difference of 6.00 units. The results further show that 78% (4.66 units) of the overall regional disparities are due to the explained part. The contribution of covariates across regional differentials for the Southeast panel shows that demographics are the highest contributor, and lifestyle characteristics are the second highest contributor to the regional disparities in this region.

Southwest

The result of the decomposition analysis shows that there is a significant regional gap between London and the Southwest region. Evidence suggests that 164% (6.20 units) of the aggregated regional difference is attributed to the differences in observed characteristics. The contribution of covariates across regional differentials for the Southwest panel shows demographic factors as the highest contributor in the lower tail of the distribution. The neighbourhood-level characteristics are the second highest contributor to the eGFR disparities in the Southwest region. Crime level is the highest individual contributor, while air quality is the second individual contributor in the neighbourhood-level factors.

4.3.3 OAXACA-BLINDER DECOMPOSITION ANALYSIS OF SYSTOLIC BLOOD PRESSURE DIFFERENTIALS

Table 4.4 shows the RIF-OB decomposition results for different quantiles of the systolic blood pressure distribution. The decomposition shows the difference in systolic blood pressure between London and the rest of the English regions. A negative difference means the systolic blood pressure value is lower in London than in other areas, suggesting lower hypertension levels. For this analysis, the upper tail of the distribution (Q75 and Q90), where the risk of hypertension is located, are of most interest. The decomposition table shows the explained and unexplained parts. **Figure 4.2 and Table 4.5** present the result of the contribution of covariates across the quantiles of the systolic blood pressure for all the regions. The results concentrate mainly on the explained part. The percentage of the outcome difference explained by each covariate is calculated by dividing the explained differences by the total difference, which may be a positive or negative percentage contribution to regional disparities in hypertension. While positive contribution means that the covariates increase regional disparities in that region, negative contribution implies that the covariates decrease regional disparities. For this analysis, the focus is on the covariates with negative values because when they are divided by the total difference presented in the analysis (which are negative values), the results are positive, suggesting that the variables increase regional disparities in systolic blood pressure. Variables that increase regional disparities are important for policy implications as local authorities may carry out targeted policies to decrease the contributions of such variables, thereby reducing regional inequalities.

Table 6.4 Oaxaca-Blinder decomposition of the regional differentials across quantiles of the systolic blood pressure distribution

London vs Northeast

	Q25	%	Q50	%	Q75	%	Q90	%
London	110.5***		120.3***		130.6***		140.9***	
	(0.74)		(0.79)		(0.86)		(1.271)	
Northeast	114.7***		126.6***		138.6***		152.3***	
	(0.98)		(1.04)		(1.07)		(1.85)	
Difference	-4.15***		-6.36***		-7.99***		-11.39***	
	(1.23)		(1.31)		(1.38)		(2.25)	
Explained	1.96	-47	-0.72	11	-2.76	35	2.38	-21
	(2.08)		(1.99)		(2.07)		(3.50)	
Unexplained	-6.10***	147	-5.64**	89	-5.22**	65	-13.76***	121
	(2.27)		(2.25)		(2.26)		(4.04)	

London vs Northwest

	Q25	%	Q50	%	Q75	%	Q90	%
London	110.5***		120.3***		130.6***		140.9***	
	(0.74)		(0.79)		(0.86)		(1.27)	
Northwest	116.6***		126.2***		137.6***		149.5***	
	(0.59)		(0.62)		(0.77)		(0.99)	
Difference	-6.09***		-5.89***		-6.98***		-8.64***	
	(0.95)		(1.01)		(1.16)		(1.61)	
Explained	-1.80	30	-1.24	21	-2.68*	38	-2.94*	34
	(1.11)		(1.05)		(1.38)		(1.58)	
Unexplained	-4.29***	70	-4.65***	79	-4.30***	62	-5.71***	66
	(1.36)		(1.32)		(1.56)		(2.01)	

London vs Yorkshire and Humber

	Q25	%	Q50	%	Q75	%	Q90	%
London	110.5***		120.3***		130.6***		140.9***	
	(0.74)		(0.79)		(0.86)		(1.27)	
Yorkshire & Humber	115.0***		124.7***		136.1***		146.9***	
	(0.67)		(0.77)		(0.89)		(1.31)	
Difference	-4.49***		-4.47***		-5.47***		-5.98***	
	(0.10)		(1.11)		(1.24)		(1.82)	
Explained	-2.15	48	-2.93**	65	-5.06***	93	-5.05**	84
	(1.32)		(1.45)		(1.64)		(2.24)	
Unexplained	-2.34	52	-1.54	35	-0.41	7	-0.94	16
	(1.63)		(1.72)		(1.91)		(2.49)	

London vs East Midlands

	Q25	%	Q50	%	Q75	%	Q90	%
London	110.5***		120.3***		130.6***		140.9***	
	(0.74)		(0.79)		(0.86)		(1.27)	
East Midlands	115.5***		126.1***		138.4***		150.1***	
	(0.72)		(0.73)		(0.93)		(1.30)	
Difference	-5.01***		-5.81***		-7.79***		-9.21***	
	(1.03)		(1.08)		(1.27)		(1.82)	
Explained	1.19	-24	-0.08	1	-1.20	15	-2.26	24
	(1.51)		(1.64)		(2.12)		(2.45)	
Unexplained	-6.20***	124	-5.73***	99	-6.59***	85	-6.95**	76
	(1.70)		(1.87)		(2.40)		(2.80)	

London vs West Midlands

	Q25	%	Q50	%	Q75	%	Q90	%
London	110.5***		120.3***		130.6***		140.9***	
	(0.74)		(0.79)		(0.86)		(1.27)	
West Midlands	111.8***		121.7***		133.1***		144.6***	
	(0.70)		(0.66)		(0.87)		(1.15)	
Difference	-1.30		-1.42		-2.44**		-3.71**	
	(1.02)		(1.03)		(1.22)		(1.71)	
Explained	-3.39**	261	-1.60	113	-2.28	94	0.72	-19
	(1.35)		(1.29)		(1.52)		(2.20)	
Unexplained	2.09	161	0.18	-13	-0.16	6	-4.43*	119
	(1.67)		(1.56)		(1.75)		(2.68)	

London vs East of England

	Q25	%	Q50	%	Q75	%	Q90	%
London	110.5***		120.3***		130.6***		140.9***	
	(0.74)		(0.79)		(0.86)		(1.27)	
East of England	114.9***		125.4***		135.9***		146.3***	
	(0.67)		(0.65)		(0.70)		(0.94)	
Difference	-4.36***		-5.10***		-5.26***		-5.46***	
	(0.10)		(1.02)		(1.11)		(1.58)	
Explained	-2.62*	60	-1.37	27	-2.23	42	0.68	-12
	(1.54)		(1.45)		(1.61)		(2.15)	
Unexplained	-1.75	40	-3.73**	73	-3.03	58	-6.14**	112
	(1.79)		(1.69)		(1.89)		(2.69)	

London vs Southeast

	Q25	%	Q50	%	Q75	%	Q90	%
London	110.5***		120.3***		130.6***		140.9***	
	(0.74)		(0.79)		(0.86)		(1.27)	
Southeast	113.7***		123.9***		136.1***		146.8***	
	(0.51)		(0.59)		(0.69)		(0.78)	
Difference	-3.16***		-3.62***		-5.46***		-5.94***	
	(0.90)		(0.99)		(1.11)		(1.49)	
Explained	-2.52**	80	-2.16*	60	-0.99	18	1.92	-32
	(1.20)		(1.30)		(1.50)		(1.89)	
Unexplained	-0.64	20	-1.47	40	-4.47**	82	-7.86***	132
	(1.43)		(1.51)		(1.76)		(2.40)	

London vs Southwest

	Q25	%	Q50	%	Q75	%	Q90	%
London	110.5***		120.3***		130.6***		140.9***	
	(0.74)		(0.79)		(0.86)		(1.27)	
Southwest	114.7***		123.8***		135.9***		147.0***	
	(0.62)		(0.63)		(0.82)		(1.01)	
Difference	-4.15***		-3.57***		-5.29***		-6.14***	
	(0.97)		(1.01)		(1.19)		(1.62)	
Explained	-2.34*	56	-5.26***	147	-3.86**	73	-4.25**	69
	(1.23)		(1.23)		(1.64)		(2.05)	
Unexplained	-1.81	44	1.69	-47	-1.43	27	-1.89	31
	(1.55)		(1.46)		(1.86)		(2.38)	

Note: Estimation is weighted using UKHLS blood person sample weight.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Northeast

The aggregated decomposition results show regional disparities in systolic blood pressure distribution. Neighbourhood-level characteristics contribute around 27% to regional disparities in systolic blood pressure in Q75, which is graphically presented in Figure 4.2. A more detailed look at the role of the individual neighbourhood-level characteristics at Q75 reveals that road distance to a GP (15%) is the dominant contributor, while skill deprivation and air quality are smaller but still significant contributors (Appendix: Table A11).

Figure 4.2 Contribution of covariates across regional differentials – Systolic blood pressure

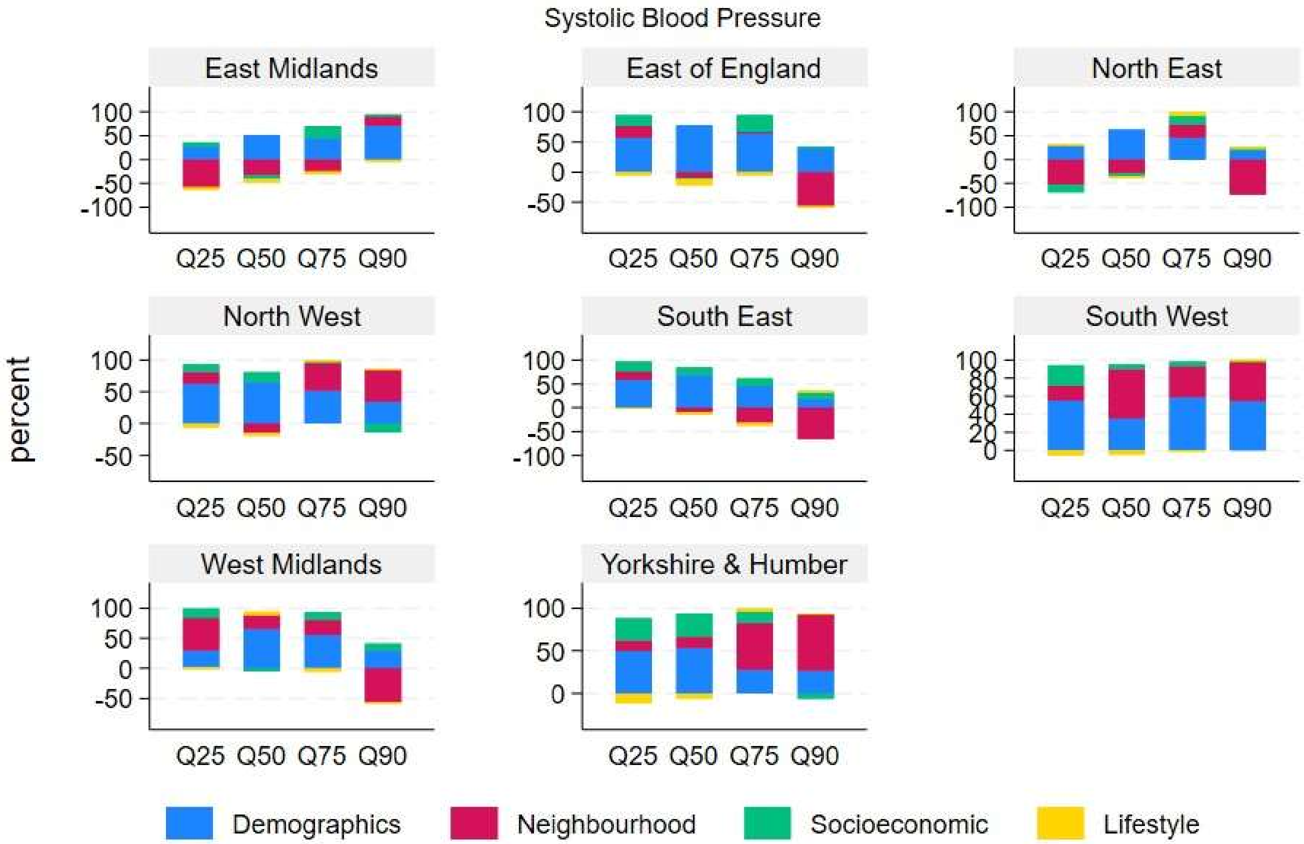

Table 7 Contribution of covariates across regional differentials – Systolic blood pressure

Northeast

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	29.2	62.7	46.2	19.1
Neighbourhood factors	-52.6	-28.9	26.9	-73.0
Socioeconomic status	-16.0	-7.7	18.2	3.8
Lifestyle	2.2	-0.7	8.7	4.1

Northwest

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	63.4	65.7	51.8	34.8
Neighbourhood factors	18.0	-14.7	43.9	49.7
Socioeconomic status	12.2	15.1	1.9	-13.5
Lifestyle	-6.4	-4.4	2.4	2.0

Yorkshire and Humber

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	60.0	70.9	37.1	25.6
Neighbourhood factors	-35.3	-6.7	46.8	63.0
Socioeconomic status	0.1	17.5	11.7	-9.8
Lifestyle	-4.6	-4.9	4.4	1.6

East Midlands

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	47.7	69.0	43.7	49.7
Neighbourhood factors	-43.6	-13.6	37.5	41.6
Socioeconomic status	3.7	11.7	16.0	-6.6
Lifestyle	-5.0	-5.6	2.8	2.1

West Midlands

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	65.3	91.1	49.8	89.4
Neighbourhood factors	13.2	2.8	34.3	-6.0
Socioeconomic status	17.2	5.8	15.4	3.3
Lifestyle	-4.3	-0.3	-0.5	1.3

East of England

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	63.9	92.1	52.0	70.9
Neighbourhood factors	14.3	0.7	29.5	-26.2
Socioeconomic status	17.4	4.9	17.3	2.1
Lifestyle	-4.5	-2.3	-1.2	0.7

Southeast

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	62.9	86.9	57.9	52.7
Neighbourhood factors	14.9	-2.3	20.3	-40.1
Socioeconomic status	18.0	7.7	19.4	6.6
Lifestyle	-4.2	-3.1	-2.4	0.6

Southwest

	Q25	Q50	Q75	Q90
	%	%	%	%
Demographics	61.9	72.4	58.1	63.7
Neighbourhood factors	15.1	16.9	22.8	-28.9
Socioeconomic status	18.6	7.0	16.8	6.8
Lifestyle	-4.4	-3.7	-2.3	0.6

Northwest

Northwest has a higher systolic blood pressure value across the distribution than the London region, which signifies a higher risk of hypertension (Q75 and Q90). The results suggest that neighbourhood factors drive these disparities in the upper quantiles by 44% and 50%, respectively. The detailed decomposition of the individual contribution of covariates between the regions shows that skill deprivation contributes the highest in the 90th quantile by 20% (Appendix: Table A12).

Yorkshire and Humber

The Yorkshire and Humber region's result shows that the neighbourhood environment is the main contributor to regional disparities in systolic blood pressure in the upper quantile of the distribution (Q90), with around 63%. The detailed individual decomposition of the contribution of covariates suggests skill deprivation is the highest contributor to these disparities. The result of this analysis can be found in the Appendix (Table A13).

East Midlands

Oaxaca-Blinder decomposition analysis showed that 24% of the differences in systolic blood pressure between East Midlands and London in the upper quantile (Q90) was explained by the sum of demographic factors and the neighbourhood environment. The total explained by measured variables includes counterbalancing factors, some of which contribute to, and others diminish the disparity of systolic blood pressure between the regions. The table in the Appendix reports detailed decomposition results of the explained effect across the systolic blood pressure distribution; they display the contribution of each covariate (or group of covariates). The findings reveal that the regional gap is driven mainly by age, income, and skill deprivation differences.

West Midlands

The result shows that across the various quantiles of the distribution, people living in the East Midlands region are found to have higher systolic blood pressure values than their peers in the London region, with a regional difference of 2.44 units (Q75). The contribution of covariates across regional differentials for the West Midlands panel shows demographic factors as the highest contributor in the upper tail of the distribution. The neighbourhood-level characteristics are the second highest contributor to the systolic blood pressure differences. Skill deprivation is the highest individual contributor, followed by income deprivation.

East of England

The OB decomposition of the East of England panel shows that systolic blood pressure values are higher in the East of England region than the London region by 5.263 units in Q75 and 5.463 units in Q90. The result shows that 42% of the aggregated regional health differences in the Q75 are due to the differences in the explained part. The contribution of covariates across regional differentials in systolic blood pressure for the East of England panel (Appendix: Table A16) shows that demographics and socioeconomic status contribute the highest with little contribution from the neighbourhood environment.

Southeast

The decomposition analysis shows a significant regional difference of 5.94-unit points between London and the Southeast region. The result shows that 132% (-7.86 units) of the aggregated regional systolic blood pressure differences in the Q90 are due to the differences in the unexplained part. However, for the sake of this analysis focusing on the explained part, I will be looking at covariates in the explained part driving these regional disparities[8]. The contribution of covariates across regional differentials for the Southeast panel shows that the population's demographics and socioeconomic status drive the regional inequalities in systolic blood pressure in this area.

Southwest

The decomposition analysis results show a significant regional gap in systolic blood pressure between London and the Southwest region. The results reveal that 69% (-4.25 units) of the overall regional disparity is attributed to the differences in the observed characteristics. The contribution of covariates across regional differentials for the Southeast panel shows demographics as the highest contributor to the regional gap in the upper tail of the distribution. The neighbourhood-level factors are the second highest contributor to the systolic blood pressure disparities. Income deprivation and road distance to a GP are the highest individual contributors in the neighbourhood environment.

[8] In health inequalities literature, the explained part of the Oaxaca-Blinder decomposition is often of greater interest because it identifies specific, observable, and potential modifiable factors contributing to health disparities. This focus aligns with the goals of developing effective, evidence-based policies and interventions to reduce health inequalities and improve overall public health outcomes.

4.4 DISCUSSION

This study contributes to the existing literature by examining the contributions of the neighbourhood environment to CKD and hypertension prevalence in England by decomposing the effect of neighbourhood-level environment by geographical region. The findings from the OB decomposition indicate regional disparities in CKD (Q25) and hypertension (Q75 and Q90) across regions in England. Findings show that London typically has a better average eGFR and systolic blood pressure. Hence, the London region was used as a reference for comparison. Recent Office for National Statistics (2022) findings show that London scores highly for healthy people compared to other regions of England.

The results indicate that the observed difference in the considered covariates can explain some regional disparities in eGFR. Although demographic factors account for part of the contribution of covariates across regional differentials, the neighbourhood environment also exerts a dominant role in most regions at the lower tail of the eGFR distribution. The contribution of the neighbourhood-level factors dominates the Northeast, Yorkshire, and Humber regions and is the second largest in Northwest, East Midlands, East of England, and Southwest. For example, the regional analysis of the Northeast shows that the neighbourhood environment accounts for 62% of the total regional disparities in eGFR, while demographic factors account for 30%.

The set of neighbourhood-level characteristics that play the most important role at the lower tails of the eGFR distribution are crime levels and skill deprivation. Crime fosters environments of chronic stress, violence, and poor access to resources, while skill deprivation limits educational opportunities, employment, and health literacy (Latkin and Curry, 2003). Together, these factors exacerbate the risk of CKD.

Previous studies have argued that residents in areas with better walkability, built infrastructure, and air quality are less likely to be affected by chronic diseases (Mujahid et al., 2008; Lapedis et al., 2020; Davillas and Jones, 2020). Socioeconomic status and lifestyle factors also have independent contributions above the role of the neighbourhood environment in some regions. For example, socioeconomic status contributed about 23% to the regional difference in the Northwest compared to the neighbourhood-level factors, making socioeconomic status the second largest contributor to regional disparity in this area.

For systolic blood pressure, demographic factors, especially the age of the population, were found to contribute the highest to regional disparities in hypertension across the region of England. The neighbourhood environment also contributed to regional inequality at the upper tail of the distribution as either the highest or second highest contributor to the regional gap. The contribution of the neighbourhood-level factors dominates for Northwest and Yorkshire and Humber regions and is the second largest for Northeast (Q75), East Midlands (Q90), and West Midlands (Q75). For example, the decomposition analysis of the Yorkshire and Humber region reveals that the neighbourhood factors explain 63% of the total regional disparities in systolic blood pressure while demographic factors explain 26%.

The detailed decomposition of the contribution of individual covariates to regional disparities in systolic blood pressure (focusing on the neighbourhood environment) shows that skill and income deprivation, as well as road distance to the GP, play the most significant role in widening the disparities of hypertension prevalence in these regions. Geographical barriers like road distance to a GP can increase systolic blood pressure levels due to limited access to healthcare services, delayed diagnosis, and reduced utilisation of healthcare facilities. Previous studies have shown that small-area deprivation is one of the sources of inequalities in hypertension (Siegel et al., 2015).

The findings of this research show that neighbourhoods with disadvantaged environments, such as those of higher socioeconomic position (SEP) deprivation, crime levels, geographic barriers and lower air quality levels, may influence individuals' eGFR and systolic blood pressure levels, especially at the lower tails (higher tails) of its distribution. The evidence accords with existing literature that has found significant associations between health measures and environmental risk factors (for example, Diez Roux, 2001; Chaparro et al., 2018; Davillas and Jones, 2020; Chaparro et al., 2018; Bernard et al., 2007; Richardson et al., 2013) and extends them by using new health outcomes and quantifying the relative contribution of the neighbourhood environment, as opposed to individual-level characteristics, across the whole distribution of the eGFR and systolic blood pressure measures.

No known previous literature focuses on regional disparities in CKD or hypertension in the UK or England and investigates the association of individual and neighbourhood characteristics in this disease. Investigating the association of the neighbourhood environment to regional disparities in CKD is essential for area policymaking, as the neighbourhood-level characteristics are adaptable. The neighbourhood environment still plays an independent role. Therefore, efforts to tackle CKD and hypertension need approaches that combine individual-based interventions (people) with neighbourhood environmental factors (place of residence).

4.5 SUMMARY

This chapter advances the understanding of the contribution of neighbourhood-level characteristics to the regional disparities in chronic kidney disease and hypertension across regions in England. Overall, the results suggest that policies that aim to tackle chronic kidney disease and hypertension should specifically target not just people but also their neighbourhood environment.

The next chapter seeks to fill some gaps in research by attempting to investigate the underlying source of coastal and inland disparities in chronic kidney disease and systolic blood pressure in the East of England region. Unlike broader regional comparisons, a coastal versus inland disparities focus allows for a more targeted understanding of localised health inequalities.

CHAPTER 5

COASTAL-INLAND DISPARITIES IN CHRONIC KIDNEY DISEASE AND HYPERTENSION IN THE EAST OF ENGLAND REGION.

5.0 BACKGROUND

This chapter considers CKD and hypertension in the East of England, with an interest in examining the disparity between coastal and inland areas of this English region. Coastal communities are regions that border the sea or ocean and often have distinctive geographical, economic, social, and environmental characteristics (Coastal Communities, 2022). Recent debate amongst academics and health experts underscores the interest in coastal versus inland health disparities. The Chief Medical Officer's Annual Report (2021) on health in coastal communities highlighted the high proportion of poor health conditions that are concentrated in England's coastal communities. This is further echoed by the ONS (2020) and Bird (2021) reports, which showed that deprivation, unemployment, poor education, housing problems and flooding are worse in coastal communities than inland communities. Also, Depledge et al. (2017) reported that people living in the coastal region of England are more likely to report chronic health conditions than those living in non-coastal areas. Asthana and Gibson (2021) further observed an excess of many long-term conditions in coastal regions compared with inland areas with similar demographics and deprivation. In contrast, other studies suggest coastal communities have better health outcomes than inland communities (Wanezaki et al., 2016; Wheeler et al., 2013; White et al., 2013). White et al. (2014) studied coastal proximity, health, and well-being, finding that living within 5km from the coast was associated with better general health.

This chapter contributes to the ongoing debate by addressing two key questions:

- Are there regional disparities in CKD and hypertension between coastal and non-coastal communities in the East of England?
- What are the underlying sources of these health disparities?

An Oaxaca-Blinder (OB) decomposition analysis at various quantiles of the eGFR and systolic blood pressure distributions was used to investigate disparities in terms of these health outcomes and highlight the associations. Specifically, the OB decomposition was used to examine the extent to which the regional inequalities in eGFR and systolic blood pressure are explained by differences in the distribution of the observed characteristics (explained part) and differences in the effects of the factors through the estimated model parameters (unexplained part) on the outcomes. This research builds on previous health inequalities literature that has used RIF-unconditional quantile regression of OB decomposition to explore regional, gender, and ethnic disparities (Hussein, 2014; Carrieri and Jones, 2017; Di Paola and Raftopoulou, 2018).

5.1 DATA AND VARIABLES

The data used in this research is from the United Kingdom Household Longitudinal Study (UKHLS), a large and nationally representative dataset. The focus was only on the East of England region.

The East of England is one of the nine regions of England in the UK. It includes cities and towns divided into coastal and inland communities. The East of England is home to over 6.3 million individuals (ONS, 2021). The East of England region has some of the most affluent localities in the country but also some of the most deprived. The life expectancy gap between those living in the most and least deprived areas for males has increased over the years (OHID, 2021). Thousands of people are living with CKD and hypertension in the East of England region. Approximately 870,000 people in the region have CKD, over 13% of the East of England population (Anglia Water, 2023). Also, around 968,000 people have been diagnosed with high blood pressure, accounting for over 15% of the population (British Heart Foundation, 2023).

5.1.1 COASTAL AND INLAND DISTRICTS OF EAST OF ENGLAND

Data from 48 local authority districts in the East of England region are categorised into either coastal (defined by any border with adjacent to the sea) or inland areas. There are 11 coastal districts: Colchester, Great Yarmouth, Ipswich, King's Lynn and West Norfolk, Maldon, North Norfolk, Rochford, Southend-on-Sea, Suffolk Coastal District, Tendering and Waveney.

The region has 37 inland districts: Babergh, Basildon, Bedford Unitary, Braintree, Breckland, Brentwood, Broadland, Broxbourne, Cambridge, Castle Point, Central Bedfordshire, Chelmsford, City of Peterborough, Dacorum, East Cambridgeshire, East Hertfordshire, Epping Forest, Fenland, Forest Heath, Harlow, Hertsmere, Huntingdonshire, Luton, Mid Suffolk, North Hertfordshire, Norwich, Rochford, South Cambridgeshire, South Norfolk, St. Albans, St. Edmundsbury, Stevenage, Three Rivers, Thurrock, Uttlesford, Watford, and Welwyn Hatfield.

5.1.2 OUTCOME VARIABLE

The eGFR and systolic blood pressure variables were explained in Chapter 2. Lower values of the eGFR (≤89mL) are used to indicate the risk of chronic kidney disease, with higher values indicating better kidney functioning. Higher systolic blood pressure values indicate hypertension, defined as greater than 140mmHg.

5.1.3 EXPLANATORY VARIABLES

A set of explanatory variables typically associated with chronic conditions following previous literature (Davillas and Pudney, 2020; Carrieri and Jones, 2017) were used in the analysis.

Demographic characteristics include age and sex. Socioeconomic characteristics include the log of household income (equivalised using the OECD modified scale), education (degree, A-level, O-level and no education), job status (unemployed, self-employed, paid employment, and retired), and house ownership (renting or own a home). Lifestyle characteristics include physical activity (no activity or some form of activity), smoking status (never smoked, ex-smoker, and smoker), alcohol consumption (never taken alcohol, frequent in-take, and rare in-take) and weekly fruit consumption (never consumed fruit, 1-3 days weekly fruit consumption, 4-6 days weekly fruit consumption, and daily fruit consumption).

5.1.4 SMALL AREA-LEVEL CHARACTERISTICS

The analysis used small area-level characteristics as proxies for the neighbourhood environment. Including the neighbourhood-level characteristics allows for the quantification of the contribution of the neighbourhood environment to CKD and hypertension inequalities in the coastal versus inland communities in the East of England.

Income, skill, and education were considered in this analysis. According to Baker (2019), income, skill, and education are associated with health conditions. Higher values of income, skill, and education mean a more significant part of the LSOA-level population is deprived. Road distance to a General Practitioner (GP) was included. It is captured by the weighted mean[9] LSOA road distance to the closest GP in kilometres.

5.2 STATISTICAL ANALYSIS

This section uses the Oaxaca-Blinder decomposition to divide the eGFR and systolic blood pressure differences between the coastal and inland communities and quantify each explanatory variable's contributions to the differences in the East of England region. Information on Oaxaca-Blinder decomposition is presented in Chapter Two.

5.2.1 SAMPLE CHARACTERISTICS

Table 5.1 presents the descriptive statistics of the overall inland and coastal area samples. In the sample, 27% have an estimated glomerular filtration rate (eGFR) of 89mL or below, similar to the inland area of approximately 27%. Of the coastal sample, 30% are found to have an eGFR of 89mL or below. Also, 38% of the participants living in coastal communities have a systolic blood pressure of 140mmHg or higher compared to the inland region of 32%. These differences imply that individuals from the coastal communities have a higher risk of CKD and hypertension than those from the inland area. The average age of the inland communities is approximately 52 years compared to 56 in the coastal district sample. This difference is not unexpected, as the risk of developing these conditions increases with age.

In this sample, skill, income, and employment deprivation are higher on average for people living in the coastal area than those living in a non-coastal neighbourhood. This is consistent with the annual report of the Chief Medical Officer (2021), which highlighted the prevalence of neighbourhood deprivation (e.g., employment, income)

[9] The use of a weighted mean takes into account the distribution of the population within each LSOA. This means that areas with more people contribute more to the average distance, making the measure more representative of the actual experience of the population in that area.

in coastal communities. On average, the population of coastal areas has lower levels of education: about 21% of the population in the coastal area have no basic qualification, compared to 14% in the inland area. This result is consistent with the ONS (2020) findings. The household income of coastal communities is lower than that of their neighbours in the inland communities. The population from the coastal area has a higher unemployment rate of around 17% compared to the inland area of 15%.

Regarding lifestyle factors, around 31% of the coastal area population in this sample is not physically active compared to 27% of the non-coastal area. This result contrasts with Wheeler et al. (2012), who found that coastal proximity increased physical activity. Finally, on average, the sample shows a higher proportion of about 22% of smokers living in the coastal area than 19% in the inland communities.

Table 5.1 Sample characteristics

Characteristics	Inland areas	Coastal areas	Overall
Dependent variables			
eGFR			
Continuous - Mean (SD)	93.32 (224.31)	87.66 (23.40)	92.076 (24.21)
As categorical (≤89mL) – n (%)	269 (26.79)	82 (29.60)	351 (27.40)
Systolic blood pressure			
Continuous - Mean (SD)	126.38 (16.57)	129.29 (16.13)	127.006 (16.51)
As categorical (≥140mmHg) – n (%)	322 (32.07)	104 (37.55)	426 (33.26)
Demographics			
Age - Mean (SD)	52.10 (17.14)	56.49 (16.90)	53.049 (17.18)
Male	443 (44.12)	129 (46.57)	572 (44.65)
Female	561 (55.88)	148 (53.43)	709 (55.35)
Neighbourhood-level factors			
Skills deprivation - Mean (SD)	18.70 (13.96)	27.30 (14.27)	20.56 (14.46)
Income deprivation - Mean (SD)	175.32 (118.26)	241.37 (146.33)	189.606 (127.73)
Employment deprivation - Mean (SD)	67.39 (40.66)	95.56 (58.28)	73.482 (46.50)
Road distance to a GP/km - Mean (SD)	2.12 (1.90)	2.14 (2.27)	2.129 (1.99)
Socioeconomic status			
Log of household income – Mean (SD)	7.37 (0.64)	7.18 (0.60)	7.34 (0.64)
Education			
No qualification	139 (13.84)	58 (20.94)	197 (15.38)
O-level	332 (33.07)	111 (40.07)	443 (34.58)
A-level	308 (30.68)	73 (26.35)	381 (29.74)
Degree	225 (22.41)	35 (12.64)	260 (20.30)
Job-status			
Unemployed	146 (14.54)	47 (16.97)	193 (15.07)
Self-employed	73 (7.27)	24 (8.66)	97 (7.57)
Paid employment	502 (50.00)	87 (31.41)	589 (45.98)
Retired	283 (28.19)	119 (42.96)	402 (31.38)
House ownership			
Rent	244 (24.30)	52 (18.77)	296 (23.11)
Own a home	760 (75.70)	225 (81.23)	985 (76.89)
Lifestyle factors			
Physical activity			
Not Active	271 (26.99)	86 (31.05)	357 (27.87)
Active	733 (73.01)	191 (68.95)	924 (72.13)
Smoking status			
Never smoked	434 (43.23)	107 (38.63)	541 (42.23)
Ex-smoker	377 (37.55)	109 (39.35)	486 (37.94)
Smoker	193 (19.22)	61 (22.02)	254 (19.83)
Alcohol consumption			
Never drank alcohol	83 (8.27)	25 (9.03)	108 (8.43)
Rare in-take	351 (34.96)	95 (34.30)	446 (34.82)
Frequent in-take	570 (56.77)	157 (56.68)	727 (56.75)
Week fruit consumption			
Never	56 (5.58)	13 (4.69)	69 (5.39)
1-3 days	262 (26.10)	66 (23.83)	328 (25.61)
4-6 days	193 (19.22)	46 (16.61)	239 (18.66)
Every day	493 (49.10)	152 (54.87)	645 (50.35)
Sample size	**1,004**	**277**	**1,281**

Note: Data are Mean (SD) for continuous variables and frequency (percentage) for categorical variables. SD: Standard Deviation

5.3 RESULTS

5.3.1 OAXACA-BLINDER DECOMPOSITION ANALYSIS OF eGFR DIFFERENCES

Table 5.2 presents the aggregated RIF decomposition results at different quantiles of the unconditional distribution of eGFR. The decomposition shows differences in eGFR measure between the inland and coastal communities. A positive difference means that the eGFR value is higher, i.e. better, in the inland community than in the coastal community. The estimated difference is positive and statistically significant in the lower tail of the eGFR distribution associated with chronic kidney disease.

The explained part shows the proportion of the differences explained by observed differences in the covariates on the eGFR. The unexplained part is the estimated proportion of the differences not attributable to the differences in explanatory factors. The results show that 100% (7.55 points) of the overall inland and coastal communities' eGFR gap in Q10 can be attributed to the differences in the levels of observed covariates. There is also a significant eGFR difference in the Q25 of 83% (6.92 points). The explained part is also significant for all the higher quantiles (Q50, Q75, Q90). For the unexplained part, the impact of the covariates on the eGFR is not significant across most of the quantiles. The result shows that the difference in the observed covariates mainly contributes to the differences in CKD between the inland and coastal regions.

The detailed contribution of covariates to the area differences in eGFR is presented in Table 5.3, Figure 5.1, and Table B.1 (in the Appendix). The decomposition result shows a large contribution of demographics, 6.19 units or 66%, at the lowest levels of eGFR. This shows that demographic factors influence the coastal-inland area difference. The explained part, due to differences in neighbourhood-level characteristics, is not positive (-0.94) for the lowest levels of eGFR. This means

Table 5.2 Oaxaca-Blinder decomposition differentials across quantiles of the eGFR distribution between coastal and inland communities in the East of England region

	Q10	%	Q25	%	Q50	%	Q75	%	Q90	%
Inland communities	63.64***		79.90***		95.74***		115.8***		130.2***	
	(1.89)		(1.54)		(1.61)		(1.88)		(2.17)	
Coastal communities	56.09***		71.53***		91.97***		103.0***		117.8***	
	(3.20)		(3.19)		(2.50)		(2.43)		(3.53)	
Difference	7.55**		8.36**		3.77		12.79***		12.37***	
	(3.72)		(3.54)		(2.97)		(3.07)		(4.14)	
Explained	7.55**	100	6.92**	83	4.74*	126	6.94**	54	8.44**	68
	(3.54)		(3.22)		(2.72)		(2.76)		(4.02)	
Unexplained	-0.01	-0.0	1.44	17	-0.97	-26	5.85*	46	3.93	32
	(3.47)		(3.28)		(3.01)		(3.40)		(4.68)	

Note: Estimations are weighted using UKHLS blood person weights.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the contribution of the neighbourhood environment to area differences is small. Looking at the individual contribution of the neighbourhood-level characteristics (Appendix: Table B1), skill deprivation (7.8%) contributes the most, followed by employment deprivation (5.8%) towards the observable differences in the explained part.

The overall contribution of socioeconomic status is high and positive for both Q10 and Q25 (extremely low levels of the eGFR measure). The contribution of household income is substantial, particularly from the 10th (30%) and 25th (16%) percentile, and it is also due to differences in the association of eGFR to income across areas (Appendix: Table B1). Aside from household income being the highest contributor to the differences in eGFR between the coastal and inland areas in the socioeconomic characteristic variables, house ownership is the second highest and predominant across the quantiles of the eGFR distribution. For the lifestyle characteristics, the result for Q10 shows that smoking status contributes to differences in the eGFR gap between the coastal and inland communities in the East of England region. The result also indicates that for Q25, alcohol consumption in the coastal area is more than in the inland area by 0.8%, thereby causing disparities in eGFR levels.

Figure 5.1 Contribution of covariates across quintiles of the eGFR distribution

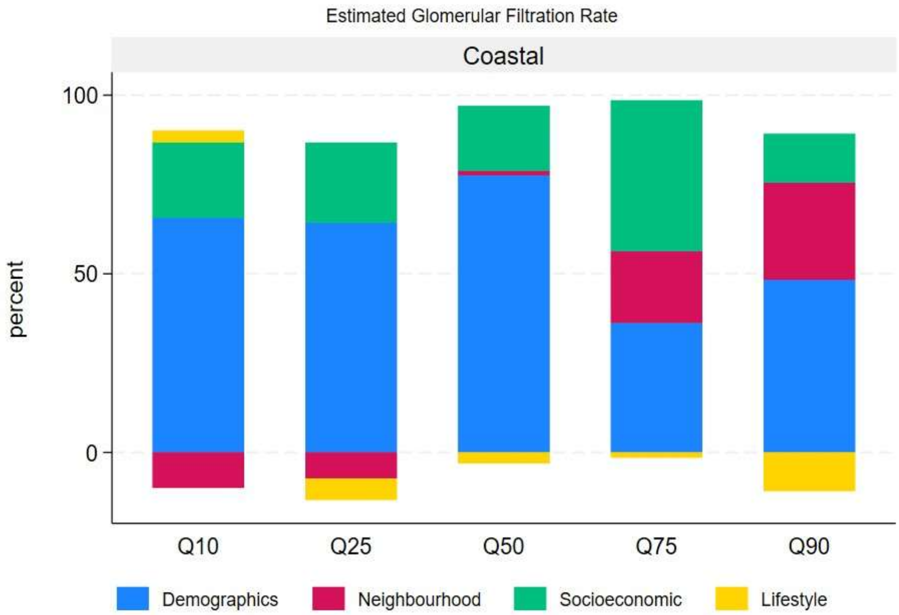

Table 5.3 Contribution of covariates across quintiles of the eGFR distribution

	Q10	Q25	Q50	Q75	Q90
	%	%	%	%	%
Demographics	65.7	64.3	77.6	36.3	48.3
Neighbourhood	-9.9	-7.3	1.3	20.1	27.3
Socioeconomic status	21.2	22.4	18.1	42.2	13.6
Lifestyle	3.2	-6.0	-3.0	-1.4	-10.8

5.3.3 OAXACA-BLINDER DECOMPOSITION ANALYSIS OF SYSTOLIC BLOOD PRESSURE DISTRIBUTION

The results of the OB decomposition at the 10th, 25th, 50th, 75th, and 90th quintiles distribution of the systolic blood pressure is shown in Table 5.4. The decomposition is expressed as a difference between covariate distribution for inland areas minus that for coastal regions. A negative difference means that the systolic blood pressure value is lower among individuals in the inland communities. Like the eGFR, the inland communities have a better systolic blood pressure value. However, focus is given to the 75th and 90th quantiles, as these are the ranges where the risk of hypertension is most concentrated. The results show no significant area disparities in the 90th percentile; however, Q75 is significant. Also, none of the estimates for the explained part is statistically significant except for the 50th quantile. The Q75 suggests that 43% (-1.27 points) of the overall inland and coastal communities' systolic blood pressure disparity is due to the differences in the level of the observed covariates.

Table 5.4 Oaxaca-Blinder decomposition differentials across quantiles of the systolic blood pressure distribution between coastal and inland communities in the East of England region

	Q10	%	Q25	%	Q50	%	Q75	%	Q90	%
Inland communities	106.5***		114.5***		124.8***		135.6***		146.1***	
	(0.81)		(0.77)		(0.79)		(0.82)		(1.10)	
Coastal communities	109.5***		118.3***		128.3***		138.6***		150.4***	
	(1.53)		(1.45)		(1.47)		(1.59)		(2.63)	
Difference	-3.03*		-3.77**		-3.47**		-2.97*		-4.24	
	(1.73)		(1.64)		(1.67)		(1.79)		(2.85)	
Explained	-1.25	41	-2.32	62	-3.56**	102	-1.27	43	-2.82	66
	(1.40)		(1.41)		(1.49)		(1.52)		(2.79)	
Unexplained	-1.78	59	-1.45	38	0.084	-2	-1.70	57	-1.43	34
	(2.23)		(2.09)		(2.01)		(1.99)		(3.30)	

Note: Estimations are weighted using UKHLS nurse visit weights.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 5.2 and Table 5.5 present the detailed contribution of covariates across the systolic blood pressure distribution. The decomposition results show the positive contribution of demographics and socioeconomic status at the highest systolic blood pressure distribution level. This means that socio-demographic factors contribute to area differences in the East of England region, with age (2.97 units) contributing the highest to this disparity. The overall contribution of the socioeconomic status is positive, with education contributing the highest (Appendix: Table B2).

Figure 5.2 Contribution of covariates across quintiles of the systolic blood pressure distribution

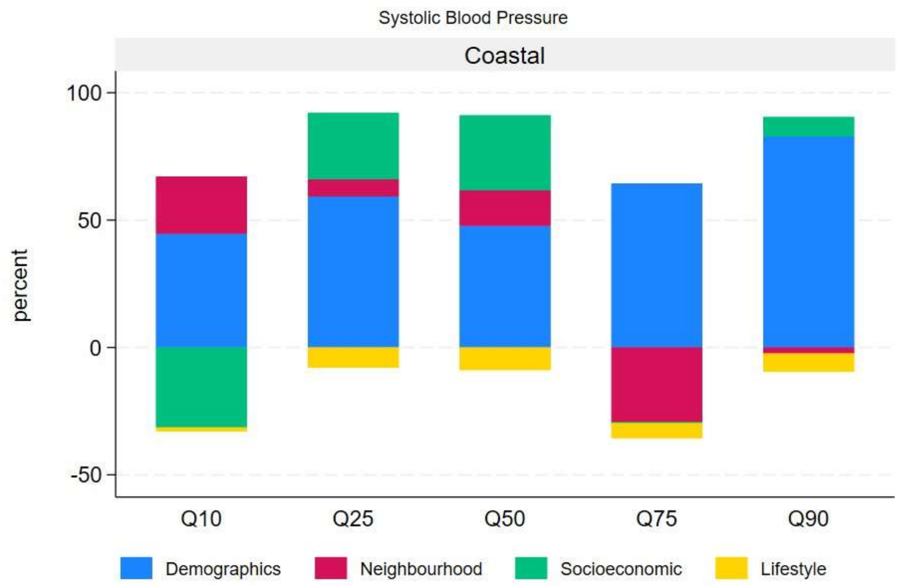

Table 5.5 Contribution of covariates across quintiles of the systolic blood pressure distribution

	Q10	Q25	Q50	Q75	Q90
	%	%	%	%	%
Demographics	44.7	59.3	47.8	64.4	82.8
Neighbourhood	22.4	6.7	13.9	-20.2	-2.4
Socioeconomic status	-31.4	26.0	29.4	-9.5	7.7
Lifestyle	-1.5	-8.0	-8.9	-5.9	-7.1

5.4 DISCUSSION

This chapter examined if there are disparities in CKD and hypertension between coastal and inland communities and, if such disparities exist, what the underlying sources of such disparities could be, with particular emphasis on understanding coastal public health in the East of England region. Coastal communities were found to have lower eGFR levels than the inland areas, translating to higher risks of CKD. This disparity is mainly due to the explained part of the decomposition result.

ESTIMATED GLOMERULAR FILTRATION RATE

The average age of people living in the coastal areas is higher than that of their inland neighbours. The decomposition results indicate a large contribution of demographic factors towards the coastal-inland disparities in CKD of 66% at the 10th and 64% at the 25th quantile. The age of the population contributes to the higher share of this disparity at the lower tail of the distribution. Barton et al. (2022) argued that coastal areas tend to draw older and retired citizens with existing health problems.

In this study, overall neighbourhood-level factors do not contribute substantially to the coastal-inland disparities in CKD. However, among the various neighbourhood-level characteristics, skill deprivation (7.8%) contributes the most to area disparities. Evidence exists that skill deprivation is associated with several health problems and is higher in coastal communities than in non-coastal communities (Jokela, 2015; ONS, 2020). Socioeconomic status is the second largest contributor (21%) to the overall coastal-inland inequalities in CKD, among which household income contributes the largest. This means, on average, inland areas have higher household income than coastal ones. According to a report by the BBC (2022), one in five jobs pays below the living wage in coastal areas, with household income lower than in non-coastal areas.

In comparison, data from the Living Wage Foundation indicates that, as of April 2023, approximately 12.9% of employee jobs across the UK are paid below the living wage (LWF, 2023). This suggests that coastal areas have a higher proportion of low-paying jobs compared to the national average. Also, the ONS (2020) found that coastal communities have some of the country's highest unemployment and lowest pay. The analysis also suggests that smoking status increases the coastal-inland disparities in CKD by 11%. Though smoking rates are falling nationally, coastal smoking is higher than inland communities and has been a key concern (Chief Medical Officer, 2021; Farhud, 2015).

This study offers an added perspective on the factors that contribute to the coastal area CKD inequalities and supports the theory that coastal communities have a higher disease burden across a range of physical conditions (Chief Medical Annual Report, 2021; Asthana and Gibson, 2021). Even though social epidemiology has found that CKD is caused heterogeneously by factors such as obesity and diabetes mellitus, both of which are influenced by broader social determinants like socioeconomic status, food accessibility, and environmental pollution, most approaches to addressing CKD or any chronic conditions rely primarily on individual-level interventions. These interventions, such as lifestyle modification programs, medication adherence strategies, and patient education initiatives, often overlook the structural and environmental factors that contribute to disease risk (Kovesdy, 2022; Hsu et al., 2021; Salgado et al., 2012). For example, individuals in low-income communities may struggle to adopt healthier lifestyles due to limited access to fresh food, inadequate healthcare resources, and higher exposure to environmental toxins. A more comprehensive approach would incorporate community-based initiatives, policy changes to improve food and healthcare access, and urban planning strategies to reduce environmental health risks.

SYSTOLIC BLOOD PRESSURE

The results compare differences in systolic blood pressure between inland and coastal communities across different quantiles (Q10, Q25, Q50, Q75, and Q90). At every quantile, coastal communities consistently show higher values than inland communities. Differences were observed for systolic blood pressure. Coastal communities have higher systolic blood pressure levels compared to the non-coastal areas, indicating a higher risk of hypertension. The difference is significant in the 75th quantile of the distribution where the risk of hypertension is concentrated. Also, neither the explained nor unexplained part in the upper quantile is statistically significant, making it hard to know what part (factors) contributes to the disparities in hypertension.

Systolic blood pressure is a critical indicator of cardiovascular health, with elevated levels being a major risk factor for hypertension, stroke, and heart disease (Whelton et al., 2018). The observed disparities in SBP between inland and coastal communities underscore potential health inequalities that warrant further investigation. Several factors contribute to these differences, including socioeconomic status, environmental factors, and lifestyle behaviours (Nakagomi et al., 2022). Coastal communities, which exhibit consistently higher systolic blood pressure levels across quantiles, may experience unique environmental and social determinants of health, such as increased stress due to economic instability (e.g., reliance on seasonal employment), greater exposure to airborne pollutants and salt-heavy diets, or limited access to high-quality healthcare services (Brook et al., 2010). The decomposition analysis suggests that both explained and unexplained components contribute to the inland-coastal SBP gap, indicating that while measurable factors like income, education, and neighbourhood-level factors play a role, underlying structural determinants such as psychosocial stress, urbanisation, and dietary patterns may also be influential (Chaturvedi et al., 2024). Addressing these disparities requires a multifaceted approach, including targeted health policies, improved primary healthcare access, and public health initiatives focusing on nutrition, physical activity, and stress management. Future research could further explore the intersection of environmental, economic, and behavioural factors in shaping SBP disparities, ensuring that policy responses are tailored to the unique challenges of different geographic regions.

GENERAL DISCUSSION

The findings of this study have policy implications for local authorities in the East of England. Even though the region has some of the most affluent localities in the country, coastal-inland disparities in CKD and hypertension exist. This highlights the need for a more holistic and systems-based approach to addressing coastal-inland disparities in CKD, recognizing that different factors vary in their modifiability and the ease with which they can be addressed. Given that socioeconomic status (household income) is a substantial contributor to these disparities, policy responses must extend beyond traditional public health measures and involve cross-sector collaboration. While economic interventions, such as raising average job pay in coastal areas to match that of inland communities, may help boost household income, this approach is complex, requiring long-term changes and may be less immediately impactful especially in areas with an aging or largely retired population. In contrast, targeted interventions for older people, such as improving healthcare accessibility, social support networks, and community-based health initiatives, may be more feasible and yield more immediate benefits (Lyu and Fan, 2024; Tung et al., 2018).

Moreover, efforts to reduce coastal-inland inequalities should incorporate a systems-thinking approach, recognizing that health disparities are shaped by interconnected social, economic, and environmental factors. This means implementing place-based interventions that address multiple determinants simultaneously, for example, investing in accessible healthcare services, improving transportation links to better connect residents with healthcare and employment opportunities, and creating age-friendly environments that promote well-being among older adults. Public health teams alone may not have the capacity to address all these disparities, but collaborations between health, economic, and social policy sectors can ensure that interventions are comprehensive and sustainable. By adopting a multi-agency, community-driven approach, policymakers can design solutions that are not only realistic and achievable but also tailored to the specific needs of coastal populations.

5.5 SUMMARY

The Oaxaca-Blinder decomposition and unconditional quantile regression were used to examine coastal-inland disparities in CKD within the East of England, allowing for a more granular understanding of how contributing factors operate within a single region. While Chapters 3 and 4 focused on interregional comparisons, Chapter 5's within-region approach provided insights into how regional disparities manifest at a more localised scale. This comparison highlighted the importance of systematically grouping variables such as socioeconomic, demographic, and environmental factors to assess their distinct contributions to health disparities. The methodology underscored that while broad interregional patterns exist, the relative impact of different factors can vary significantly within a specific region, necessitating a tailored approach when addressing health inequalities. The findings show coastal disparities in CKD and hypertension, with age and household income contributing the most.

CHAPTER 6

DISCUSSION AND CONCLUSIONS

6.0 THESIS OVERVIEW

The research presented in this thesis investigated the regional inequalities in health in the UK, mainly focusing on the contribution of individual-level characteristics and the role of the small area-level environment. Regional health inequalities in the UK represent a significant public health challenge, characterised by stark differences in health outcomes across different geographical areas. A complex interplay of demographic, socioeconomic, lifestyle and neighbourhood environmental factors influences these disparities. Understanding these inequalities is crucial to developing effective public health policies to reduce regional health disparities and improve overall population health. Results from the three empirical studies comprising this thesis provide insight into factors contributing to regional disparities in health and the extent to which the neighbourhood-level characteristics contribute to these health inequalities. The focus on chronic diseases arises from public health concerns and the severe implications each has for the population and life expectancies. This thesis has four core research questions and uses three empirical studies to investigate their possible answers.

6.1 SUMMARY OF FINDINGS

Chapter 3 explores what lies behind the observed regional differences in health in the UK. Using biomarker data from a large nationally representative sample of adults across the UK, the study was able to address two of the research questions posed by this thesis: Are there regional health disparities in the UK and what lies behind the differences in health outcomes? The health outcome variables include Body Mass Index (BMI), systolic blood pressure (SBP), cholesterol ratio and estimated glomerular filtration rate (eGFR). The findings show that regional health inequalities do exist, and London has better outcomes on these measures than other UK regions. The least squares regression results show that health outcomes generally decline as age increases, which is unsurprising. The Oaxaca-Blinder decomposition results indicate that differences in BMI and cholesterol ratios are statistically significantly higher in six out of ten regions compared to London, with all regions exhibiting higher values than the London region. Health outcomes in terms of systolic blood pressure are statistically significantly worse in nine regions compared to London. These regional differences are driven mainly by the differential covariate effects (or the unexplained part of the OB decomposition) across areas. In contrast, the eGFR results reveal statistically significant regional differences in all regions compared to London, but the explained part of the decomposition analysis drives the disparities, i.e. due to differences in observed characteristics. The detailed decomposition results show education as the main factor contributing to regional disparities in BMI, systolic blood pressure, cholesterol ratio and eGFR. In other words, the main reason why Londoners are healthier with respect to these outcomes is attributable to people living in the London region being better educated than people from the rest of the country. However, the causal mechanism for this is unclear, and the relationship may not be direct. Therefore, a significant part of the regional gap in the health outcome variables may be mitigated by implementing policies focused on improving education across regions in the UK, or education may simply be a ‘flag’ for other causal factors.

Findings align with existing literature suggesting that education is associated with regional health inequalities. For example, Di Paola et al. (2018) argue that regional health differentials in BMI exist between the North and South of Spain and are mainly explained by differences in socioeconomic status, which consists primarily of education and human capital. Similarly, Ergin and Kunst (2015) studied regional inequalities in self-rated health and disability in younger and older generations. They argued that health differentials exist between the West and East of Turkey. They suggest that regional differences are mainly explained by education. Ballas et al. (2012) report that regional educational inequalities in several EU countries tend to exacerbate income, wealth, social status, and health disparities, thus perpetuating inter-regional disparities. Investigating how educational inequalities lead to disparities in income, employment, and health through a complex interplay of factors is a clear area for further research.

Regional inequalities are vast; therefore, exemplars are used in Chapter 4 onwards to illustrate key differences in selected conditions. The focus on CKD and hypertension is driven by their significance as major public health concerns. Therefore, Chapter Four considers the contribution of the small area environment to regional disparities in chronic kidney disease (CKD) and hypertension in England. The United Kingdom Household Longitudinal Study (UKHLS) was linked to neighbourhood-level data from the English deprivation indices at the lower layer super output area (LSOA) level. The London region was used as a reference group, and I found that it has on average better glomerular filtration rate (eGFR) and systolic blood pressure levels than England's other eight regions. The eGFR (≤89) was used as a marker for the risk of CKD, and systolic blood pressure (≤140mmHg) was used as a marker for hypertension. The Oaxaca-Blinder decomposition combined with unconditional quantile regression analysis (focusing only on average regional gaps may miss significant differences that could occur at other points of the distribution) was used to examine regional differences in eGFR, with a particular focus on how these differences vary across the eGFR distribution. This approach also allowed for an assessment of the significance of neighbourhood-level characteristics at different quantiles, providing a more nuanced understanding of their impact. Findings showed regional disparities between the regions compared to London, with neighbourhood-level characteristics being one of the main drivers of regional inequalities. The neighbourhood environment exerts a dominant role in most regions at the lower tail of the eGFR distribution. The contribution of the neighbourhood-level factors dominated the Northeast and Yorkshire and Humber regions and was the second largest contributor to regional disparities in CKD for Northwest, East Midlands, East of England, and Southwest. For example, the regional analysis of the Northeast shows that the neighbourhood environment contributes to the total regional disparities of 62% while demographic factors are 30%. Detailed decomposition indicated crime levels and skill deprivation are the neighbourhood-level characteristics playing the most significant role at the lower tail of the eGFR distribution.

Systolic blood pressure results showed that there are regional differences in hypertension. Demographic factors, especially the age of the population, were found to contribute the most to regional disparities in hypertension across the region of England. The neighbourhood environment also contributed to regional differences at the upper tail of the distribution. The contribution of the neighbourhood-level factors dominates for Northwest and Yorkshire and Humber regions and is the second largest contributor to regional disparities in hypertension for Northeast (Q75), East Midlands (Q90), and West Midlands (Q75). For example, the decomposition analysis of the Yorkshire and Humber region indicated that the neighbourhood factors explain 63% of the total regional disparities in systolic blood pressure while demographic factors explain 26%. Detailed decomposition of the contribution of individual covariates to regional disparities in systolic blood pressure, focusing on the neighbourhood environment, showed that skill and income deprivation, as well as road distance to the GP, play the most significant role in explaining the disparities of hypertension in these regions. This study suggests that to reduce the gap of regional disparities in hypertension, targeted policies aiming to improve the skills and income in deprived neighbourhoods are advised.

The evidence from this study suggests that the small area environment exerts a sizable contribution to variation in CKD and hypertension, even though its role is partially explained by the observed individual-level characteristics included in the analyses. Findings from this chapter provide evidence that neighbourhoods with disadvantaged environments, such as those of higher skill deprivation and income deprivation, higher crime levels, and road distance to a GP, are more likely to suffer from CKD and hypertension. Findings are consistent with existing work, although previous literature does not use examples of CKD and hypertension. Chaparro et al. (2018) explored neighbourhood deprivation and health biomarkers in Britain, finding an association between health measures and environmental factors. Similarly, the findings of Diez-Roux (2017) showed that living in deprived neighbourhoods is associated with an increased prevalence of coronary heart disease. Another finding by Norton and Eggers (2020) evidenced that the risk for CKD and end-stage renal disease is increased among individuals living in deprived neighbourhoods.

The last study looked at CKD and hypertension in the East of England, with an interest in understanding the difference between coastal and inland areas. Regional disparities highlight broad health inequalities across the UK, but they may mask important intra-regional differences. A coastal and inland disparities focus allows for a more targeted understanding of localised health inequalities, ensuring that policy interventions address the unique vulnerabilities of coastal populations. This chapter contributed to the ongoing debate by addressing the last main research question: "What are the underlying sources of chronic kidney diseases and hypertension disparities between coastal and non-coastal areas in the East of England region?" To address these questions, the Oaxaca-Blinder (OB) decomposition at various quantiles of the eGFR and systolic blood pressure distributions was again used to analyse regional disparities and understand the associated factors. Findings show that the average age of people living in the coastal areas is higher than that of their inland neighbours. This could be due to factors such as retirees choosing to move to coastal regions for scenic beauty or a more relaxed lifestyle (White et al., 2014). The decomposition results indicated a substantial contribution of demographic factors towards the coastal-inland disparities in CKD of 66% at the 10th and 64% at the 25th quantile. The neighbourhood-level factors do not contribute significantly to the coastal-inland disparities in CKD and hypertension. However, the individual contribution to the CKD analysis shows that skill deprivation (7.8%) contributes the most in the area disparities. Socioeconomic status is the second largest contributor (21%) to the overall coastal-inland inequalities in CKD, with household income contributing the largest. However, the decomposition result for the disparities in systolic blood pressure highlighted area-level disparities. The coastal communities have higher systolic blood pressure values compared to the non-coastal region, signifying a higher risk of hypertension. The difference is only significant in the 75th quantile of the analysis. The result shows that demographics contribute the highest to the coastal differences. This chapter concludes by suggesting that socioeconomic status (household income) substantially contributes to the coastal-inland disparities in CKD. Again, causality cannot necessarily be inferred.

The geographical location of a community, whether coastal or inland, can significantly influence health outcomes (Wanezaki et al., 2016; Hjorthen et al., 2020). The coastal disparity result shows how living in a coastal region contributes to CKD and hypertension and highlights the complex interplay of demographics (age), socioeconomic (household income), and environmental deprivation. The finding re-echoes existing literature, which evidences that a high proportion of poor health conditions in England are concentrated in coastal communities (Chief Medical Officer, 2021). Depledge et al. (2017) investigated the health and well-being of coastal communities. They reported that people living in the coastal region of England are more likely to report chronic conditions than those living in non-coastal areas. Asthana and Gibson (2021) find that coastal differences are partly explained by age and deprivation, which are rightly aligned with the CKD result. Chapter 5 of the thesis provides additional insight into the factors contributing to CKD and hypertension disparities in coastal areas and supports the theory that coastal communities experience a higher disease burden across various physical conditions (Chief Medical Annual Report, 2021; Asthana and Gibson, 2021).

6.2 WHAT KNOWLEDGE HAS THIS THESIS CONTRIBUTED?

This research makes several new contributions to the limited literature on regional health Inequalities in the UK. First, to the best of my knowledge, no previous literature focuses on regional disparities in CKD and hypertension in England or the UK. My thesis is the first to use a nationally representative dataset for the UK to investigate the contribution of individual-level characteristics and the role of the small area environment to CKD and hypertension disparities in England, introducing the neighbourhood-level characteristics to examine the association of the neighbourhood environment to regional disparities in health. Findings evidence that the neighbourhood environment is an important contributor to disparities in health, and interventions need to address both individual and their neighbourhood environment.

In the first empirical chapter (Chapter 3), I used four biomarkers relevant to critical chronic conditions and have profound implications for the population and life expectancy. Using biomarkers to assess risks of outcomes directly can help overcome the lack of good health information while also providing an immediate assessment of objective health disparities for individuals and groups.

This study introduces the standard Oaxaca-Blinder decomposition and the quantiles-based distributional Oaxaca-Blinder decomposition. In doing this, this thesis was able to disentangle the contribution of each covariate and their corresponding coefficients to these differences. The distributional decomposition was helpful in terms of focusing on tails where the diseases being looked at are concentrated. It is important to note that decomposition analysis informs the factors that health policy needs to address and helps policymakers identify factors that most significantly contribute to health inequalities. By pinpointing these factors, policies can be tailored more effectively to address the root causes of regional health disparities. Additionally, the analysis helps identify areas where disparities are less explained, highlighting more intractable issues that may require broader structural interventions. Chapter 5 contributes to the ongoing debate on coastal health disparities in England by giving an added perspective on the factors contributing to coastal areas' CKD and hypertension disparities.

This study suggests that efforts to tackle regional disparities in CKD and hypertension in England need approaches that combine individual-level interventions and the neighbourhood environment (place of residence) to be effective. Lastly, the findings of this study have significant policy implications for the local authorities in East of

England. Despite the region's affluence, disparities in chronic kidney disease (CKD) and hypertension persist between coastal and inland areas. This study underscores the need for targeted improvements in coastal communities.

6.3 STUDY STRENGTHS AND LIMITATIONS

The key strength of this thesis is that it uses biomarkers as health outcome variables relevant to critical chronic conditions. Using lab-based biomarkers directly instead of participant-reported outcomes can help overcome the lack of good information and minimise measurement errors and recall bias associated with self-reported outcomes. Another strength of this research is that it uses a large representative sample of the general population for the analysis, allowing control for many covariates and factors that may explain regional inequalities in health. Sample weights were used in the statistical analysis, making the results representative of the target population. This study covers the whole of Great Britain in Chapter 3 to compare differences in health across the government office regions. Finally, this study performs the decomposition analysis of regional differentials in health along the entire distribution points of health status. Decomposition analyses are valuable for identifying how differences in covariates contribute to overall disparities in the outcome, providing detailed insights into the specific factors driving these differences.

One major limitation of this thesis is the potential for endogeneity bias, where unobserved factors may influence both the covariates and the outcome variable. As the analyses are observational, they document associations rather than establish causal relationships. Additional waves of Understanding Society data are required to explore whether the observed relationships between health outcomes and neighbourhood-level characteristics are causal. This could be achieved through longitudinal analysis, which tracks changes over time, or by employing instrumental variable approaches to address potential endogeneity and unobserved confounding factors. Care should be given to interpreting the Oaxaca-Blinder decomposition as only being indicative because estimates of the associations between the covariates and the health outcome variables could be affected by omitted variables. Any omitted variables that affect health (CKD and hypertension) will have their share of the difference erroneously attributed to differences in coefficient (i.e., the unexplained part). Ethnicity could be considered an important omitted variable, given the UK's diverse population and the well-documented health disparities among different ethnic groups. For example, certain groups, such as Black Africans and Caribbeans, have a relatively high prevalence of hypertension.

Ethnicity was not included in the analysis as the sample was predominantly composed of the white population (95%) compared to the non-whites (5%). The small proportion of the non-white population can lead to issues with statistical power when analysing outcomes for this group. The low representation might result in insufficient sample sizes to detect significant differences or relationships, making it challenging to draw reliable conclusions about the non-white population. Nevertheless, I acknowledge that excluding ethnicity may oversimplify the complex drivers of health inequalities. Even if statistical power is reduced, incorporating ethnicity could still provide valuable insights and improve the interpretation of other factors. Future work could explore different ways of including ethnicity in the analysis, given its significance of shaping health outcomes.

For the first empirical work (Chapter 3) of this thesis, Northern Ireland was not added to the analysis because nurse recruitment proved difficult in Northern Ireland, so there was no biomarker data recorded for them, making the analysis centred around Great Britain (England, Wales, and Scotland). Additionally, Chapter 4 focuses solely on the English population due to the unavailability of comparable cross-sectional neighbourhood-level data for the rest of the UK at the Lower Layer Super Output Area (LSOA) level. This limitation arises because the UKHLS data could not be consistently linked to small-area data outside England.

6.4 FUTURE WORK

The limitations of the analysis described above provide a framework for future research, relating both to methodological, data, and base reference aspects. These are summarised below.

Methodological issues

A critical methodological area requiring deeper investigation is incorporating causality into the Oaxaca-Blinder decomposition. An and Glynn (2021) suggested that treatment effect deviation (TED) can be considered an alternative causality method instead of an OB decomposition or as a sensitivity analysis. The TED assesses how the omission of specific covariates can influence the estimated treatment effect. In this case, it examines whether regional differences excluding London affect the estimated disparities in health outcomes. Sensitivity analyses can further test the robustness of these findings by applying alternative model specifications and assumptions to account for potential unobserved confounders. This can help to identify whether the results are driven by specific assumptions or model choices. Therefore, the causal effect of the small area characteristics in mitigating regional disparities in CKD and hypertension and even other health-related variables can be addressed in future research.

Data issues

The results of this analysis highlight the importance of addressing neighbourhood environments while also considering broader structural and individual factors to effectively reduce regional health inequalities. They are based on data collected just before the abolishment of the strategic health authorities and the enhanced role of the local, smaller area-level authorities. Therefore, future research can be carried out on up-to-date CKD and hypertension or any health-related biomarker data released in 2026 linked to up-to-date English Indices of Deprivation detailed neighbourhood-level characteristics that are publicly available. This is needed to assess the effectiveness of the result analysed in this thesis and the small-area local authorities.

Base reference issues

Using London as a base for comparison with the rest of the UK regions can sometimes be problematic:

- Population diversity: London is one of the most ethnically diverse cities in the world, with a higher proportion of residents from various ethnic backgrounds than other regions. This diversity can significantly influence health outcomes, economic conditions, and social dynamics.
- Healthcare infrastructure: London has a higher concentration of hospitals, specialists, and healthcare facilities. This access can lead to better health outcomes compared to other regions with fewer healthcare resources.
- Policy focuses: London often receives more attention and funding due to its economic significance and being a centre of power for the UK government. Regional policies may vary, impacting development and services.

Therefore, future work could focus on up-to-date CKD and hypertension, or any health-related biomarker data released in 2026 from the UKHLS and then linked to up-to-date English Indices of Deprivation detailed neighbourhood-level characteristics that are publicly available.

6.5 CONCLUSION

Even though steady improvements in the population's health have been evident over recent decades, preventable inequalities in health still persist within and between regions in the UK. This thesis was carried out to determine the underlying factors contributing to these persistent inequalities. The summary of my findings underscores the fact that education is important in reducing regional health disparities. Also, the neighbourhood environment should not be ignored when policies are being implemented to tackle regional inequalities in chronic kidney disease and hypertension. This thesis shows that individual-level characteristics and the small area environment contribute to these disparities. Lastly, coastal disparities in CKD and hypertension exist in the East of England region, and targeted interventions for coastal community improvement are important.

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APPENDIX A: CHAPTER FOUR

A.1 OLS REGRESSION RESULTS OF ESTIMATED GLOMERULAR FILTRATION RATE

Table A 1. Estimated Glomerular Filtration Rate Results - OLS regression.

Variables	Coefficients (SE)	95% C.I.
Demographics		
30-39	-8.257^{***} (1.191)	[-10.59, -5.922]
40-64	-23.91^{***} (0.928)	[-25.73, -22.09]
65-74	-39.22^{***} (1.124)	[-41.43, -37.02]
75+	-53.11^{***} (1.391)	[-55.83, -50.38]
Female	24.95^{***} (0.550)	[23.87, 26.03]
Regions		
Northeast	-2.034 (1.401)	[-4.780, 0.712]
Northwest	1.012 (1.277)	[-1.492, 3.516]
Yorkshire and Humber	-2.153 (1.338)	[-4.776, 0.470]
East Midlands	-1.025 (1.397)	[-3.764, 1.714]
West Midlands	-0.237 (1.458)	[-3.094, 2.621]
East of England	-2.189^{*} (1.307)	[-4.750, 0.372]
Southeast	-0.023 (1.292)	[-2.556, 2.511]
Southwest	-0.232 (1.289)	[-2.759, 2.295]
Neighbourhood-level factors		
Crime deprived areas	0.500 (0.726)	[-0.923, 1.924]
Air quality	-8.690 (9.585)	[-27.48, 10.10]
Road distance to a GP	0.006 (0.157)	[-0.302, 0.314]
Income deprivation	0.011^{***} (0.003)	[0.005, 0.016]
Skills deprivation	-0.063^{***} (0.022)	[-0.107, -0.019]
Socioeconomic status		
Log of household income	-1.240^{**} (0.526)	[-2.271, -0.209]
Job status: employed	-1.279^{*} (0.757)	[-2.762, 0.205]
House ownership: owned	0.393 (0.754)	[-1.084, 1.870]
Education: Degree	3.696^{***} (1.110)	[1.520, 5.872]
Education: A-level	2.822^{***} (0.928)	[1.002, 4.642]
Education: O-level	2.130^{**} (0.871)	[0.423, 3.837]
Lifestyle characteristics		
Weekly fruit intake: 1-3 days	-1.175 (1.075)	[-3.283, 0.933]
Weekly fruit intake: 4-6 days	0.193 (1.183)	[-2.125, 2.512]
Weekly fruit intake: every day	-0.793 (1.061)	[-2.873, 1.287]
Physical activity	0.418 (0.705)	[-0.964, 1.799]
Smoking status: ex-smoker	-1.696^{***} (0.578)	[-2.830, -0.562]
smoker	1.347^{*} (0.776)	[-0.175, 2.868]
Constant	113.4^{***} (4.388)	[104.8, 122.0]
Joint significance test		
Regional dummies (p-values)	0.012	
Observations	6,862	

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample weights applied.
Note: C.I. – Confidence interval

A.2 DETAILED DECOMPOSITION OF ESTIMATED GLOMERULAR FILTRATION RATE ACROSS THE REGIONS

Table A 2. The individual contribution of covariates across quantiles of the eGFR distribution: London vs Northeast.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	3.141***	2.175**	2.572*	3.682**
	(1.170)	(1.070)	(1.321)	(1.840)
Sex	0.121	0.135	0.115	0.0965
	(1.063)	(1.186)	(1.011)	(0.850)
Neighbourhood-level characteristics				
Crime levels	1.366	-0.0203	-1.478	-2.368
	(1.088)	(1.081)	(1.202)	(1.665)
Air quality	0.165	0.996**	0.0421	-0.629
	(0.433)	(0.490)	(0.587)	(0.934)
Road distance to a GP	1.795*	1.227	-0.0656	-0.0995
	(1.062)	(0.900)	(0.958)	(1.148)
Income deprivation	-0.0115	0.0788	-0.445	-0.359
	(0.782)	(1.023)	(1.185)	(1.792)
Skills deprivation	3.251	0.917	-1.086	1.465
	(2.043)	(2.365)	(3.002)	(4.309)
Socioeconomic status				
Log of household income	-1.012	-0.737	-0.892	-0.154
	(0.803)	(0.845)	(0.822)	(0.940)
Job-status	0.266	-0.00747	0.157	-0.190
	(0.272)	(0.197)	(0.264)	(0.351)
House ownership	-0.212	0.181	0.237	0.194
	(0.456)	(0.445)	(0.494)	(0.694)
Education	0.245	0.809	1.327	1.473
	(0.697)	(0.747)	(0.908)	(1.256)
Lifestyle factors				
Weekly fruit intake	0.00842	0.272	0.148	0.756
	(0.461)	(0.455)	(0.454)	(0.527)
Physical activity	0.199	0.297	-0.346	-0.0176
	(0.355)	(0.352)	(0.413)	(0.396)
Smoking status	-0.0487	0.0243	-0.0297	-0.0584
	(0.248)	(0.113)	(0.123)	(0.321)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 3. The individual contribution of covariates across quantiles of the eGFR distribution: London vs Northwest.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	4.626***	3.769***	4.121***	4.744***
	(1.112)	(0.983)	(1.086)	(1.357)
Sex	-0.166	-0.211	-0.163	-0.120
	(0.749)	(0.952)	(0.737)	(0.541)
Neighbourhood-level characteristics				
Crime levels	-0.563	-0.727	-1.274	-1.055
	(0.696)	(0.694)	(0.809)	(0.852)
Air quality	-0.581	-0.143	0.187	0.066
	(0.357)	(0.373)	(0.401)	(0.452)
Road distance to a GP	-0.416	-0.129	-0.986	-0.093
	(0.557)	(0.526)	(0.669)	(0.825)
Income deprivation	0.782	0.593	0.526	1.418*
	(0.514)	(0.457)	(0.553)	(0.725)
Skills deprivation	2.329**	1.322	-0.347	3.202**
	(1.120)	(1.088)	(1.324)	(1.499)
Socioeconomic status				
Log of household income	-0.706*	-0.814**	-0.384	0.429
	(0.407)	(0.409)	(0.441)	(0.491)
Job-status	0.104	-0.042	0.044	-0.468
	(0.181)	(0.189)	(0.254)	(0.370)
House ownership	0.153	0.336	-0.083	-0.381
	(0.385)	(0.387)	(0.473)	(0.574)
Education	1.034**	1.790***	1.842***	0.681
	(0.500)	(0.567)	(0.698)	(0.626)
Lifestyle factors				
Weekly fruit	-0.146	0.044	-0.160	-0.543
	(0.203)	(0.157)	(0.214)	(0.332)
Physical activity	-0.018	0.203	-0.347	-0.419
	(0.231)	(0.230)	(0.267)	(0.316)
Smoking status	-0.047	-0.036	-0.137	0.002
	(0.249)	(0.157)	(0.223)	(0.112)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 4. The individual contribution of covariates across quantiles of the eGFR distribution: London vs Yorkshire and Humber.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	3.676***	4.258***	4.854***	6.372***
	(0.912)	(1.011)	(1.179)	(1.740)
Sex	0.092	0.122	0.108	0.082
	(0.800)	(1.065)	(0.940)	(0.711)
Neighbourhood-level characteristics				
Crime levels	0.333	0.497	0.783	0.258
	(0.422)	(0.499)	(0.563)	(0.665)
Air quality	1.228	-0.184	0.262	-1.542
	(0.832)	(1.018)	(0.915)	(1.476)
Road distance to a GP	-0.008	-0.621	0.009	0.612
	(0.623)	(0.578)	(0.646)	(0.670)
Income deprivation	1.225	1.079	-0.907	1.613
	(0.942)	(1.069)	(1.084)	(1.691)
Skills deprivation	1.337	0.591	-1.168	2.681
	(1.303)	(1.529)	(1.570)	(2.319)
Socioeconomic status				
Log of household income	-0.146	-0.057	-0.727	1.139
	(0.495)	(0.518)	(0.568)	(0.645)
Job-status	0.312	0.054	-0.416	-0.738
	(0.246)	(0.237)	(0.324)	(0.496)
House ownership	0.378	-0.254	-0.318	0.191
	(0.357)	(0.403)	(0.411)	(0.586)
Education	0.238	0.099	0.632	-1.775*
	(0.574)	(0.717)	(0.797)	(0.912)
Lifestyle factors				
Weekly fruit	-0.537*	-0.167	-0.143	1.201**
	(0.309)	(0.309)	(0.345)	(0.553)
Physical activity	0.064	0.136	-0.164	0.239
	(0.216)	(0.238)	(0.267)	(0.329)
Smoking status	0.097	-0.193	0.116	-0.004
	(0.201)	(0.308)	(0.253)	(0.290)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 5. The individual contribution of covariates across quantiles of the eGFR distribution: London vs East Midlands.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	3.958***	3.247***	4.040***	5.852***
	(1.076)	(1.013)	(1.271)	(2.074)
Sex	0.182	0.196	0.194	0.156
	(0.791)	(0.854)	(0.843)	(0.681)
Neighbourhood-level characteristics				
Crime level	0.886	-0.121	-0.235	-1.639
	(0.894)	(0.778)	(1.045)	(1.428)
Air quality	0.018	0.038	-0.010	-0.018
	(0.0562)	(0.0554)	(0.0419)	(0.0510)
Road distance to a GP	0.772	0.821	0.447	0.641
	(0.896)	(0.809)	(1.011)	(1.136)
Income deprivation	-0.517	1.130	3.068*	5.664**
	(1.232)	(1.276)	(1.789)	(2.574)
Skills deprivation	0.374	1.836	0.538	3.137
	(1.549)	(1.545)	(2.133)	(3.065)
Socioeconomic status				
Log of household income	0.156	0.599*	-0.396	-0.023
	(0.559)	(0.363)	(0.435)	(0.478)
Job-status	-0.038	-0.063	-0.147	-0.502
	(0.121)	(0.135)	(0.212)	(0.511)
House ownership	0.451	-0.621	-0.745	-2.763*
	(0.672)	(0.640)	(0.884)	(1.428)
Education	-0.765	-0.634	1.729**	2.025
	(0.793)	(0.666)	(0.863)	(1.298)
Lifestyle factors				
Weekly fruit	-0.088	-0.022	-0.481	0.020
	(0.297)	(0.315)	(0.376)	(0.443)
Physical activity	-0.151	-0.047	-0.121	-0.075
	(0.241)	(0.195)	(0.241)	(0.273)
Smoking status	0.063	-0.049	0.024	-0.024
	(0.138)	(0.238)	(0.0692)	(0.129)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 6. The individual contribution of covariates across quantiles of the eGFR distribution: London vs West Midlands.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	4.313***	4.291***	5.444***	7.208***
	(1.057)	(1.093)	(1.343)	(1.951)
Sex	0.374	0.655	0.642	0.564
	(0.592)	(1.034)	(1.014)	(0.893)
Neighbourhood-level characteristics				
Crime level	-0.824	-0.866	0.834	-0.501
	(1.068)	(1.100)	(1.254)	(2.161)
Air quality	-0.650	-0.401	0.050	0.025
	(0.382)	(0.302)	(0.347)	(0.406)
Road distance to a GP	0.775	-0.057	-0.860	-1.006
	(0.701)	(0.618)	(0.651)	(1.068)
Income deprivation	0.541	0.539	0.313	2.125
	(0.952)	(0.993)	(1.104)	(1.884)
Skills deprivation	-0.447	0.320	0.395	2.472
	(1.615)	(1.549)	(1.679)	(2.437)
Socioeconomic status				
Log of household income	0.145	-0.206	-0.140	-0.031
	(0.352)	(0.342)	(0.341)	(0.501)
Job-status	0.113	-0.070	-0.276	-0.292
	(0.149)	(0.141)	(0.255)	(0.350)
House ownership	0.690	0.398	-0.218	-0.159
	(0.570)	(0.570)	(0.586)	(1.004)
Education	0.760	0.768	1.003	0.706
	(0.599)	(0.618)	(0.650)	(1.159)
Lifestyle factors				
Weekly fruit	0.225	-0.324	0.038	0.657
	(0.310)	(0.281)	(0.326)	(0.469)
Physical activity	0.292	0.352	-0.509	-1.161*
	(0.298)	(0.275)	(0.298)	(0.604)
Smoking status	0.157	-0.020	-0.022	-0.083
	(0.225)	(0.0978)	(0.174)	(0.238)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 7. The individual contribution of covariates across quantiles of the eGFR distribution: London vs East of England.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	4.695***	4.265***	5.393***	4.678***
	(1.076)	(1.007)	(1.211)	(1.464)
Sex	0.601	0.719	0.817	0.687
	(0.725)	(0.866)	(0.985)	(0.831)
Neighbourhood-level characteristics				
Crime level	2.178*	-0.230	-0.590	1.070
	(1.156)	(1.132)	(1.456)	(1.983)
Air quality	-0.073	0.008	0.017	0.060
	(0.140)	(0.0289)	(0.0493)	(0.121)
Road distance to a GP	-0.756	-0.024	0.045	-0.983
	(0.799)	(0.804)	(0.823)	(1.009)
Income deprivation	1.977	0.657	1.095	1.402
	(1.748)	(1.807)	(2.430)	(2.965)
Skills deprivation	0.937	0.099	-0.158	1.301
	(0.975)	(0.960)	(1.312)	(1.708)
Socioeconomic status				
Log of household income	-0.092	0.025	-0.037	0.005
	(0.200)	(0.180)	(0.223)	(0.275)
Job-status	0.028	0.116	-0.157	-0.417
	(0.135)	(0.154)	(0.205)	(0.371)
House ownership	0.260	-0.028	0.372	0.293
	(0.427)	(0.409)	(0.532)	(0.725)
Education	-0.058	-0.855*	-0.239	-0.268
	(0.447)	(0.493)	(0.627)	(0.713)
Lifestyle factors				
Weekly fruit	-0.031	-0.024	0.004	0.192
	(0.103)	(0.194)	(0.264)	(0.373)
Physical activity	-0.080	-0.054	0.094	0.109
	(0.106)	(0.0893)	(0.123)	(0.139)
Smoking status	-0.015	-0.223	-0.372	-0.891*
	(0.286)	(0.265)	(0.339)	(0.485)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 8. The individual contribution of covariates across quantiles of the eGFR distribution: London vs Southeast.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	3.798***	4.590***	4.645***	4.936***
	(0.892)	(1.038)	(1.101)	(1.496)
Sex	0.529	0.786	0.691	0.437
	(0.702)	(1.042)	(0.917)	(0.583)
Neighbourhood-level characteristics				
Crime level	0.381	0.840	1.234	2.793
	(0.929)	(0.990)	(1.218)	(1.765)
Air quality	-0.175	-0.030	0.314	0.444*
	(0.145)	(0.147)	(0.219)	(0.227)
Road distance to a GP	-0.432	-0.665	0.946	0.002
	(0.564)	(0.636)	(0.617)	(0.886)
Income deprivation	0.509	2.608	2.692	2.513
	(2.174)	(2.301)	(2.966)	(4.496)
Skills deprivation	-0.111	0.228	0.343	0.473
	(0.225)	(0.267)	(0.344)	(0.512)
Socioeconomic status				
Log of household income	0.027	0.049	-0.002	0.010
	(0.0686)	(0.118)	(0.0389)	(0.0562)
Job-status	-0.017	-0.105	-0.071	-0.058
	(0.0485)	(0.181)	(0.132)	(0.128)
House ownership	-0.417	-0.928*	0.518	1.122
	(0.488)	(0.559)	(0.627)	(0.917)
Education	0.224	0.415	0.494	-0.056
	(0.227)	(0.262)	(0.333)	(0.363)
Lifestyle factors				
Weekly fruit	-0.012	0.098	0.226	0.264
	(0.162)	(0.167)	(0.227)	(0.398)
Physical activity	0.009	0.034	-0.030	0.035
	(0.0416)	(0.0614)	(0.0601)	(0.0704)
Smoking status	0.344*	0.093	-0.075	-0.079
	(0.201)	(0.148)	(0.175)	(0.207)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 9. The individual contribution of covariates across quantiles of the eGFR distribution: London vs Southwest.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	4.870***	4.920***	4.286***	5.474***
	(1.049)	(1.090)	(1.127)	(1.595)
Sex	0.280	0.371	0.374	0.266
	(0.704)	(0.934)	(0.939)	(0.670)
Neighbourhood-level characteristics				
Crime level	2.304**	1.799*	1.412	-2.848*
	(1.028)	(1.069)	(1.336)	(1.722)
Air quality	0.169	-0.638	-0.276	-0.541
	(0.354)	(0.631)	(0.676)	(0.680)
Road distance to a GP	-1.465**	0.102	-0.676	0.956
	(0.730)	(0.685)	(0.818)	(0.850)
Income deprivation	-0.052	-1.352	0.966	0.810
	(1.598)	(1.845)	(2.050)	(2.788)
Skills deprivation	-0.097	0.287	-0.579	0.122
	(0.694)	(0.820)	(0.799)	(1.024)
Socioeconomic status				
Log of household income	0.096	-0.010	0.251	0.194
	(0.198)	(0.253)	(0.261)	(0.314)
Job-status	-0.001	0.0004	0.001	0.007
	(0.023)	(0.014)	(0.034)	(0.212)
House ownership	-0.061	0.379	0.870	0.372
	(0.385)	(0.454)	(0.538)	(0.660)
Education	-0.090	0.449	0.555	0.739
	(0.417)	(0.444)	(0.494)	(0.615)
Lifestyle factors				
Weekly fruit	-0.151	-0.224	-0.504	-0.391
	(0.178)	(0.191)	(0.311)	(0.336)
Physical activity	0.290	0.078	0.203	-0.011
	(0.201)	(0.169)	(0.193)	(0.243)
Smoking status	0.105	0.079	-0.209	-0.022
	(0.235)	(0.266)	(0.192)	(0.179)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.3 OLS REGRESSION RESULTS OF SYSTOLIC BLOOD PRESSURE

Table A 10. Systolic blood pressure Results - OLS regression.

Variables	Coefficients (SE)	95% C.I.
Demographics		
30-39	1.226** (0.518)	[0.210, 2.242]
40-64	8.846*** (0.461)	[7.943, 9.748]
65-74	14.49*** (0.688)	[13.14, 15.84]
75+	18.35*** (0.919)	[16.55, 20.15]
Female	-7.452*** (0.347)	[-8.132, -6.772]
Regions		
Northeast	4.350*** (0.934)	[2.519, 6.181]
Northwest	4.143*** (0.749)	[2.675, 5.612]
Yorkshire & Humber	2.262*** (0.836)	[0.623, 3.901]
East Midlands	3.765*** (0.851)	[2.097, 5.432]
West Midlands	-0.651 (0.801)	[-2.222, 0.920]
East of England	1.929** (0.788)	[0.383, 3.474]
Southeast	1.592** (0.735)	[0.151, 3.032]
Southwest	1.552** (0.770)	[0.043, 3.062]
Neighbourhood-level factors		
Crime deprived areas	0.182 (0.415)	[-0.631, 0.996]
Air quality	1.232 (5.352)	[-9.258, 11.72]
Road distance to a GP	0.241** (0.107)	[0.032, 0.450]
Income deprivation	-0.001(0.002)	[-0.004, 0.002]
Skills deprivation	0.005(0.015)	[-0.024, 0.034]
Socioeconomic status		
log of household income	-0.055 (0.336)	[-0.714, 0.603]
Job status: employed	0.343 (0.427)	[-0.493, 1.180]
House ownership: Owned	-0.094 (0.451)	[-0.979, 0.791]
Education: Degree	-2.915*** (0.713)	[-4.312, -1.518]
Education: A-level	-1.685*** (0.651)	[-2.960, -0.410]
Education: O-level	-1.786*** (0.627)	[-3.014, -0.557]
Lifestyle characteristics		
Weekly fruit intake: 1-3 days	0.778 (0.708)	[-0.610, 2.166]
Weekly fruit intake: 4-6 days	0.955 (0.739)	[-0.493, 2.404]
Weekly fruit intake: every day	0.248 (0.700)	[-1.123, 1.619]
Physical activity	-0.677 (0.439)	[-1.538, 0.183]
Smoking status: ex-smoker	-0.855** (0.396)	[-1.631, -0.078]
Smoking status: smoker	0.211 (0.476)	[-0.723, 1.145]
Constant	121.6*** (2.752)	[116.2, 127.0]
Joint significance test		
Regional dummies (p-values)	0.000	
Observations	9,594	

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, C.I. – Confidence interval. Sample weights applied.

A.4 DETAILED DECOMPOSITION RESULTS OF SYSTOLIC BLOOD PRESSURE ACROSS THE REGIONS

Table A 11. The individual contribution of covariates across quantiles of the systolic blood pressure distribution: London vs Northeast.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	-1.213**	-1.424**	-0.995*	-0.866
	(0.498)	(0.569)	(0.531)	(0.740)
Sex	-0.318	-0.356	-0.280	-0.119
	(0.289)	(0.322)	(0.258)	(0.169)
Neighbourhood-level characteristics				
Crime level	1.420**	0.878	0.762	0.984
	(0.652)	(0.673)	(0.710)	(1.283)
Air quality	-0.158	-0.041	-0.110	-0.387
	(0.189)	(0.175)	(0.190)	(0.431)
Road distance to a GP	-1.137***	-0.883	-1.200	-1.236
	(0.434)	(0.635)	(0.788)	(1.417)
Income deprivation	0.301	0.272	0.106	0.780
	(0.371)	(0.344)	(0.329)	(0.571)
Skills deprivation	2.336	0.593	-0.301	3.630*
	(1.549)	(1.344)	(1.397)	(2.205)
Socioeconomic status				
Log of household income	0.565	0.420	0.556	0.607
	(0.348)	(0.330)	(0.387)	(0.725)
Job-status	-0.023	-0.001	-0.017	-0.044
	(0.0681)	(0.0297)	(0.0553)	(0.134)
House ownership	-0.155	-0.100	-0.213	-0.328
	(0.206)	(0.212)	(0.215)	(0.396)
Education	0.455	-0.099	-0.830*	-0.430
	(0.420)	(0.544)	(0.494)	(0.853)
Lifestyle factors				
Weekly fruit	-0.155	-0.013	-0.270	-0.238
	(0.203)	(0.237)	(0.255)	(0.434)
Physical activity	0.062	-0.012	-0.063	-0.090
	(0.0881)	(0.0551)	(0.0914)	(0.150)
Smoking status	-0.021	0.045	0.093	0.115
	(0.0730)	(0.0918)	(0.114)	(0.166)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 12. The individual contribution of covariates across quantiles of the systolic blood pressure distribution: London vs Northwest.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	-0.868***	-0.871***	-1.108**	-1.302**
	(0.314)	(0.332)	(0.436)	(0.510)
Sex	-0.442	-0.446	-0.282	-0.101
	(0.270)	(0.273)	(0.180)	(0.099)
Neighbourhood-level characteristics				
Crime level	-0.435	-0.472	-0.485	-0.532
	(0.390)	(0.409)	(0.493)	(0.633)
Air quality	-0.142	-0.107	0.027	-0.023
	(0.175)	(0.188)	(0.231)	(0.331)
Road distance to a GP	0.029	-0.063	-0.372	0.611
	(0.312)	(0.339)	(0.505)	(0.427)
Income deprivation	0.067	0.331	0.068	-0.311
	(0.257)	(0.233)	(0.249)	(0.316)
Skills deprivation	0.108	0.607	-0.417	-1.744
	(0.733)	(0.653)	(0.833)	(1.083)
Socioeconomic status				
Log of household income	0.020	0.0001	0.162	0.437*
	(0.094)	(0.101)	(0.144)	(0.265)
Job-status	0.077	0.062	-0.033	-0.118
	(0.087)	(0.074)	(0.056)	(0.130)
House ownership	0.045	-0.034	-0.044	0.025
	(0.202)	(0.207)	(0.241)	(0.303)
Education	-0.396*	-0.332	-0.134	0.201
	(0.236)	(0.248)	(0.281)	(0.345)
Lifestyle factors				
Weekly fruit	0.165	0.089	0.057	0.072
	(0.106)	(0.093)	(0.104)	(0.142)
Physical activity	-0.022	0.017	-0.096	-0.143
	(0.0388)	(0.0376)	(0.097)	(0.142)
Smoking status	-0.011	-0.017	-0.026	-0.010
	(0.046)	(0.052)	(0.058)	(0.059)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 13. The individual contribution of covariates across quantiles of the systolic blood pressure distribution: London vs Yorkshire and Humber.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	-0.712**	-1.215***	-1.143***	-1.452***
	(0.302)	(0.444)	(0.396)	(0.552)
Sex	-0.686**	-0.566**	-0.255*	-0.078
	(0.300)	(0.255)	(0.153)	(0.167)
Neighbourhood-level characteristics				
Crime level	-0.183	-0.676**	-0.589*	-1.038**
	(0.248)	(0.294)	(0.328)	(0.477)
Air quality	0.221	-0.066	0.840*	1.268*
	(0.456)	(0.461)	(0.471)	(0.746)
Road distance to a GP	0.247	-0.032	-0.234	0.011
	(0.337)	(0.368)	(0.596)	(0.722)
Income deprivation	-0.151	0.061	-0.763	-0.966
	(0.424)	(0.465)	(0.468)	(0.640)
Skills deprivation	-0.488	0.291	-2.061**	-3.044**
	(0.855)	(0.884)	(0.990)	(1.535)
Socioeconomic status				
Log of household income	-0.395*	-0.450	-0.769*	0.722
	(0.230)	(0.332)	(0.466)	(0.524)
Job-status	0.0003	0.042	0.015	-0.125
	(0.035)	(0.067)	(0.048)	(0.176)
House ownership	-0.054	0.013	-0.085	0.209
	(0.147)	(0.162)	(0.181)	(0.272)
Education	-0.279	-0.524	0.163	-0.462
	(0.311)	(0.362)	(0.429)	(0.578)
Lifestyle factors				
Weekly fruit	0.212	0.119	-0.002	-0.023
	(0.163)	(0.155)	(0.164)	(0.212)
Physical activity	0.085	0.017	-0.047	-0.137
	(0.080)	(0.057)	(0.076)	(0.154)
Smoking status	0.036	0.061	-0.134	0.066
	(0.079)	(0.104)	(0.136)	(0.183)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 14. The individual contribution of covariates across quantiles of the systolic blood pressure distribution: London vs East Midlands.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	-1.003***	-1.068***	-1.262***	-1.700***
	(0.342)	(0.352)	(0.384)	(0.539)
Sex	-0.160	-0.160	-0.107	-0.086
	(0.315)	(0.315)	(0.212)	(0.173)
Neighbourhood-level characteristics				
Crime level	-0.488	0.370	1.079*	1.010
	(0.438)	(0.425)	(0.584)	(0.837)
Air quality	0.004	0.006	-0.006	-0.005
	(0.016)	(0.026)	(0.024)	(0.023)
Road distance to a GP	1.335***	0.060	-0.842	0.156
	(0.488)	(0.488)	(0.658)	(0.927)
Income deprivation	0.961	0.065	0.348	-0.986
	(0.618)	(0.753)	(1.016)	(1.214)
Skills deprivation	0.723	0.285	0.166	-0.667
	(0.841)	(0.883)	(1.137)	(1.455)
Socioeconomic status				
Log of household income	0.013	-0.015	-0.017	-0.183
	(0.112)	(0.124)	(0.173)	(0.259)
Job-status	0.024	-0.001	-0.059	-0.086
	(0.049)	(0.030)	(0.098)	(0.144)
House ownership	0.190	0.740**	-0.192	0.687
	(0.302)	(0.313)	(0.400)	(0.638)
Education	-0.659*	-0.526	-0.484	-0.523
	(0.367)	(0.337)	(0.446)	(0.640)
Lifestyle factors				
Weekly fruit	0.059	0.153	0.125	0.107
	(0.117)	(0.126)	(0.156)	(0.221)
Physical activity	-0.022	-0.063	-0.034	-0.018
	(0.050)	(0.135)	(0.076)	(0.054)
Smoking status	0.211	0.074	0.086	0.040
	(0.133)	(0.073)	(0.098)	(0.130)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 15. The individual contribution of covariates across quantiles of the systolic blood pressure distribution: London vs West Midlands.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	-0.653**	-0.886***	-1.189***	-1.135**
	(0.273)	(0.315)	(0.434)	(0.483)
Sex	-0.363	-0.297	-0.248	-0.132
	(0.361)	(0.297)	(0.251)	(0.145)
Neighbourhood-level characteristics				
Crime level	0.252	0.917**	1.218**	0.544
	(0.468)	(0.426)	(0.545)	(0.766)
Air quality	-0.267	-0.082	-0.009	0.209
	(0.174)	(0.178)	(0.196)	(0.197)
Road distance to a GP	-0.515	-0.156	-0.089	-0.968
	(0.313)	(0.306)	(0.467)	(0.691)
Income deprivation	-0.653*	-0.570*	-0.720**	0.386
	(0.338)	(0.294)	(0.336)	(0.450)
Skills deprivation	-0.663	-0.505	-1.064	2.249
	(0.887)	(0.853)	(0.993)	(1.481)
Socioeconomic status				
Log of household income	-0.082	-0.001	-0.163	-0.395
	(0.109)	(0.107)	(0.186)	(0.272)
Job-status	0.001	-0.002	-0.010	-0.003
	(0.010)	(0.018)	(0.077)	(0.024)
House ownership	0.244	0.319	0.314	0.035
	(0.209)	(0.202)	(0.264)	(0.334)
Education	-0.704**	-0.222	-0.476	-0.122
	(0.306)	(0.265)	(0.348)	(0.439)
Lifestyle Factors				
Weekly fruit	0.007	-0.031	0.141	0.144
	(0.087)	(0.082)	(0.139)	(0.184)
Physical activity	-0.039	-0.104	-0.007	-0.188
	(0.081)	(0.088)	(0.100)	(0.172)
Smoking status	0.041	0.016	0.024	0.095
	(0.077)	(0.037)	(0.083)	(0.149)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 16. The individual contribution of covariates across quantiles of the systolic blood pressure distribution: London vs East of England.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	-1.222***	-1.502***	-1.477***	-1.491***
	(0.360)	(0.367)	(0.435)	(0.492)
Sex	-0.468	-0.414	-0.152	-0.161
	(0.294)	(0.260)	(0.110)	(0.127)
Neighbourhood-level characteristics				
Crime level	-1.963***	-0.446	-0.592	0.839
	(0.683)	(0.596)	(0.611)	(0.850)
Air quality	-0.045	-0.061	-0.069	-0.110
	(0.044)	(0.057)	(0.067)	(0.099)
Road distance to a GP	-0.805*	-0.892*	-0.371	-0.446
	(0.436)	(0.482)	(0.448)	(0.666)
Income deprivation	1.829**	1.427*	0.726	0.849
	(0.919)	(0.837)	(0.986)	(1.205)
Skills deprivation	0.429	0.257	0.278	1.201
	(0.629)	(0.576)	(0.654)	(0.854)
Socioeconomic status				
Log of household income	-0.034	-0.040	-0.037	-0.058
	(0.058)	(0.066)	(0.064)	(0.101)
Job-status	-0.002	-0.029	-0.007	-0.026
	(0.027)	(0.054)	(0.028)	(0.056)
House ownership	-0.522*	-0.079	-0.351	-0.084
	(0.295)	(0.264)	(0.286)	(0.369)
Education	0.027	0.153	-0.311	0.100
	(0.237)	(0.233)	(0.253)	(0.344)
Lifestyle factors				
Weekly fruit	-0.012	-0.033	-0.039	-0.024
	(0.054)	(0.067)	(0.060)	(0.115)
Physical activity	0.013	0.026	0.049	0.031
	(0.032)	(0.042)	(0.069)	(0.057)
Smoking status	0.158	0.262*	0.123	0.061
	(0.127)	(0.147)	(0.140)	(0.178)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 17. The individual contribution of covariates across quantiles of the systolic blood pressure distribution: London vs Southeast.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	-1.215***	-1.836***	-1.726***	-1.127***
	(0.287)	(0.409)	(0.412)	(0.344)
Sex	-0.359	-0.291	-0.175	-0.047
	(0.275)	(0.225)	(0.140)	(0.064)
Neighbourhood-level characteristics				
Crime level	0.529	0.413	-0.345	-0.479
	(0.509)	(0.542)	(0.633)	(0.662)
Air quality	-0.048	-0.026	0.015	0.016
	(0.036)	(0.039)	(0.046)	(0.060)
Road distance to a GP	-0.214	0.358	0.440	0.980**
	(0.303)	(0.376)	(0.429)	(0.403)
Income deprivation	-0.758	-0.504	0.953	3.194*
	(1.056)	(1.111)	(1.409)	(1.685)
Skills deprivation	0.026	0.051	0.268	0.304
	(0.137)	(0.154)	(0.191)	(0.246)
Socioeconomic status				
Log of household income	-0.005	-0.128	-0.108	-0.059
	(0.077)	(0.104)	(0.109)	(0.119)
Job-status	0.002	-0.025	-0.007	0.020
	(0.021)	(0.044)	(0.026)	(0.042)
House ownership	-0.224	-0.148	-0.305	-0.637**
	(0.219)	(0.233)	(0.292)	(0.325)
Education	-0.336**	-0.186	-0.242	-0.177
	(0.139)	(0.139)	(0.167)	(0.168)
Lifestyle factors				
Weekly fruit intake	0.065	0.095	0.055	-0.100
	(0.080)	(0.095)	(0.119)	(0.124)
Physical activity	0.010	0.067	0.080	0.090
	(0.032)	(0.065)	(0.080)	(0.095)
Smoking status	0.008	0.003	0.108	-0.055
	(0.085)	(0.097)	(0.119)	(0.146)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 18. The individual contribution of covariates across quantiles of the systolic blood pressure distribution: London vs Southwest.

Explained	Q25	Q50	Q75	Q90
Demographics				
Age group	-1.102***	-1.706***	-2.215***	-2.276***
	(0.317)	(0.406)	(0.542)	(0.571)
Sex	-0.350	-0.360	-0.141	-0.0536
	(0.238)	(0.244)	(0.111)	(0.084)
Neighbourhood-level characteristics				
Crime level	0.752	0.279	1.174	1.551*
	(0.594)	(0.525)	(0.728)	(0.879)
Air quality	-0.008	-0.137	-0.003	-0.040
	(0.233)	(0.213)	(0.296)	(0.262)
Road distance to a GP	-0.527	-1.168***	-0.989*	-1.286
	(0.391)	(0.411)	(0.576)	(0.824)
Income deprivation	-0.629	-1.407*	-0.983	-1.943*
	(0.803)	(0.744)	(0.990)	(1.169)
Skills deprivation	-0.031	-0.749*	-0.574	-0.121
	(0.452)	(0.455)	(0.649)	(0.800)
Socioeconomic status				
Log of household income	0.100	0.137	-0.046	-0.112
	(0.102)	(0.104)	(0.123)	(0.170)
Job-status	0.002	0.002	0.003	-0.005
	(0.022)	(0.030)	(0.045)	(0.062)
House ownership	-0.087	-0.015	-0.157	0.103
	(0.191)	(0.184)	(0.242)	(0.322)
Education	-0.600**	-0.412*	0.007	-0.045
	(0.261)	(0.237)	(0.299)	(0.381)
Lifestyle factors				
Weekly fruit intake	0.018	0.034	0.018	-0.025
	(0.053)	(0.062)	(0.089)	(0.116)
Physical activity	0.014	-0.055	0.001	-0.060
	(0.035)	(0.063)	(0.044)	(0.085)
Smoking status	0.115	0.297**	0.044	0.065
	(0.123)	(0.134)	(0.167)	(0.210)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX B: CHAPTER FIVE

B.1 DETAILED DECOMPOSITION OF THE CONTRIBUTION OF COVARIATES ACROSS QUINTILES OF THE eGFR DISTRIBUTION

Table B 1. Detailed decomposition of the contribution of covariates across quintiles of the eGFR distribution.

Explained	Q10	Q25	Q50	Q75	Q90
Demographics					
Age	5.209*	4.794**	2.706*	1.271	3.553*
	(2.681)	(2.394)	(1.596)	(1.109)	(2.051)
Sex	0.980	1.268	1.208	1.321	1.652
	(0.974)	(1.225)	(1.147)	(1.248)	(1.575)
Neighbourhood-level characteristics					
Skills deprivation	0.586	0.935	0.283	-1.978	-1.057
	(2.519)	(2.511)	(2.053)	(1.924)	(2.740)
Income deprivation	-1.974	-0.508	0.705	5.942*	6.310*
	(3.301)	(3.474)	(2.631)	(3.104)	(3.762)
Employment deprivation	0.435	-1.134	-0.707	-2.494	-2.140
	(2.958)	(3.785)	(2.582)	(2.221)	(3.238)
Road distance to a GP	0.017	0.017	-0.217	-0.036	-0.178
	(0.184)	(0.172)	(0.323)	(0.108)	(0.293)
Socioeconomic status					
Log of household income	2.254	1.370	-0.814	-0.873	-2.284
	(1.746)	(1.486)	(1.236)	(0.954)	(1.895)
Education	-1.614	0.126	0.675	0.359	1.038
	(1.565)	(1.195)	(0.864)	(0.872)	(1.308)
Job-status	0.576	-0.059	-0.137	2.076	0.701
	(1.552)	(1.993)	(1.403)	(1.514)	(1.920)
House ownership	0.777	0.677	1.188	1.449	2.009
	(0.818)	(0.815)	(0.885)	(0.966)	(1.364)
Lifestyle factors					
Physical activity	-0.357	-0.421	-0.107	-0.046	-0.272
	(0.498)	(0.471)	(0.265)	(0.237)	(0.389)
Smoking status	0.824	0.017	-0.186	-0.317	-1.341
	(1.066)	(0.466)	(0.356)	(0.398)	(1.145)
Alcohol consumption	-0.028	0.067	-0.031	0.195	0.197
	(0.266)	(0.191)	(0.189)	(0.409)	(0.565)
Weekly fruit intake	-0.134	-0.222	0.171	0.066	0.251
	(0.364)	(0.596)	(0.477)	(0.502)	(0.692)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 19. Detailed decomposition of the contribution of covariates across quintiles of the systolic blood pressure distribution

Explained	Q10	Q25	Q50	Q75	Q90
Demographics					
Age	-1.372	-1.303	-1.993**	-2.842**	-2.970*
	(0.954)	(0.988)	(1.007)	(1.175)	(1.695)
Sex	-0.262	-0.331	-0.072	-0.0001	0.086
	(0.310)	(0.377)	(0.138)	(0.122)	(0.233)
Neighbourhood-level characteristics					
Skills deprivation	-1.330	0.214	0.676	1.138	2.833
	(1.197)	(1.193)	(1.131)	(1.308)	(2.132)
Income deprivation	2.067	0.688	-0.863	-1.177	-3.588
	(2.766)	(2.561)	(2.108)	(2.344)	(4.011)
Employment deprivation	-1.548	-1.086	-0.428	1.325	0.773
	(2.513)	(2.211)	(2.080)	(2.227)	(3.281)
Road distance to a GP	-0.010	-0.001	0.013	0.016	0.065
	(0.047)	(0.027)	(0.058)	(0.070)	(0.261)
Socioeconomic status					
Log of household income	0.469	0.020	-1.039*	-0.270	0.286
	(0.621)	(0.555)	(0.628)	(0.756)	(1.050)
Education	0.529	0.226	0.517	-0.573	-1.093
	(0.594)	(0.613)	(0.592)	(0.607)	(0.969)
Job-status	0.425	-0.422	-0.479	0.895	0.872
	(0.836)	(0.876)	(0.881)	(0.971)	(1.830)
House ownership	-0.274	-0.542	-0.270	-0.042	-0.332
	(0.522)	(0.481)	(0.368)	(0.349)	(0.603)
Lifestyle factors					
Physical activity	0.147	0.078	0.173	0.071	0.095
	(0.250)	(0.143)	(0.282)	(0.143)	(0.204)
Smoking status	0.005	0.006	0.048	-0.019	0.009
	(0.160)	(0.108)	(0.283)	(0.076)	(0.104)
Alcohol consumption	-0.045	0.024	0.068	0.085	0.117
	(0.139)	(0.098)	(0.180)	(0.149)	(0.415)
weekly fruit intake	-0.051	0.111	0.096	0.124	0.030
	(0.263)	(0.278)	(0.200)	(0.211)	(0.306)

Note: Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$