Mind the Gap: Geographical Inequalities in Health during the Age of Austerity

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Ramjee Bhandari

Abstract

Background

Stockton-on-Tees has the highest geographical inequalities in health in England, with the life expectancy at birth gap between the most and deprived neighbourhoods standing at over 17 years for men and 11 years for women. It is well acknowledged that place can create inequalities in health but there is a debate within geographical research as to whether the health and wellbeing of an individual is determined by their own attributes (the compositional theory) or the political economy and environmental attributes of the area where they live (contextual approach). More recently, it has been argued that these determinants interact with each other, signifying that they are 'mutually reinforcing'.

Method

This is one of the first studies that provides the detailed empirical examination of the geographical health divide by estimating the gap and trend in physical and general health (as measured by EQ5D, EQ5D-VAS and SF8PCS) between the most and least deprived areas. It uses a novel statistical technique to examine the causal role of compositional and contextual factors and their interaction during a time of economic recession and austerity. Using a longitudinal survey that recruited a stratified random sample, individual-level survey data was combined with secondary data sources and analysed using multi-level models with 95 percent confidence intervals obtained from nonparametric bootstrapping. In addition, trend analysis was performed to explore the role of austerity.

Results

The main findings indicate that there is a significant gap in health between the two areas, which remained constant throughout the study period, and that compositional level material factors, contextual factors and their interaction appear to explain this gap. Contrary to the dominant policy discourse in this area, individual behavioural and psychosocial factors did not make a significant contribution towards explaining health inequalities in the study area. Austerity measures are exacerbating inequalities in general and physical health by disproportionately impacting those in deprived areas. The findings are discussed in relation to geographical theories of health inequalities and the context of austerity. The study concludes by exploring the avenues for further research and key policy implications.

Keywords:

Health Inequality; Longitudinal Survey; General and Physical Health; Multilevel Models; Stockton-on-Tees; Welfare.

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To my wife Chandika

&

Daughter Ava

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List of Abbreviations

Abbreviations	Definition
AIC	Akaike Information Criterion
ANOVA	Analysis of Variance
AR1	First Order Autoregressive
BHPS	British Household Panel Survey
BIC	Bayesian Information Criterion
BL	Baseline Survey
BRMA	Broad Rental Market Areas
CCGs	Clinical Commissioning Groups
CI	Confidence Interval
COPD	Chronic Obstructive Pulmonary Disease
CORINE	Coordination of Information on the Environment
CPI	Consumer Price Index
CRESH	Centre for Research on Environment Society and Health
CS	Compound Symmetric
CTB	Council Tax Benefits
CTC	Child Tax Credits
DCLG	Department for Communities and Local Government
DLA	Disability Living Allowance
DWP	Department of Work and Pensions
EMA	Education Maintenance Allowance
EQ5D	EuroQuol-5D
EQ-VAS	EuroQuol-Visual Analogue Scales

ESA	Employment and Support Allowance
FMI	Fraction of Missing Information
GCSE	General Certificate of Secondary Education
GIS	Geographic Information System
GLMM	Generalised Linear Mixed Modelling
GP	General Practitioner
HB	Housing Benefit
IB	Incapacity Benefit
ICC	Intra-Class Correlation Coefficient
IGC	Individual Growth Curve
IMD	Index of Multiple Deprivations
IMF	International Monetary Fund
IS	Income Support
LHA	Local Housing Allowance
LSOAs	Lower Super Output Areas
MAUI	Multi-Attribute Utility Instrument
MCMC	Markov chain Monte Carlo
MED	Multiple Environmental Deprivation
MEDIx	Multiple Environmental Deprivation Index
MI	Multiple Imputations
ML	Maximum Likelihood
MLM	Multilevel Modelling
NDDs	Non-Dependant Deductions
NHS	National Health Services
ONS	Office for National Statistics

OS	Ordnance Survey
OSM	Open Street Map
PIP	Personal Independence Payment
PRS	Private Rented Sector
RE	Relative Efficiency
RIV	Relative Increase in Variance
SDA	Severe Disablement Allowance
SDOH	Social Determinants of Health
SE	Standard Error
SES	Socioeconomic Status
SF8-MCS	Standard Form-Mental Component Summary
SF8-PCS	Standard Form-Physical Component Summary
UN	Unstructured Covariance
W2	Wave 2 Survey
W3	Wave 3 Survey
W4	Wave 4 Survey
WHO	World Health Organization
WTC	Working Tax Credit

Declarations

The material contained in this thesis has not previously been submitted for a degree in this or any other institution. It is the sole work of the author.

Copyright

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Chapter 1: Introduction

Background

I come from an underdeveloped country (Nepal) in the global south, where health inequalities are *'so rampant that despite it being vividly obvious'* (Rasaili, 2007), we are 'used' to it. The issue of health inequalities though is grave, it is often not the priority of the government (World Health Organization, 2013). As a public health student, I started to understand about the local health context of Nepal, and compared it with the health and social systems in developed countries. In some of the modules of my public health degree, I had a chance to study the National Health Service (NHS) in the UK which was highlighted as being 'one of the best' health systems in the world.

Back in 2013, I came to Durham University to do a Master's Degree in Risk Health and Public Policy. It was then that I got to learn more about the health inequalities that persist in the UK, between and within different tiers of administrative and geographic units. Professor Clare Bambra delivered a lecture for one of the modules and introduced me to the idea of "north-south" health divide in England. The term itself and the facts presented during the lecture were overwhelming to me, and made me think from health geography perspectives and not the public health perspective I was used to. I had a belief that the country with global influence and socially and economically strong status had no inequalities, in any form. It was mind-boggling when I learnt that "*all cities have a north*" (Bambra, 2016; p. 85), and there are areas within a city which are more deprived and have poorer health than the others. Men in the most deprived areas of Stockton-on-Tees can expect to live 17 years less than their counterparts

(11.4-year gap in life expectancy for women) in the least deprived areas, which are often in close proximity to one another (Public Health England, 2015). This is similar to differences in life expectancy between the US and Ghana or the UK and Nepal (where I come from) (World Health Organization, 2016). Within a short distance, this big difference in average life expectancy is evident, that too in a country where many believe has no inequality. This is why I decided to undertake this research project. I wanted to unpack the headline life expectancy gap by looking in more detail at other underpinning health measures as well as their determinants. Understanding the causes of Stockton-on-Tees' geographical health inequalities is therefore, of great significance, to academia and to policymakers. Building up the evidence base to understand how this health divide is created/sustained and how it could be addressed was the motivation for doing this research. I decided to undertake this research project because I wanted to explore the level of inequalities in general and physical health of people living in the most and the least deprived areas of Stockton-on-Tees. In addition, I wanted to explore the causes behind the gaps and how things changed during a period of austerity.

Health inequalities and the challenges

'Health inequalities' is a broad term indicating the gap in health outcomes between different population groups, for example, based on socioeconomic status and area of residence. Understanding health inequalities is never free from challenges, and this is particularly true when we consider the complexities that drive health inequalities. The consequences of health inequalities, on the other hand, are far reaching, and impact upon the economic and social development of a nation. The unacceptable gap in health between individuals, due to the deprivation level of the place where they live raises serious questions about the effectiveness and fitness for purpose of the liberal welfare systems that countries like the UK follow (Beckfield et al., 2015). It is of particular significance, that although there is a universal agreement that health inequalities are unacceptable disparities within societies, they still persist between and within countries and in all welfare regimes. There is ongoing research to explore and understand the phenomena that keep health inequalities alive despite the many initiatives designed to tackle them.

Alongside this level of inequalities, the ongoing and announced cuts in public spending in the UK, that began with the Coalition Government of 2010 and have continued under the Conservatives since 2015 were geographically patterned. Furthermore, the worst hit areas were those that were already the most socially disadvantaged (Beatty and Fothergill, 2016). Academics and public health agencies have all voiced concerns about the negative health consequences of the austerity programme. Health is a cross-cutting issue, which is linked to all other social sectors which have been affected by the spending cuts. The negative health impacts seen are either a direct result of financial cuts in health care or an indirect outcome of the constriction in other social programmes, particularly welfare services and local authority cuts (Bambra and Garthwaite, 2014). After the public spending cuts, the North East region, where the study site (Stockton-on-Tees) lies, saw the highest reduction of people working in the public sector (12 percent) (Pearce, 2013). This highlights the necessity of understanding the geographical impacts of austerity and welfare reform programmes on health

The geographical health divide

It is well acknowledged that place can create inequalities in health but there is a debate within geographical research as to whether the health and wellbeing of an individual is determined by their own attributes (the compositional theory) and/or the political economy and environmental attributes of the area where the person lives (contextual approach) (Macintyre et al., 2002). More recently, it has been argued that these determinants interact with each other, and are 'mutually reinforcing' Cummins et al. (2007). The compositional explanation asserts that the health of a given area is the result of the characteristics of the people who live there (demographic, behavioural and socioeconomic). The contextual explanation, on the other hand, argues that area-level health is determined by the nature of the place itself, in terms of its economic, social, cultural and physical environment. The profile of the people within a community (demographic [age, sex and ethnicity], health-related behavioural [smoking, alcohol, physical activity, diet, drugs] and socio-economic [income, education, occupation]) influences its health outcomes.

A complex relationship exists between place, the people who live there and health. Complex in the sense that the characteristics of people (composition) and the nature and attributes of the place (context) act both individually and collectively (Macintyre et al., 2002). Further, it has been argued that these health divides between areas are political in nature, influenced by the wider socio-political and macroeconomic context, for example, economic recession and austerity (Schrecker and Bambra, 2015). Health inequalities are the results of complex phenomena and their fundamental causes *'lie upstream, in the social, economic and political environment in which we live and work*' (Smith et al., 2016; p. 12). Furthermore, prevailing health inequalities are a significant challenge to societies that are based on equality and protected human rights. With this in the background, addressing health inequalities requires policies that tackle inequalities in income and the socio-environmental context. Health is supposed to be universally enjoyed, regardless of where someone lives. i.e. place should make no difference.

Neighbourhoods that are the most deprived have worse health outcomes than those that are less deprived – this phenomena also follows a spatial gradient, with each increase in deprivation resulting there is a decrease in average health (Bambra, 2016). Local-level spatial analyses have recently received more importance because of the increased recognition of the role a neighbourhood plays in shaping the geographical health divide. Attempting to study the local context, however, brings significant challenges: such as the availability of appropriate data and the scale of the geographical units where the study is to be carried out. However, with this research project the opportunity to analyse the longitudinal survey dataset, which is available at a finer geographical scale provides a more accurate basis to make inferences and derive conclusions on the relationship between place, health inequalities and austerity.

Before I began the research, I had many questions, including:

- Are health inequalities affected by the place of residence?
- Is it justified that those who live in most deprived areas have poor health outcomes than those living in the least deprived areas?
- Through what mechanisms do the compositional and contextual factors influence health inequalities?
- Do these factors contribute directly to the gap or is the influence indirect?

With this in the background, the research project and this thesis aims to unpack the complex issue of geographical health inequalities in Stockton-on-Tees during a time of austerity. This thesis is thus an exploration of what happens to physical and general health in a time of unprecedented welfare cuts; an account of policy-induced *geographical health divide.*

Study context

My PhD is a part of the five year (2013-2018) '*Local Health Inequalities in an Age of Austerity: The Stockton-on-Tees Study'* (http://research.ncl.ac.uk/health.inequalities/), funded by the Leverhulme Trust. This interdisciplinary case study has attempted to explore the health divide in Stockton-on-Tees by combining insights from geography, social epidemiology, psychology, sociology, anthropology, history and social policy. The welfare cuts implemented in the UK after 2010 have been linked to the health divide in the country, and caused pronounced damage in the most deprived groups (Bambra and Garthwaite, 2014). The political and economic context has impacted both individuals and local areas. This emphasises the need for exploring and understanding how local health inequalities are shaped or sustained during an "age of austerity". The borough of Stockton-on-Tees is an important case because of highest health inequalities in England. Life expectancy at birth reveals a gap between the most and least deprived neighbourhoods of 17.3 years (it was 15 years when the study was designed) for men and 11.4 years for women (Public Health England, 2015). Life expectancy though is only a headline indicator, signifying the need to explore the extent and determinants of other aspects of health inequalities in that area (Bambra, 2016; p. 93).

Using data from the prospective cohort study, my PhD examines the gaps and their trends in health outcomes between the most and the least deprived areas of Stockton-on-Tees. I provide the first detailed empirical examination of the biggest geographical health divide in England using validated measures of physical and general health within a household survey. As part of the longitudinal survey, data about the individuals and their households were collected. This included information on health outcomes and the social determinants of health such as demographic, material, psychosocial, behavioural and neighbourhood factors. Using data from the longitudinal survey, my research has explored how the gaps have changed over time and what factors are associated with these gaps. Though the survey also covered mental health outcome measures, my research was focused on physical and general health and exploring the gap revealed by these measures. However, a linked study has used the mental health outcome measures to explore the gap and their associated factors (see Mattheys et al. (2016)).

This thesis adopts a critical social science perspective on health and wellbeing. This recognises the significance of the characteristics of an individual and also the factors at a higher level—the neighbourhood and the wider socio-political context. This thesis also asserts the importance of the interaction between individual and collective characteristics. My PhD was designed to explore the health gaps between the most and the least deprived areas of Stockton-on-Tees, and to investigate the cause of these gaps. It uses a novel approach. My thesis utilises methodological innovation to understand the production and reproduction of health inequalities. I piloted a different statistical technique to examine the contribution of compositional and contextual factors and their interaction in explaining this gap. This research attempted to operationalise the relative contributions of compositional and contextual factors on the health gap using multilevel modelling, a novel approach to the study of health inequalities. Uniquely, I did this in a time of economic recession and austerity within the UK. This research also considers three aspects of the health divide in the same study: the gap, its contributors and the role of time. Scheufle and Moy (2000) argue that ‘time factor’ represents the “process of formation, change, and reinforcement”. Therefore, to explore the role of austerity in the health divide, ‘time’ was considered as a proxy. This was done because the austerity-induced welfare reform programmes were phased gradually and the basic assumption adopted was that time is equivalent to austerity.

There are few studies that incorporate the gaps in general and physical health and their contributing factors, and even fewer comparing their trends at a local level (Bambra, 2013a). Furthermore, studies to explore the human cost of austerity are limited, as most are conducted from an economic perspective (Karanikolos et al., 2013a, Karanikolos et al., 2013b, Kentikelenis et al., 2014, McKee et al., 2012). Pearce (2013) has highlighted three key critiques of contemporary research which explores the impacts of austerity. Firstly, most of these studies rely on or extrapolate from the economic recessions of the past. Secondly, medicine and public health have largely dominated the research. Lastly, geographical and social perspectives are often missing in these studies. The geographical and social perspectives can cover areas that other perspectives would normally miss. These perspectives would, for example, explore the linkage of physical systems and human-societal dynamics and also include spatial representation.

The studies in the UK conducted to date which explore the extent of geographical health inequalities during austerity have also been conducted on a national scale and utilised national level datasets (Barnes et al., 2016, Barr et al., 2015, Loopstra et al., 2015, Niedzwiedz et al., 2016). National level statistics are often criticised for failing to represent and explain the proximal area level situations or even the inequalities that persist between and within regional and local levels (Bambra, 2013a, Cummins et al., 2005, Shouls et al., 1996). Those studies exploring different localities have also focused on local authority level data rather than looking at a finer geographical scale such as neighbourhood or ward level. The indicators used have often been mortality rather than morbidity. This identifies a clear need for more localised studies that apply geographical theories to better understand the extent and causes of geographical inequalities in health and the impact of austerity. Furthermore, focusing at a local scale has provided me with a unique opportunity to get detailed primary information on health and the social determinants at a small geographical scale, which is not the case with secondary data (such as the census or Health Survey for England). In addition to this, the analysis of the data collected from the longitudinal survey shows the trend and pattern of health inequalities during a period of austerity. My research will, therefore, be of interest not only to those who study health inequalities in the UK but also to the international public health research community who are tackling similar geographical inequalities in health in major urban settings (Bambra, 2016).

This study is one of the first to examine localised geographical inequalities in health in a detailed way using multiple health indicators. A robust and well-designed longitudinal survey which utilised stratified random sample was adopted. Use of validated health outcome measures and tools to record the explanatory variables makes this research comparable to a wide range of academic research. The research found a significant health gap between the most and the least deprived areas of Stockton-on-Tees. There were both direct contributions from the compositional and contextual factors and also indirect clustered effects of these factors which all contributed to the health gap. I argue that these findings around the contributions of compositional and contextual factors in creating the health gap could be generalised to other areas. This research is significant because it evaluates austerity's influence in shaping the social landscape in Stockton-on-Tees, and shows that there are more pronounced impacts in the most deprived areas.

Amongst the compositional factors, material factors are an important aspect of overall health and wellbeing, and continuous cuts to benefits and services directly worsen the socio-economic position of people already in poverty. This study has found that these material factors, which are mostly related to income and deprivation are the key determinants of poor general and physical health.

I therefore, argue that the policy initiatives should be directed towards addressing material deprivation as a means to tackle health inequalities. This study has further established that 'place' and its attributes matter for health inequalities; these contextual factors either contribute directly or interact with the compositional factors in causing the health gaps. The disproportionate exposure of health-damaging factors in the most deprived neighbourhoods and the resulting health gap has highlighted the 'environmental (in)justices' as an important cause of health inequalities in Stockton-on-Tees (Pearce, 2015).

Organisation of this Thesis

This thesis consists of seven chapters.

Chapter Two reviews the existing evidence base around health, wellbeing, health inequalities and the impact of austerity measures on general and physical health. The chapter starts by reviewing the academic literature on relevant conceptual and theoretical frameworks that may provide an understanding of health and wellbeing. The chapter highlights the important contribution of different social determinants of health and how they can result in health inequalities. The chapter then moves on to explore the aspects of health inequalities with reference to place and while doing so, I shed light on the mechanisms and effects of the neighbourhood in health inequalities. The notion of spatial inequalities in health is discussed, incorporating geographical debates around context/composition. I then explore the global financial crisis followed by the background and impacts of austerity policies within the UK, which is followed by the exploration of the spatial health impacts of austerity. In the final part, I explore the relevance of Stockton-on-Tees as a case study to understanding geographical health inequalities. These theoretical and conceptual ideas provide the background to the research methods and the findings.

In ***Chapter Three,*** I outline the methodological approach deployed, my research aims and questions along with the rationale for choosing them. In this chapter, I provide a detailed explanation of the survey design, the tools used and the statistical analyses performed to explore the health divide. I have used data from the longitudinal survey combined with contextual data from secondary sources, I present a discussion of the relevance and appropriateness of this approach in understanding patterns and trend of geographical health inequalities.

Chapter Four explores the gap in general (as measured by EQ-VAS and EQ5D scores) and physical health (SF8PCS scores) between the participants from the most and the least deprived areas of Stockton-on-Tees. EQ5D-VAS represents the perceived health status of the participant, which is measured on a scale of 0-100, 0 being the worst and 100 the best health state they can imagine (Warren et al., 2014). The EQ5D scores range between – 0.594 and 1.00, the latter being better health. SF8PCS measures the physical health status in a scale of 0-100: the higher the score, better is the physical health state (Garthwaite et al., 2014).

The chapter provides a detailed overview of the multilevel modelling approach which was applied to the longitudinal data. The chapter highlights the existence of a significant gap in physical and general health in Stockton-on-Tees, and the significant direct as well as indirect contributions of individual-compositional and area-level contextual factors in determining this gap, By looking at the trend, it demonstrates that the gap in general health remained almost constant while the physical health gap constantly widened between the two areas over the survey period. The findings are related to the ongoing austerity programme and welfare reforms. This chapter concludes that ‘place’ and its attributes are important determinants of health inequalities, they either contribute directly or interact with compositional factors in having the cumulative impact on general and physical health.

Chapter Five presents the trend and nature of the gap in general and physical health between the most and least deprived areas of Stockton-on-Tees. This chapter investigates the role of ‘time’ in explaining the gap in general and physical health. With the basic assumption of time being equivalent to austerity, this chapter explores and also tries to quantify the role of austerity in the health gap in Stockton-on-Tees. It explores and quantifies the rate of change in the health gap for both areas by applying the individual growth curve. The chapter highlights that the gap in general health as measured by EQ5D-VAS changes in a quadratic rate, while the gap in physical health as measured by SF8PCS and gap in general health as measured by EQ5D change in a linear rate.

In ***Chapter Six***, I synthesise the research findings and relate them back to the initial research aims and questions. I then present the principal findings of the statistical analyses and relate them to the existing literature. In this chapter, I discuss the overall trend and pattern of health inequalities between the most and the least deprived neighbourhoods of Stockton-on-Tees. Exploring the relative contributions of compositional and contextual circumstances of the health gap, I present their possible links to the welfare reform and public spending cuts. I argue that the compositional and contextual factors impact health inequalities on their own and also make an indirect/clustered contribution too. I also argue the importance of the significant interaction of the compositional and contextual factors in shaping the health outcomes. Linking my findings to the wider literature, I situate my contributions to the evidence on the geographical health inequalities and link to austerity programmes. Finally, the chapter explores areas for further research.

Finally, ***Chapter Seven*** concludes my thesis by summarising the key findings and by presenting the policy implications of the research.

Chapter 2: Review of the Academic Literature

Introduction

In this chapter, I review the existing literature in the fields of health, wellbeing, health inequalities and link them with ideas about financial crisis and austerity. I also review literature which suggests a causal relationship between financial crisis and widening health inequalities. I begin by exploring the concepts of health and wellbeing with a focus on their determinants and the measures that can be used to assess them. I then discuss the aspects of health inequalities with reference to place specifically. While doing so I shed light on the mechanisms and effects of neighbourhood in contributing to health inequalities. The review then discusses the ongoing debate on the role of compositional and contextual factors in understanding health inequalities. There is then an exploration of the global financial crisis followed by the background and impacts of austerity policies within the UK. This is followed by a discussion of the spatial health impacts of austerity. In the final part, I explore the relevance of Stockton-on-Tees as a case study to understanding geographical health inequalities.

Understanding health and wellbeing

The World Health Organisation (WHO) defines health as ‘a state of complete physical, mental and social wellbeing and not merely the absence of disease or infirmity’ (World Health Organization, 1995). This now- familiar assertion was an innovative proposition in 1948. It has not been without criticism—particularly in its conceptual link to wellbeing (Huber et al., 2011). Jormfeldt (2014) has argued that this WHO definition has resulted in the ‘medicalisation’ of health and wellbeing, which is mostly dominated by the biomedical model and is focused on the symptoms of diseases.

However, the interconnectedness of the three dimensions of physical, mental and social wellbeing is still relevant today (The Lancet, 2009). With the holistic view of health and wellbeing, the primary focus shifts from a specific body part or symptoms of a disease to an overall performance of an individual. The holistic approach looks into the physical, emotional and social factors of an individual and explores how these factors in a collective way produce the health outcome. The principle of the holistic approach is to understand how an individual functions within their environmental and social setting. In 1986, the first international conference on health promotion developed a charter (widely known as the ‘Ottawa Charter’), which was based on the holistic understanding of health and wellbeing.

> *To reach a state of complete physical, mental and social well-being, an individual or group must be able to identify and to realize aspirations, to satisfy needs, and to change or cope with the environment. Health is, therefore, seen as a resource for everyday life, not the objective of living. Health is a positive concept emphasizing social and personal resources, as well as physical capacities.*
>
> (World Health Organization, 1986)

The charter highlights health and wellbeing as resources and not the final objective of living. It also signifies the path that can lead an individual to the ideal state of physical, mental and social wellbeing. When looking at health and wellbeing from a holistic perspective, an individuals’ health and wellbeing is determined by objective and subjective elements. While the objective elements tend to measure societal perspective, the subjective elements assess the reflections on individual’s personal judgements and experiences (Thorburn, 2015). Because of the multidimensional nature of health and wellbeing, its measurement is not straightforward and it requires various scales and techniques to capture as much information as possible (Oswald and Wu, 2010).

This thesis adopts a critical social science perspective of health and wellbeing, which recognises the significance of the characteristics of an individual and also the factors at a more macro-level. This thesis also asserts the importance of the interaction between individual and collective characteristics. In addition, exploration of the determinants of health and wellbeing from a social science perspective will also help understand the complex and dynamic nature of the societies that shape health and wellbeing (Nyman and Nilsen, 2016). This approach not only helps when trying to understand the issue at an individual level but also looks at the differential exposure and social constructs which lead to health inequalities. By assessing health and wellbeing from a macro concept, it is possible to move beyond the traditional approach of individual subjectivity (La Placa et al., 2013). As argued by Knight and McNaught (2011), effective measures of health and wellbeing are able to demonstrate the dynamic construction of these states from an interplay of the individual and social structures at a macro-level. My research does this by exploring the relative contribution of compositional and contextual factors in explaining the health gap and how it changes during a period of two years. The following section begins with the exploration of the social determinants of health and wellbeing and then moves towards the methods for measuring health and wellbeing.

Determinants of health and wellbeing

During the 1970s, public health policy in the UK was criticised for placing more emphasis on individuals and their illnesses than structural determinants. The evidence during that period showed that the biomedical model of health was not offering effective results (Wade and Halligan, 2004). It was when the term 'social determinants of health' was introduced, which not only included the individual factors but also the wider social issues that can shape health and wellbeing (Graham and Kelly, 2004). The 'rainbow of health' model of Dahlgren and Whitehead (1991) has been extensively used in public health research, as a conceptual framework of determinants of health (see Figure 2.1, below). It includes individual factors and also considers wider contextual social issues. It is, however, limited in that it is unable to represent the interaction that can influence the outcome.

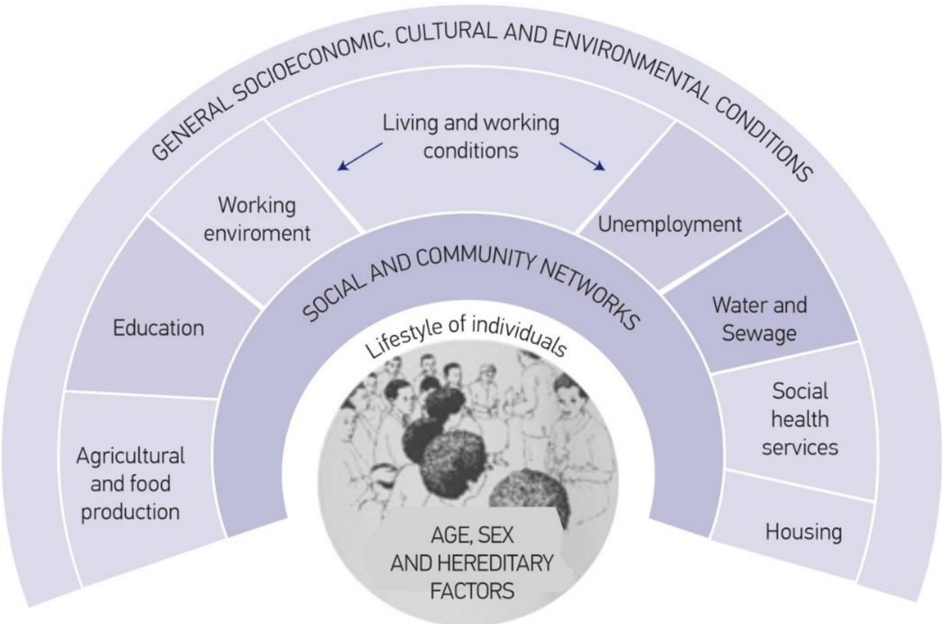

Figure 2.1: Dahlgren and Whitehead's determinants of health model (Dahlgren and Whitehead, 1991; p.11)

Social determinants of health (SDOH) are the collective set of conditions in which an individual is born, grows up, work and live and which directly or indirectly impacts their health. In their broader form, they are also identified as employment status; work and working environment; access to essential services (including healthcare); and housing and living environment (Bambra, 2011, Marmot, 2005). An independent group under the WHO Regional Office for Europe developed a perspective looking at the 'causes of the causes' for health inequality through the lens of SDOH. Solar and Irwin (2010) later revised the framework to make it even more comprehensive considering the inter-layer interactions (see Figure 2.2, below).

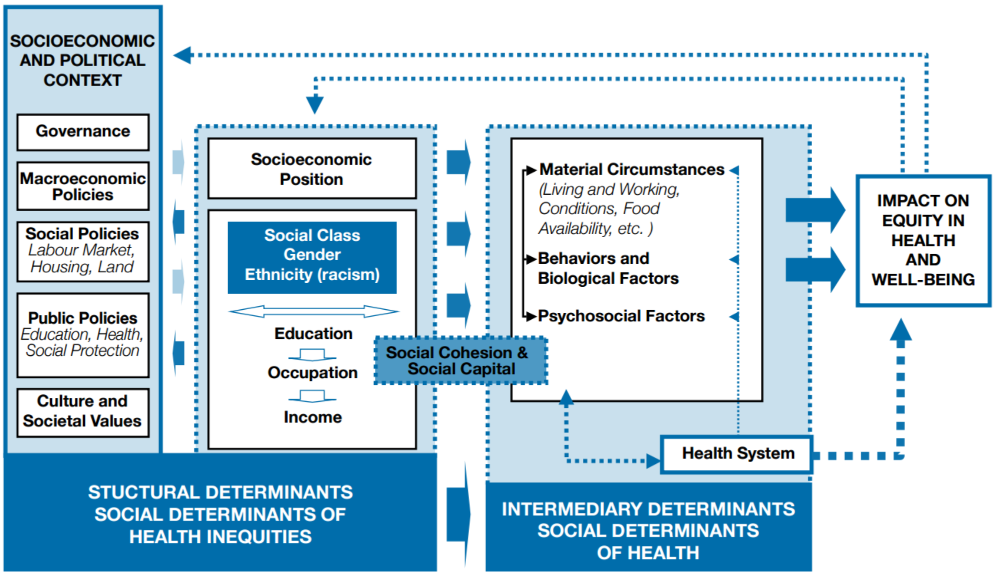

Figure 2.2: Conceptual framework from commission of SDOH (Solar and Irwin, 2010, p. 6)

Connecting the determinants to people's lives

Working conditions

The health inequalities literature has rightly recognised the impact of working environment on an individual's life. Work and working conditions have a strong relationship with health and health inequalities. Manual workers jobs are more likely to have health-damaging impacts than non-manual work (Bambra, 2016). Health damaging impacts of the working environment are mostly linked to exposure to physical (such as hazardous chemicals, noise, vibration and heat) or psychosocial conditions of the work. While exposure to hazardous chemicals (such as mercury and lead) are associated with cardio-pulmonary diseases (for example chronic obstructive pulmonary diseases – COPD and certain cancers), exposure to vibration and monotonous work are associated with musculoskeletal diseases (Bernal et al., 2015). Prolonged exposure to loud noise is associated with hearing loss (Basner et al., 2014), increased stress levels, higher blood pressure and decreased cognitive performance (Lie et al., 2016). Psychosocial work environment (such as time pressure, job control and job security) impacts health from psychological and social influences (Bambra, 2011). Bambra (2011) further argues that the psychosocial work environment moves along with the social gradient. While the working class are mostly involved in physical workloads, jobs with more psychosocial work demands are common among the middle classes (Hammig and Bauer, 2013). Patterns of work distribution are also found to be the cause of health inequalities amongst employees (Bambra, 2011). Moving further, the macro-level political context and broad structural rules and norms governing society determine these micro-level working environments through policies and legislation (Dragano et al., 2011).

Unemployment and worklessness

There is a strong research base that shows the relationship between unemployment and poor health (Beatty et al., 2017, Warren et al., 2013). There is a two-way relationship between health and unemployment: the term 'health-related worklessness' signifies the decreased job prospect of an individual following a sickness or disability (Bambra, 2011). Unemployment is an important life event, which not only induces stress but is a primary determinant of health inequalities (Marmot et al., 2010, Marmot and Allen, 2014). The health impacts of unemployment can be understood from two inter-related pathways: a material pathway (wage loss and change in services as a result of lost income) and a psychosocial pathway (such as stress and stigma). Unemployment is associated with poor mental health conditions (Mattheys et al., 2016), poor self-reported health (Heggebø and Elstad, 2017) and health-damaging behaviours (Skalicka et al., 2009). The health impacts of unemployment are not limited to an individual, can also expand to families (Bambra, 2011) and also result in geographical inequalities in health (Moller et al., 2013).

Access to essential goods and services (including healthcare)

Access to essential services (such as healthcare, healthy food, safe water and sanitation) are the basic determinants of good health. Macro-level political context determines the availability and access of these services, for example, stronger agricultural and food policies result in quality food products, at a fairer price and with easy access (Dahlgren and Whitehead, 1991). In contrast, these food policies can also lead to over-nutrition, which results in obesity. Swinburn et al. (2011) argue that 'pandemic' of obesity is a result of the change in the global food system (which is mostly focused on producing more processed food) and the restriction to healthy food. The '*obesogenic environment'* (Bambra, 2011) and 'food desert' (Cummins and Macintyre, 2002) are terms used to define the limited access to an affordable and healthy diet in highly populated urban and in deprived areas. Access to green space is associated with increased physical activity and psychological wellbeing (Wolch et al., 2014). Green spaces have '*salutogenic'* (i.e. health promoting) properties (see Environmental mechanisms, page 46) but are disproportionately located, with higher access and availability in the less deprived areas (Pearce, 2015). Marmot et al. (2008) argue that the access to health care system is a fundamental social determinant of health, which influences and is also influenced by other social determinants of health. There could be an imbalance between the need and access to health care, also termed as '*inverse care law'*, which indicates inadequate health care services in areas of higher need (Tudor Hart, 1971). A study in Scotland by Mercer and Watt (2007) has found a longer waiting time to access health care in the most deprived areas. Health care services can impact health inequalities from an 'institutional mechanism' (see Institutional mechanisms, page 48). These services and health affecting institutions (also referred to as 'opportunity structures'; e.g. GP surgeries, fast food outlets) are socially constructed and have possibilities of varied quality, availability and access (Macintyre et al., 2002, Sykes and Musterd, 2011).

Housing and living environment

Housing and living environment is a material determinant of health and wellbeing (Bambra, 2011). Housing issues (such as dampness, over-crowding and no heating) are associated with poor health. Persistent exposure to housing problems results in poorer health conditions and the exposure in the past could have health consequences in the present (Pevalin et al., 2017). The health impacts of the immediate environment to the place of residence is explored in more detail later in the chapter (see Health inequalities and place, page 31).

Measuring general health and wellbeing

As highlighted in the previous sections, defining health and wellbeing is a complex task as it may differ with context. It is the case because cultural diversity and relativity usually mediate the understanding of health and wellbeing (Huppert and Baylis, 2004). Chavez et al. (2005) argue that though health and wellbeing is a subject that is gaining an increased interest, there is a lack of clarity on how it can be identified, measured and achieved. In biomedical (clinical) terms, health and wellbeing are assessed in terms of diseases and their symptoms or biomarkers. When it comes to the holistic health and wellbeing, assessment is directed towards identifying the interrelationships of the biological, psychological and social dimensions of the individual (Chan et al., 2016). There is a strong relationship between physical health and wellbeing, but the direction of the association is not always clear (Huppert and Baylis, 2004).

Two major schools of thoughts are helpful in understanding health and wellbeing: the eudemonic and the hedonic. The eudemonic school of thought highlights the importance of meaningful life based on ‘self-actualisation’ (Ivtzan et al., 2013) and full physical functionality of a person or ‘positive functioning’ (Joseph and Wood, 2010). The hedonic school of thought, on the other hand, emphasises the importance of emotions such as happiness, anger, stress and pain in determining health and wellbeing (Steptoe et al., 2015). While they sound different, Kashdan et al. (2008) argue that a clear distinction between eudemonic and hedonic wellbeing is hard to achieve because they conceptually overlap and my understanding of health and wellbeing fits into this argument. In line with this, my approach was to use both concepts of wellbeing and without any clear line of distinction. Subjective and objective measurements continue to generate useful evidence to understand health and wellbeing of an individual. Use of these measures in combinations can appropriately quantify health and wellbeing (Oswald and Wu, 2010). Huppert and Baylis (2004) argue that including physical as well as subjective emotional components to the health outcome measures can make a better assessment of the overall health and wellbeing. In this research three contrasting measures of general health and wellbeing were used to quantify general and physical health of the people from Stockton-on-Tees. General health was assessed using EuroQol (EQ5D and EQ5D-VAS) and physical health was measured using 'quality metric short form (SF8)'. Both EuroQol and SF8 have been well-validated for use in the general population. These three measures appropriately incorporate the eudemonic and the hedonic aspects of health and wellbeing. These measures are discussed in details in ***Chapter 3 (Methodology)***.

Health inequalities

Understanding health inequalities is never free of challenges, and this is particularly true when we consider the complexities that drive health inequalities. Bartley (2004), Sisson (2007) and Bambra (2011) have proposed five theories to study health inequalities: materialist, cultural-behavioural, psycho-social, *life course* and political economy theory. All these theories have strong links to socio-economic class, as well as geographical and environmental contexts.

Table 2.1: Relationship between income (material deprivation) and health inequalities

Explanation	Synopsis of the Argument
Psychosocial (micro): Social status	Income inequality results in "invidious processes of social comparison" that enforce social hierarchies causing chronic stress leading to poorer health outcomes for those at the bottom.
Psychosocial (macro): Social cohesion	Income inequality erodes social bonds that allow people to work together, decreases social resources, and results in less trust and civic participation, greater crime, and other unhealthy conditions.
Neo-material (micro): Individual income	Income inequality means fewer economic resources among the poorest, resulting in lessened ability to avoid risks, cure injury or disease, and/or prevent illness.
Neo-material (macro): Social disinvestment	Income inequality results in less investment in social and environmental conditions (safe housing, good schools, etc.) necessary for promoting health among the poorest.
Statistical artefact	The poorest in any society are usually the sickest. A society with high levels of income inequality has high numbers of poor and consequently will have more people who are sick.
Health selection	People are not sick because they are poor. Rather, poor Health lowers one's income and limits one's earning potential

*Source: (*World Health Organization, 2010, p. 31*)*

As argued by the materialistic model of health inequality, socioeconomic status and the structural components, usually the place and context (see details in later sections) of societies are the causes of the prevailing health inequalities. Factors considered by this model are external, out of an individual's control (Sisson, 2007). The socio-economic position is usually the major factor determining the access and utilization of resources and services, with a possibility of creating inequalities. More recently, 'neo-materialists' explanation reinforces the importance of the state's role in protecting the health of its citizens. Jayasinghe (2011) argues countries with less problem of income inequalities have narrower health gaps. The exposure to a toxic or unsafe environment at work, public spheres or at home is associated with poor health. In addition, Scambler (2012) links the issue of 'risk behaviours', which is related to 'cultural behavioural model' to material deprivation. Macintyre (1997) classifies physical aspects of the societies (such as the geographical location of residence) as 'hard' materials, whereas socioeconomic factors (wealth quintiles) as 'soft' materials that determine health inequalities. World Health Organization (2010) has further elaborated how income (material deprivation) can bring health inequalities, see *Table 2.1*.

Likewise, the cultural-behavioural model explains the causes of inequalities as the consequences of social class and social positions (Macintyre, 1997). Smith et al. (1994) argue that people from lower social class backgrounds and those residing in deprived areas are more prone to adopt harmful health behaviours, resulting in unequal health outcomes. Family/household and neighbourhoods are the basic spheres of the cultural and behavioural development of an individual. Social-interactive mechanisms (for details, see page 44) importantly justify the relevance and role of neighbourhoods in defining a behaviours, which could be health promoting or damaging (Galster, 2010).

Closely linked to the cultural-behavioural theory, the psychosocial theory looks at the role of psychosocial risk factors in creating health inequalities (Elstad, 1998). Cultural attributes shape the social support and stress coping strategies. The abundance of contextual psychological stressors (crime & antisocial behaviours, negative life events, poor social capital) is the key issue that causes poor health outcomes. People living in deprived areas are hypothesized to experience more of these stressors, hence resulting in place-based health inequalities (Bambra, 2011, Singh-Manoux and Marmot, 2005, Sisson, 2007).

Life course theory describes health inequality as a result of current contextual and environmental factors as well as prior conditions of the place. Work by Wadsworth (1997) signifies the importance of a life course perspective in health inequalities. His work has highlighted how time-related vulnerability and time associated vulnerability can bring about health gaps. Geographical health inequalities can result from either 'amplification' of contextual effects (for example see work of Missinne et al. (2014) as they are cumulative in nature or critical/latent effects of exposure to the contextual factors (Sisson, 2007).

Finally, the political economy theory of health inequality highlights the role of the state and its policies in creating unequal societies (Bambra, 2011). In this light, inequalities as a result of policies imposed by the state can be studied by the application of this theory. Szreter and Woolcock (2004) argue for the necessity of studying the relationship between public health and the changing political economy to better understand the difference in the health outcomes. In this context, Schrecker and Bambra (2015) have reinforced the significance of 'social democratic' strand of welfare regime in creating equitable societies. They argue that

> *"It (welfare state) consists of system and processes that themselves shape society and influence stratification, and is, therefore, potentially an important macro-level political and economic determinant of health".*
>
> (Schrecker and Bambra, 2015, p. 11)

The explanations of these theories are summarised in *Table 2.2*.

Table 2.2: Summary of theories explaining health inequalities

Theories	Explanations
Materialistic	Economic and social structures in creating health gaps
Cultural-behavioural	Health affecting behaviours as a result of social class and position; which eventually creates unequal health outcomes
Psycho-social	Differential prevalence of contextual psychological stressors in neighbourhoods result in place based health inequalities
Life course	Accumulation of risk factors throughout the life could result in ‘amplification’ of contextual effects in later life.
Political economy	Role of state and its policies in creating unequal societies and health outcomes.

Tackling health inequalities

The health inequalities literature suggest four specific approaches to tackle health inequalities:

a) Focusing on the disadvantaged groups;

b) Reducing the gap between the best and the worst off groups;

c) Reducing the social gradient

d) Proportionate universalism.

The first approach aims at reducing health inequalities by focusing entirely on the most disadvantaged group. The activities involved in this approach are the improvement of socio-environmental conditions and improvement of the life opportunities of the target group (Graham and Kelly, 2004). England has a spatial distinction in the distribution of deprivation, with over 5 million people living in the most deprived areas and 98 percent of the most deprived lower super output areas (LSOAs) in urban areas (Department for Communities and Local Government, 2014). The same report has highlighted the need of area-based (targeted) interventions to address this gap (for details of those interventions see Department for Communities and Local Government (2014)).The effectiveness of these interventions are assessed comparing the outcomes of the groups with that of the general population. However, Bambra (2011) argues that this approach tries to '*equate the language of inequality to the language of disadvantage'*— deprivation is the *only* cause of inequality (Bambra, 2011; p. 183). This shift of focus from the overall population to a smaller segment (the most deprived group) can, according to Graham and Kelly (2004), widen health inequalities.

The second approach of tackling health inequalities is by reducing the gap between the best and the worst off groups. Interventions are primarily targeted towards the group that bear the greatest burden of disadvantage, be it in terms of social exclusion, exposure to risk factors or difficulty to reach (Graham and Kelly, 2004). By helping the worst off groups, the main aim of this approach is to 'close the gap' against the best off group and some case with against the national averages. The public health system in the UK intends to improve the status of public's health mostly by *'improving the health of the poorest, fastest'* (Department of Health, 2010; p. 52).

Stockton-on-Tees has the highest health inequalities in England. Life expectancy at birth reveals a gap between the most and least deprived neighbourhoods of 17.3 years for men and 11.4 years for women (Public Health England, 2015). This high level of inequalities in life expectancy provides the justification for this research project to explore the health gap between the most and the least deprived LSOAs in Stockton-on-Tees. This approach however, has disadvantages, such as the focus on small segment of the population. Furthermore, Bambra (2011) argues that this approach fails to acknowledge the contributions of wider social determinants on health inequalities.

The health inequalities literature now widely acknowledges the presence of a social gradient in health—the lower an individual's social position, the worse is their health (Marmot et al., 2010). Graham (2004) argues that this perspective captures the *'health consequences of poverty'* (p. 118). This approach, therefore, seeks to locate the causes of health inequalities in the wider population and not only in the disadvantaged circumstances but also in the systematic differences in life chances. Tackling the social gradient in health inequalities thus requires:

> *"A comprehensive policy goal: one that subsumes remedying disadvantages and narrowing health gaps within the broader goal of equalising health chances across socioeconomic groups."*
>
> (Graham, 2004; p. 125)

While the advantage of this approach is the potential of achieving maximum health benefits for a large segment of population, it requires more resources compared to the approaches of targeted interventions discussed earlier in this section.

Finally, proportionate universalism is a more recent approach that delivers interventions to wider population but with an adjustment based on the needs of specific groups. This strategy builds upon the idea of social gradient and formulates actions which are universal but at the same time proportionate to the level of disadvantage (Marmot et al., 2010). The 'minimum income for healthy living' is an example of the proportionate universalism approach the government of UK has in place (Bambra, 2011).

Health inequalities and place

With the increased recognition of the significance of place in shaping different social outcomes (Dietz, 2002), health geographers and public health researchers have long been exploring the relationship between place and health. A growing literature has identified the significance of place on people's health and health inequalities (Bambra, 2016, Cummins et al., 2005). A complex relationship exists between place, people and health. Complex in the sense that the characteristics of people (composition) and the nature and attributes of the place (context) act both individually and collectively (Cummins et al., 2007, Macintyre et al., 2002). Further, it has been argued that these health divides between areas are 'political' in nature, influenced by the wider socio-political and macroeconomic context, for example, economic recession and austerity (Schrecker and Bambra, 2015).

A critical review conducted by Pickett and Pearl (2001) has highlighted the importance of place effects on health. In the studies included in the review, Pickett and Pearl (2001) found a consistent neighbourhood effect on health even though these studies mobilised heterogeneous designs and scales of measurements. According to Ellen et al. (2001), place can influence the health of its residents from three different pathways: a) amenities, facilities and resources in the locality; b) through interaction with the physical environment; c) social environment including social capital, as well as the interaction of the three. Cummins et al. (2007) argue that there exists a "mutually reinforcing and reciprocal relationship between people and place" (p. 1835). When the wider body of literature was successful in establishing the role of place, the question then is 'how are inequalities manifested spatially'? The following sections explore the effects and mechanisms of how place can create health inequalities.

The effects of place and neighbourhood on health inequalities

Place is a relational space, which provides an opportunity for the individual to live, work and thrive (Graham and Healey, 1999). Individuals have relatively dynamic and fluid area definitions and most often, Euclidian distance (the ‘ordinary’ straight-line distance between two points in Euclidean space) misses to offer utility as it may not truly represent the realities of how the place is experienced (Cummins et al., 2007). When we think about a neighbourhood, it is not usually confined to the geographical boundaries of administrative units (such as LSOAs or wards) but to where people feel they belong to (Bernard et al., 2007, Horlings, 2016). In public health literature, place usually refers to the neighbourhoods or any geography-based attributes that result in the exposure of the population to health affecting factors (Tung et al., 2017). The relationships between place and health inequalities can be understood at multiple levels—from local areas or neighbourhood to higher spatial scales, for example regional, national and international (Cummins et al., 2007). Authors such as Marston et al. (2005) and Jonas (2006) argue the need for a more ‘sophisticated perspective’ to address the interrelated nature of interactions at different spatial scales which take place simultaneously. In contrast to this ‘sophisticated perspective’, many human geographers emphasise the role of neighbourhood in creating the spatial health gaps (Bernard et al., 2007, Cummins et al., 2005, Goldfeld et al., 2015, Lupton, 2003, Macintyre and Ellaway, 2009, Sykes and Musterd, 2011). Lupton (2003) argues that if we move to larger geographical scales than the neighbourhood to explain geographical health inequalities, the explanatory power could be limited. However, the major question remains—what is a neighbourhood, what are its characteristics and limitations? Galster (2001) has defined neighbourhood as “*a bundle of spatially based attributes associated with a cluster of residences, sometimes in conjunction with other* *land uses*" (p. 2112). He further adds on the importance of spatial attributes of a neighbourhood to understand the scales.

> *"The specification of neighbourhood as a bundle of spatially based attributes, coupled with the notion of 'externality space', allows for the potential empirical identification of behaviourally meaningful, multi-scaled boundaries of 'neighbourhood'."*
>
> (Galster, 2001, p. 2121)

Lebel et al. (2007) point out the use of concepts like locality, local community, borough and county with a similar or close meaning to the neighbourhood in contemporary social research. They have proposed two crucial elements to defining a neighbourhood: the inner characteristics (for example structural, physical and socio-economic characteristics) and the geographical scale. Neighbourhoods in this context are the opportunity structures that consist of relevant resources and socially determined factors that shape an individual's life, thereby impacting on health (Bernard et al., 2007, Pearce et al., 2012). When we look at spatially patterned health inequalities, we have to explore the distribution pattern of these resources. The abundance or scarcity of these resources may suggest some neighbourhoods are healthier than others (Macintyre, 2007).

Despite the relevance of neighbourhood effects in studying health inequalities, Galster (2008) notes six major challenges: scale of neighbourhood, mechanisms of effect, measuring relevant and appropriate characteristics, measuring exposure and dosage, measuring and quantifying effects of individual characteristics and endogeneity (mutual causality of individual and neighbourhood characteristics). One of the solutions he has proposed for these problems is to use "multi-domain databases" (for example censuses and social surveys) that measure all scales of neighbourhood characteristics.

> *"This probably will require the merging of information from a variety of sources, ranging from administrative databases to purposive social surveys."*
>
> (Galster, 2008, p. 29)

Composition and context: complexities and opportunities

Neighbourhoods that are the most deprived have worse health than those that are less deprived – this follows a spatial gradient, with each increase in deprivation resulting in a decrease in average health. In England, the gap between the most and least deprived areas is 9 years average life expectancy for men and around 7 years for women (Bambra, 2016). Traditionally, geographical research has tried to explain these differences at neighbourhood level health by looking at compositional and contextual factors – and their interaction (Cummins et al., 2007, Pickett and Pearl, 2001).

Ecob (2004) proposes the causation of inequalities in health outcomes between places could be better explained by two approaches: 'social causation' which explores the effects of places on health and 'health selection' proposes the continual migration of people in and out of any place brings about health inequalities. Social causation theory links social, environmental and political contexts into health inequalities research. 'Social causation theory' helps in understanding geographical health inequalities by compositional and contextual explanations. Several studies including Joshi et al. (2000) Cummins et al. (2005) have been successful in establishing a strong link of compositional and contextual factors in determining health outcomes.

Composition of health inequalities

The compositional explanation asserts that the health of a given area is the result of the characteristics of the people who live there (demographic, behavioural and socioeconomic) (Centre for Local Economic Strategies, 2014). Curtis and Rees Jones (1998) argue compositional explanation claim people with similar characteristics have similar health irrespective of where they live. The profile of the people within a community (demographic [age, sex and ethnicity], health-related behavioural [smoking, alcohol, physical activity, diet, drugs] and socio-economic [income, education, occupation]) influences its health outcomes.

The wider literature suggests that there are several interacting pathways linking individual-level socioeconomic status and health: behavioural, material, and psychosocial (Bartley, 2004). The 'materialist' explanation argues that it is income-levels and what a decent or high income enables compared to a lower one, such as access to health-benefitting goods and services and limiting exposures to particular material risk factors. The 'behavioural-cultural' theory asserts that the causal mechanisms are higher rates of health-damaging behaviours in lower socio-economic groups. The 'psychosocial' explanation focuses on the adverse biological consequences of psychological and social domination and subordination, superiority and inferiority.

When compositional factors are solely mobilized to understand the causation of health inequalities, Curtis and Rees Jones (1998) highlight the possibility of two problems: firstly 'ecological fallacy', which encourages researchers to make cautious conclusions as inaccurate assumptions could be generated for the individuals based on the aggregated results. Secondly, 'atomistic fallacy' may follow the study when too much emphasis is laid on individuals and the effects of neighbours and households are overlooked.

Contextual explanations

The contextual explanation, on the other hand, argues that area-level health is determined by the nature of the place itself, in terms of its economic, social, cultural and physical environment. Contextual explanation looks for relationships between the attributes of localities with health inequalities (Curtis and Rees Jones, 1998). These contextual factors refer to various aspects of the environment: physical, socio-economic or political and “*they affect health over and above the contribution of aggregate individual characteristics*” (Bernard et al., 2007, p. 1840). Of the 25 studies critically reviewed by Pickett and Pearl (2001), 23 studies reported a significant association between contextual factors and health outcomes, this figure was obtained after adjusting for compositional factors. Measuring health inequalities at an area level is more convenient than doing so at an individual level, which in turn can play an important role in developing appropriate policies to address health inequalities (Law, 2009). Bernard et al. (2007) classified contextual (environmental) factors into two major categories—physical and social components. The theoretical framework they developed consider the wider social components and addresses the relationship between these domains (see Figure 2.3).

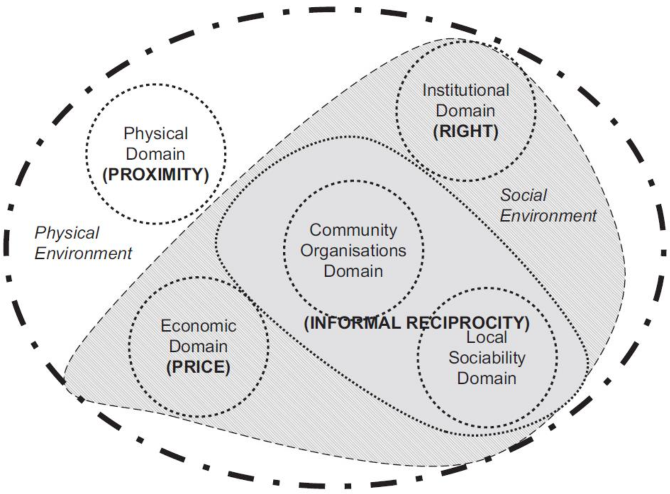

Figure 2.3: Contextual determinants and rules of access (Bernard et al., 2007, p. 1843)

Based on this theoretical framework, Table 2.3 summarises the contextual factors that are part of the physical and social environment.

Table 2.3: Summary of contextual factors ‘relevant’ to austerity research

Domain	Contextual factors
Physical	
Physical	Green space (Maas et al., 2006) (Lee and Maheswaran, 2011), Air pollution (Richardson et al., 2013), brownfield (Bambra et al., 2014b), walkability (Pearce, 2015), urbanity (Maas et al., 2006), adverse traffic conditions, with less litter, vandalism and graffiti
Social	
Economic	Job density, employment opportunities, SES condition/ area-level deprivation (King et al., 2006, Riva et al., 2007).
Institutional	Gambling (Wardle et al., 2014); access to health care services; convenience stores; supermarkets; fast food outlets; liquor stores; transportation and other municipal services
Sociability and community organisations	Neighbourhood disorders (e.g. violence, crime rate) (Bilger and Carrieri, 2013, Chiavegatto Filho et al., 2012); social interaction (which could possibly be covered by social fragmentation index); reputation of an area

Understanding the local context of health inequalities as a result of austerity requires a multidisciplinary approach. Such an approach should rely on clear theoretical grounds, and be based on geographical perspectives. A wider body of literature offers theoretical explanations of the mechanisms of contextual influence on health outcomes. Pearce (2013) has proposed four 'non-exhaustive and inter-related' themes to explain geographical health inequalities as repercussions of austerity:

a) Changing social geographies;

b) Migration, mobility and health;

c) Environmental justice, health and inequalities;

d) Blemish of place

Firstly, 'changing social geographies' theme deals with the unequal distribution of resources. It makes an impact on SDOH (see later section: Austerity and health, page 55), which influence the conditions of daily life, hence creating unequal health outcomes (Marmot et al., 2012). Pearce (2013) argues austerity imposition resulting in reduced government spending in welfare programmes affect these SDOH in one or the other form. As is evident, budget cuts are not even, some areas suffered more cuts and are now prone to greater human costs (Taylor-Robinson et al., 2013). Areas that are more affected when market-oriented economics take over the welfare system are employment, housing, healthcare and education. After the coalition government was formed in 2010, the North East region, where Stockton-on-Tees lies, saw the largest reduction of people working in the public sector 12 percent (Pearce, 2013).

Secondly, migration, mobility and health deals with the mobility of people in between the 'healthy' and 'unhealthy' places. Pearce (2013) argues the trend of selective migration can give rise to geographical health inequalities. Some studies (Brimblecombe et al., 1999, Brimblecombe et al., 2000, Martikainen et al., 2008) in the UK have explored the role of migration in widening health gaps between the geographical units. A longitudinal study conducted by Norman and Boyle (2014) using the data from the Office of National Statistics (ONS) found that geographical health inequalities were strongly linked to the rate of migration. They concluded that "*[M]igration, rather than changes in the deprivation of the area that non-migrants live in, accounts for the large majority of change"* (p. 2755).

Thirdly, 'environmental justice, health and inequalities', Pearce (2013) encourages the exploration of the role of environmental policies that changed after the imposition of austerity. This theme comes to light with the wider recognition of the physical environment as a strong determinant of population health. It is also an important predictor of area-level health inequalities (Bambra et al., 2014b, Pearce et al., 2011). To tackle the budget cuts, several local authorities have adjusted their activities, which have lead to reduced investment on health-promoting and environmental projects. A study conducted by Pearce et al. (2010) found out area level health was inversely related to the Multiple Environmental Deprivation Index (MEDIx) a composite index representing multiple dimensions of health-related environmental amenities. Another study by Bambra et al. (2014b) found a strong association between the proportion of brownfield sites in an area and the morbidity of people living near it.

Finally, by 'blemish of place', Pearce (2013) presses the importance of the perception of 'place' in creating geographical health inequalities. Quite often, place-based stigmatisation is associated with socio-economic inequalities and can be a cause of geographical discrimination (Pearce, 2013). ‘Territorial stigmatisation’ produces inequalities and marginality in an area, which in turn gives rise to place-based health inequalities (Wacquant et al., 2014). Keene and Padilla (2014) have proposed three pathways by which spatial stigma produces inequalities in health: (1) differential access to resources; (2) lack of social capital to manage and cope with the stress; and (3) issues related to place-based identity. A study conducted by Wutich et al. (2014) found a significant association between spatial stigma and social capital/bonding with the health of the population. Since 2010, the socio-economic context of the UK has significantly changed. Townsend (2014b) has highlighted how the market streets in the UK have seen proliferation and/or clustering of outlets such as fast-food takeaway, money lenders and betting shops. These outlets are mostly concentrated in more deprived areas and have more negative human consequences (Townsend, 2014a). Summary of these mechanisms has been outlined in Table 2.4 below.

Table 2.4: Summary of contextual influence of austerity

Themes	Explanations
Changing social geographies	Unequal distribution of resources leading to possible competition (see page 46)
Migration, mobility and health	Possible ‘selective migration’ due to socio-economic and environmental conditions.
Environmental justice, health and inequalities	Physical environment of a neighbourhood is a strong predictor of area-level health inequalities. Austerity possibly impacts in health-promoting environmental projects.
Blemish of place	Place-based stigmatisation can rise with the change in market and neighbourhood structure (see institutional mechanisms, page 48)

The collective dimension

Macintyre and Ellaway (2009) argue that a clear differentiation between compositional and contextual factors determining health inequalities is, in a general sense, impossible. They write:

> *"However, even though, as some have argued, it may be theoretically and methodologically impossible completely to separate compositional from contextual effects, for the purpose of policy making, and of furthering our understanding of the processes which generate and maintain inequalities in health, it is still useful to think about how neighbourhoods might influence the health and health behaviours of the residents."*
>
> (Macintyre and Ellaway, 2009, p. 87)

It is argued by many health geographers (Bernard et al., 2007, Duncan et al., 1998, Macintyre et al., 2002) that composition and context are 'mutually exclusive, competing, and culturally and historically universal'. For example, compositional-level individual factors such as employment and job status of the people living in an area are influenced by the contextual-level characteristics of the local labour market, and these contextual factors are in turn influenced by the wider political and economic environment - with, recessions and austerity, impacting again on local labour markets (Bambra, 2016).

Moving away then from the conventional approach of focusing only on the contribution of compositional *or* contextual factors, Cummins et al. (2007) suggest two approaches to understanding the relationships between place and health inequalities:

a) Context and composition are to be studied together to remove 'false dualism';

b) Time, scale and spatial components are to be added to the analysis.

This approach not only reconnects people and place but attempts to signify the importance of scale in understanding geographical health inequalities. It highlights the dynamic nature of place—how it is constructed and represented in research and how it is embedded in an individual's life. Place in this relational sense may not be defined by geographical administrative boundaries but by 'node in a network'—linked through social, economic and political relations (Horlings, 2016; p. 33).

Duncan et al. (1998) propose the use of multilevel modelling (MLM) to analyse the compositional and contextual effects in the production of health outcomes. MLM not only considers micro-scale compositional factors but also includes the macro-level contextual factors, hence considered 'conceptually realistic' in exploring the health inequalities at area-level. By considering MLM and performing composition-context analysis, Lupton (2003) has argued the evidence of place effects can be strengthened, and this can provide a sound base for policy decisions.

> *"By introducing contextual variables into the individual characteristics/ individual outcomes equation, it can re-introduce the role of the social system into analyses of individual behaviour and outcomes. Moreover, it can measure and prove the influence of the social system, rather than simply explaining it…"*
>
> (Lupton, 2003, p. 2-3)

In contrast, Williams (2003) argues that the use of multilevel modelling attempts to separate the contextual effect from compositional effect but in doing so, it gives rise to another 'false dichotomy'. By this approach, we fail to understand the 'conjoint influence' of place and individuals to bring the health outcomes. To overcome this complex situation, enhancement in the multilevel modelling (e.g. hierarchical geo-statistical modelling) and use of Geographic Information System (GIS) has been suggested by Curtis and Riva (2009). They write:

> *"…Recent developments in multilevel modelling (MLM) allow very complex structures to be addressed, including 'cross-classified' and 'multiple memberships' of geographically defined populations and measurement of 'cross-level interactions' where the context of a particular setting may have differential effects on certain types of individuals. Advances in GIS techniques for spatial analysis allow for more complex modelling of the spatial diffusion and patterning (eg, clustering) of diseases. Geographical research using these techniques is expanding, although data availability and sufficiency may impose limitations in modelling this degree of complexity."*

(Curtis and Riva, 2009, p.5)

Identifying the mechanisms of neighbourhood effects in health gaps

Differential exposure to the 'local geographical circumstances', brings about the differential health status of the population (Pearce, 2015). The ecological model/system emphasises the constant interaction between the individuals and their surrounding environment (both social and physical) in creating health gaps (Bentley, 2014, Bronfenbrenner, 1994, Shareck et al., 2013). Lupton (2003) show if similar individuals living in two different neighbourhoods have different (health) outcomes, there could be 'specific mechanisms' to describe the gap.

> *"…there needs to be some mechanism for reflecting the interactions between people and place, in order not to identify neighbourhood effects that really arise from individuals, or vice versa."*

(Lupton, 2003, p. 13**)**

The mechanism of health impacts can differ depending upon the context and dosage of such exposure. Due to the dynamic nature of the individual and the environmental attributes, single mechanisms may not sufficiently describe the reality of geographical health inequalities. Jencks and Mayer (1990) have made contributions to this area proposing five mechanisms: neighbourhood institutional resources model (public resources and service sites); collective socialisation model (role-models); contagion (social contact and interactions); competition model; and relative deprivation model**.**

Buck (2001) expanded on work by Jencks and Mayer (1990) producing nine models of neighbourhood effects: epidemic (similar to contagion model); competition (between groups to control local scarce resources); collective socialisation (role-models and culture transfer); institutional (type and quality of services within the neighbours); relative deprivation; network (social inclusion); expectation (experience based); insecurity (safety perception); and physical isolation (barriers to access services)**.** Numerous contributors have sought to explain the mechanisms which produce neighbourhood effects on health, and many of their explanations overlap. Galster (2010) has proposed four specific, yet broad mechanisms to describe the role of place in creating unequal health status these are: social-interactive mechanism; environmental mechanism; geographical mechanism and institutional mechanism**.**

Social-interactive mechanisms

Galster (2010) links these mechanisms to the 'endogenous' processes and components within the neighbourhood. Dynamic social interactions occur in every stage of the life course and can result in cumulative impacts, which even can be noted across generations (Hedman et al., 2015). The opportunities for interactions with a neighbourhood's social environment can influence (both negative and positive) on individual's norms, values and attitudes. The nature of this interaction makes a significant difference in how an individual behaves, and ultimately to health outcomes (Brannstrom and Rojas, 2012).

The health and wellbeing of the population is influenced by interactions between both the physical and social environment in the neighbourhood. Social interaction and place/neighbourhood are two inseparable entities, one depending upon the other (Lupton, 2003). The characteristics of a place may change based on prevailing social interactions, this dynamic is a result of the production and consumption relationship between them. Lupton (2003) clarifies this by pointing out *"[T]hey (Neighbourhood environment) are being constantly re-created as the people who live in them simultaneously consume and produce them"* (p. 5). Most importantly, this relationship will vary between geographies, thereby creating differential health outcomes. Galster (2010) has identified seven different processes of social interaction, which can be linked with the differing health status of people living in different places: social contagion; collective socialisation; social networks; social cohesion and control; competition; relative deprivation and parental mediation (for details, see Table 2.5, below)

Table 2.5: Summary of social-interactive mechanisms

Processes	How can it bring differential health?
Social Contagion	The health-affecting behaviours and attitudes are mostly influenced by the contact that occurs with peers and residents in their neighbours. The usual occurrence of clustered behaviour among the social contacts is common (Salathé et al., 2013).
Collective socialisation	Individuals living in a neighbourhood are encouraged to conform to the established norms and cultures, which is, in most of the case by social pressure. Exposure to disadvantaged neighbours can induce heightened risks of an individual adopting health-damaging behaviours (Wright et al., 2014).
Social Networks	Social networks have a prominent value in social capital, whose role in creating health inequalities is undeniable. The shared social identity and behaviours are the building blocks of social networks. Uphoff et al. (2013) argue places with 'better' social networks have a higher level of social equality, better health outcomes and fewer social problems.
Social cohesion and control	Social cohesion glues together the social networks, controls social disorders and acts as the buffer to minimise the negative health impacts of deprivation in the neighbourhood (Uphoff et al., 2013).
Competition	Social groups compete to use/control the limited local resources.
Relative Deprivation	Hierarchy creation based on the level of deprivation. People from most deprived areas envy least deprived areas.
Parental Mediation	Neighbourhood influence the parents' behaviours and practices, which is usually the basis of creating a conducive home environment for the children (Goldfeld et al., 2015).

Environmental mechanisms

The spatial distribution of natural and human-made attributes causes direct impacts to the mental and/or physical health of the people living in the neighbourhood. Pearce (2015) links these mechanisms to "environmental (in)justices and health". His views are directed towards describing the dispersal of environmental "*goods*" and "*bads*". The socio-spatial distribution of 'pathogens' (such as violence, pollutants) and '*salutogens'* (such as public parks and healing places) is based on the type of communities; earlier being concentrated in the socially deprived areas and later being more common in less deprived neighbourhoods. This differential distribution of environmental attributes has been found to be associated with existing/widening geographical health inequalities (Maas et al., 2006, McCartney et al., 2012, Thomas et al., 2010). Galster (2010) has proposed that there are three forms of environmental mechanisms (see Table 2.6)

Table 2.6: Summary of environmental mechanisms

Processes	How can it bring differential health?
Exposure to violence	Psychological and/or physical response to the exposure to violence in the neighbourhood
Physical surroundings	The psychological response to the condition of the built environment in the surroundings.
Toxic exposure	Presence and exposure to the unhealthy level of air, water and soil pollutants in the neighbourhood. Differential level of exposure may be established for people living in deprived and affluent places.

Geographical mechanisms

This refers to the way how 'relative spatial components' can affect the health and wellbeing of the people living in a specific geographic location. Hedman et al. (2015) argue that people living in deprived locations on a long-term basis, with limited or poor quality services become caught in a vicious cycle of poverty and ill health. Galster (2010) has proposed two forms of geographical mechanisms: spatial mismatch and public services.Frumkin (2005) highlights the role of spatial mismatch in creating geographical health inequalities by saying "p*erhaps most important, the spatial mismatch between where poor people live and where jobs are available, as well as* *the inability to get to good jobs, consigns people to ongoing poverty, a principal predictor of poor health"* (p. 290). This mismatch of economic opportunities can be aggravated by the longer commuting hours to reach work sites and can accompany the exposure to higher levels of pollution (McCartney et al., 2012).

Limited tax base resources and operational challenges are amongst the factors that determine the type and quality of public services available in the neighbourhood (Galster, 2010). Carey (2014) argues about the criticality of universal access to public services, which in the ground should be formulated based on the need of the communities. Deprived and less deprived communities may have different needs, but universal services may favour some areas, leaving others behind.

Institutional mechanisms

Sykes and Musterd (2011) raise the question of *how* institutional contexts can exert disadvantage or benefits for people living in a neighbourhood. They also shed light on the importance of the background determinants. In contrast, Galster (2010) argues that institutional mechanisms are exogenous in nature, involving external agents, those controlling the resources/institutions as identified by Sykes and Musterd (2011). Galster (2010) has identified three forms of institutional mechanisms: stigmatisation, local institutional resources and local market actors.

Stigmatisation by either public or private sectors may have negative health impacts, which are mostly psychological. Lawder et al. (2014), in their study, have successfully established the depressing effects of area-level stigmatisation. The type and nature of local institutional resources can vary depending on the level of deprivation, or alternatively can bring about advantages or disadvantages.

> *"The notion of an institutional mechanism of a neighbourhood effect refers to the fact that neighbourhoods vary in terms of the quality, availability and access to institutions and services, such as libraries, childcare facilities, health services, schools and educational programmes, and this variation can bring about advantages or disadvantages for individuals."*

(Sykes and Musterd, 2011, p. 4)

Prevalence, locations and easy access to local markets may be an important predictor of health-affecting behaviours. The mostly cited amenities bringing about a difference in the health behaviours of the individuals living in a neighbourhood are fast food restaurants, liquor stores and fresh food markets amongst many. For example, Pearce et al. (2012) and Shortt et al. (2015) argue that there is a greater availability of tobacco and alcohol outlets in more deprived areas and that they contribute to the social gradient in tobacco and alcohol related harms.

Recession, austerity and health inequalities

The financial crisis of 2007 - the worst since the Wall Street crash of 1929 led to the onset of what has been called the 'Great Recession'**.** There had been several post-war financial downturns in western European countries (e.g. the 1970s and 1990s) but none as serious on economic and social grounds as that which has affected the whole of Europe and the UK since 2008 (Ifanti et al., 2013). Recession is characterised by increased instability and decreased production and consumption as a result of increase in unemployment rate. Recession has a devastating impact on the health of the people, mostly from the financial aspect. The rate of job insecurity, redundancies and unemployment increase with recession and these situations have negative health consequences (Bambra, 2011). While the mental health impacts of the financial shock could be noticed sooner (Nordt et al., 2015), the exposure to the crisis during childhood could still have impacts in the later life (Rajmil et al., 2014). Evaluating the health effects of recession is thus a complex and challenging process. Barr and Taylor-Robinson (2016) argues that the exposure to recession is difficult to measure and that there is an uneven time lag between the exposure and health outcomes. The level of exposure can also vary between subgroups within the population and is unevenly distributed geographically—vulnerable groups are the most exposed to these risks (DryDakis, 2016). In contrast, the recessions can also have ‘paradoxical’ health effects, such as the decline in mortality rates in the developed countries during the twentieth century (Bezruchka, 2009). The paradoxical health effects are, however, only achieved through the stimulus from the government. Barr and Taylor-Robinson (2016) argues that the role of government in preventing recessions could be limited but their response does make a difference during the post crisis period. There are two sets of policy tools with the government to tackle the recession: financial stimulus packages and austerity. The expeditious financial stimulus packages are crucial in stabilising the economy and preventing the human cost of recession. Blinder and Zandi (2010) argue that the series of fiscal stimulus in the USA were the most crucial actions from the government to stop the damaging impacts of recession and help in the financial recovery. However, austerity policies are more focused on reducing government spending and this approach has more health damaging consequences (Stuckler et al., 2017).

Though there have been strong voices against austerity as a response from government, it remains in place and its impacts are ongoing (Baker, 2010). The economic recession negatively impacted the overall development and progress of many regions leading to a situation of developmental stagnation in several states, for example, Greece and Spain. After the crunch, most of the Eurozone countries developed and placed stringent fiscal policies either on their own or by the mandate of international financial institutions (McKee et al., 2012). Those countries which were supposed to be resilient to fiscal crisis are now on the brink of social disasters due to shortcomings in their social safety net policies (Ricciardi, 2013).

To mitigate the situation and to build a resilient fiscal status, these policies are often forwarded as the only sensible tactic by right-wing politicians. With either of the strategies, these austerity policies are characterised by the miscalculation of the adverse effects and the social costs associated with the harmful effects on the citizens (Kentikelenis et al., 2014).

The United Kingdom had austerity policies in hand before the real situation of crisis came into existence which has been described by Blyth (2013) as 'pre-emptive tightening'. Though this strategy was taken into consideration with a motive to adopt the austerity policies first and securing the benefits after the crisis returns to an acceptable level, but it has not given the desired outcome – of deficit reduction and economic growth. Blyth (2013) argues that compared to similar states, the economic indicators of the UK show the failure of austerity policies in tackling the economic situation and giving rise to an understanding that 'austerity hurts rather than helps' (Blyth, 2013, p. 5).

The rise in income inequalities in the UK was followed after neoliberalism was adopted from 1979, which in turn paved the way of welfare cut programmes (Schrecker and Bambra, 2015). Hall et al. (2013) argue that the Coalition government used the financial crisis as a justification to further establish the neoliberal economics and to underpin its strong commitment to neoliberal ideology, which will eventually lead to the re-distribution of wealth—from the poor to the rich. The failure of safety nets in protecting the vulnerable groups will also further expand income inequalities. The idea of neoliberal economy involves the restructuring of the state along with the market and private enterprises, for example, the 2012 Health and Social Care Act opens the way to increased marketization of the National Health Service (NHS) (Speed and Gabe, 2013). Pownall (2013) argue that the Health and Social Care Act offered three advantages to the government: to address the budget deficit, shrink the public sector and to open space for the market.

In the UK, following the 2010 election, the coalition government reduced spending on social welfare. These funding cuts in the UK are geographically patterned and the worst hit areas are those that are already the most socially disadvantaged (Beatty and Fothergill, 2016). Lowndes and Pratchett (2012) argue that the cuts were in all public services and disproportionately distributed, the local government budget was the most targeted point. They further write:

> *"To address the supposed crisis it (the coalition government) proposed to cut public services fast and deep, with £30bn of spending cuts being announced over a four year period… In total, it targeted a cut of 490,000 public sector jobs, with an average 19 percent cut over four years to Departmental budgets and a further £7bn cut in the welfare budget… Local government faced a disproportionately high share of the cuts, with the Department for Communities and Local Government (DCLG) seeing a 27 percent cut in its local government budget and a 51 percent cut in its communities' budget over the four year period."*

(Lowndes and Pratchett, 2012, p. 23)

Hall et al. (2013) argue that these welfare reform actions have widened the gap between the economically stable and the poor. Not only economic, but social and geographical effects of austerity are unequally distributed in the UK. Since the imposition of austerity, public spending has been reduced and market-led growth prioritized (Kitson et al., 2011). Public spending cuts in the UK also vary between local authorities and the worst hit areas are those most socially disadvantaged, which has increased the likelihood of widening deprivation and health inequalities (Pearce, 2013).

Whilst Lowndes and Pratchett (2012) pointed out the disproportionate budget cuts of local authorities, the work of Taylor-Robinson et al. (2013) has revealed the spatial variation of per head budget cuts, which shows a clear North-South divide (for details, see The spatial health impacts of austerity, page 61). Local authorities in the North have ‘systematically’ higher budget cuts. This shows how inequalities have spatial forms. The real challenge then comes when we attempt to generalise this observation throughout all areas within these local authorities. The geography of austerity can not only vary between larger areas, ‘within-area’ variation cannot be ignored, which is the whole point of studying Stockton-on-Tees.

The decision to reduce the state’s role in public sector has been termed as a ‘major political gamble’ by Morgan (2013). After the enforcement of austerity, the government’s role has retracted in sectors such as investment in infrastructure development and in the provision of welfare services (Pearce, 2013). Public services such as, but not limited to education, health, housing and social protection programme have all received major funding cuts. Clarke and Newman (2012) have argued that this step of retrenching public services can increase vulnerability among the people relying on them. Curtis and Leonardi (2012) in their collection of commentaries have concluded that there are differential ‘deleterious effects’ of recession and austerity, the less advantaged groups (under/unemployed people) being the worst impacted. A study by Loopstra et al. (2015) has highlighted the link between the ‘greater’ welfare cuts and the opening/use of foodbanks in the UK. Local authorities experiencing budget cuts were more likely to have foodbanks established in their areas. The same study has also demonstrated a significant link between foodbank use and unemployment. Another study by Loopstra et al. (2016b) has demonstrated a strong link between the welfare cuts and the rates of homelessness. This clearly indicates how austerity and inequalities can result in a vicious cycle and creating confusion over which is the cause and which is an outcome.

> *“Those who use public services or whose incomes derive from social protection programmes are also in line to suffer disproportionately from austerity programmes. This points to the ways in which new landscapes of inequality get mapped on to existing ones, since both public service use and benefits are already (largely) ‘targeted’ on vulnerable and impoverished groups. Plans for further ‘targeting’ will increase vulnerability as benefits become more conditional and services become increasingly means tested and difficult to access.”*
>
> (Clarke and Newman, 2012, p. 8)

Austerity policies have been criticised as having more negative impacts than positive ones (O'Hara, 2014). There have been remarks by several analysts that “austerity measures, not the recession itself” are the causative agents of ‘social disasters’, for example, by intensifying the problem of social inequalities (Arie, 2013, p. 1). The majority of the social sectors of the welfare state have been the victim of austerity policies leading to widespread criticism (Ginn, 2013, O'Hara, 2014). O'Hara (2014), has argued that austerity in the UK is ‘a fallacy’, that has done more harm than good and has increased vulnerability in society. In a working paper published by the

International Monetary Fund (IMF), the fiscal regulating body, Blanchard and Leigh (2013) have accepted the miscalculation and underestimation of austerity in uplifting the economic crisis. The paper has also highlighted that there was a slightly larger degree of underestimation associated with the reduction of government spending in the countries in the European Union. Ginn (2013) has highlighted that austerity is ‘counterproductive’ in tackling the crisis, it is ‘unfair’, and can potentially inflame social division, hence increasing the severity of prevailing inequalities. It is undeniable that population health is a cross-cutting issue when we consider austerity. Through direct and indirect pathways, austerity impacts on population health, in a disproportionate fashion, giving rise to inequalities at various scales (Stuckler and Basu, 2013).

Austerity and health

The health effects of austerity and financial crisis can be short-term because of the decline in disposable income or long-term because of the changes in the labour market—employment and working environments (Labonte and Stuckler, 2016). Stuckler et al. (2017) argue that the public health impacts of austerity are resulted either through ‘social risk effects’ or through ‘healthcare effects’. The social risk effect mechanism deals with the socio-economic consequences of austerity such as rising unemployment, poverty, food insecurity and homelessness. Whereas the healthcare effect mechanism explains how health inequalities can be the results of budget cuts to the healthcare and social sectors (Stuckler et al., 2017). Unlike other European countries, the austerity policies of UK were mostly focused on cutting incomes, minimising the administrative bodies and achieving efficiencies from substituting health care services (Wenzl et al., 2017).

Pearce (2013) has succinctly highlighted that fewer studies are directed towards the exploration of the impacts of recession and austerity in human health. He has argued that most of the studies have been directed towards the economic and political spheres and not population health. Even with this limited literature and studies, the negative consequences of austerity have been established. Austerity as a response to financial recession affects population health in one form or another (De Vogli and Owusu, 2014). Desai et al. (2012) write *"[T]he links between economic cycles and health are complex*" (p. 637), which shows how the financial recession, austerity as its response and population health can be interrelated. De Vogli and Owusu (2014) in this context present both deleterious and protective effects of recession and austerity upon population health. They have argued that the material and social conditions after austerity can impact health negatively. At the same time, 'paradoxically', reductions in mortality rates from causes like road traffic accidents can be linked to the protective effects (Stuckler and Basu, 2013). While the relationship between recession, austerity and health is now undeniable (Labonte and Stuckler, 2016), Pearce (2013) argues the impacts are not equally distributed (details of this is explored in the next section: page 61). According to him, health inequalities on different grounds are the by-product of austerity. Karanikolos et al. (2013a) argue, for the wellbeing of the individual and the society, maintenance of expenditure in the health sector and sectors other than health is equally important. With the recession, debates erupted in the UK about 'ring-fencing' the NHS budget. In this particular context, they have argued about the relevance of social determinants of health (SDOH). They believed population health is not just the result of the healthcare budget; it is indeed an outcome of its interactions with determinants other than the health care system, clearly indicating to SDOH.

In the UK, the social care (services ranging from child protection to end-of life care) fund has suffered as a result of austerity, despite an increased demand, 1.19 percent annual reduction in adult social care fund was seen between 2010 and 2014 (Watkins et al., 2017). Watkins et al. (2017) have also argued that cuts in public expenditure in social care are responsible in significant inequalities in mortality and increase in funding is the only solution to bring it back on track. After the financial hardship the UK experienced since 2008, the public health impacts of austerity has attracted more attention (Karanikolos et al., 2013b). Health is a cross-cutting issue which is linked to all other social sectors which have been affected by the crisis and the financial adjustment policies. The negative health impacts seen are either as a direct result of financial cuts in health care or as an indirect outcome of the constriction in other social programmes, particularly welfare state and local authority cuts (Bambra and Garthwaite, 2014).

Table 2.7: Timeline of welfare reform in the UK

Date	Measure
April 2008	Introduction of LHA as basis for HB in PRS, based on median rent in the BRMA for size of property needed by claimant's household. Single people under 25 restricted to rent levels in shared accommodation.
Oct 2008	Introduction of ESA as replacement for IB, and introduction of the more stringent 'work capability assessment' administered by ATOS.
April 2011	LHA rates reduced to 30th percentile of local rent levels; 5-bedroomed rate abolished.
	Up-rating of benefits restricted to CPI level.
	Child benefit frozen.
	Changes to tapers and eligibility for WTC and CTC.
April 2011-April 2014	Migration of existing IB and SDA claimants to ESA.
	'Unfreezing' of NDDs for HB and up-rating over 3 years to bring them up to where they would have been had they not been frozen in 2001
Sept 2011	EMA abolished in England
Jan 2012	LHA age for self-contained accommodation rate moves from 25 to 35.
April 2012	New lone parent rate IS claims limited to those with children under 5.
	Further changes to WTC and CTC.
	Contributory ESA time-limited to 52 weeks.
Jan 2013	Child benefit withdrawn from individuals earning more than £50000.
April 2013	CTB replaced by locally determined council tax support schemes, delivered within a 10% budget cut.
	Social Fund replaced by locally determined schemes for crisis loans and community care grants.
	HB to social tenants limited to less than actual rent if claimant has one spare bedroom (14% reduction) or more (25% reduction)
	DLA replaced by Personal Independence Payments for new claimants.
	Up-rating of working-age benefits not related to disability restricted to1%
April 2013-Oct 2017	Migration of all existing working-age DLA claimants onto PIP.
April 2013-Sept 2013	Benefit cap whereby total welfare payments made to working-age households limited (via HB) to approximate average net wage levels.
Oct 2013	Start of Universal Credit, merging all existing means-tested benefits.
Oct 2017	Full implementation of Universal Credit

Source: Edwards (2012; p. 24)

Recessions and austerity measures impact multiple (and major) domains of societies, including employment, housing, social security and finally health (Ifanti et al., 2013).

Table 2.7 (see above) summarises the timeline of different measures of welfare cuts by the government. The impacts of welfare cuts could also be delayed as the timeline for each event is different. All these domains are interconnected with the social determinants of health. Austerity measures primarily have seriously marred the employment sector with the severe loss of job opportunities. Curtis and Leonardi (2012) have succinctly shown how austerity can induce health inequality by *"…the typically deleterious effects of recession on less advantaged groups, who are more likely to become unemployed and may be most affected by restraints on welfare programmes"* (p. 1). Unemployment has been an important aspect which causes widespread social concern. Poverty has increased as a result of decreasing family income and removed social safety nets (Bini Smaghi, 2013). With these policies in action, employment has shifted to more 'precarious' forms in terms of both payment and security. This situation is described as being exacerbated by the widespread implementation of austerity policies by (Bambra et al., 2014a). With a rise in unemployment, crime rates also tend to increase - causing social unrest (Ponticelli and Voth, 2011). Research on austerity has shown that alcohol misuse and related mortality increased by 28 percent with every three percent increase in unemployment between 1970 and 2007 (Stuckler et al., 2009). In the UK unemployment rates increased from 5.2 percent in 2008 to 7.8 percent in 2010, rates were even higher in the younger population (Bell and Blanchflower, 2010). The situation is worse for Northern England as high rates of unemployment prevail in all local authorities in this region (Bambra and Garthwaite, 2014). The long-term unemployment rate in Stockton-on-Tees in 2015 stood at more than 8.7 percent which is almost double the national average of 4.6 percent (Public Health England, 2016).

The spatial health impacts of austerity

Causation and instances of the health effects of austerity are complex, as is the issue of health inequalities. This situation gets even more complex when a spatial component is attached to this interaction. While linking health with the financial recession, Desai et al. (2012) write *"[T]he socio-economic contexts and structures through which economic conditions influence both health processes and levels of health inequality are different in each country"* (p. 637). When we understand 'each country' in this statement as a 'spatial' unit, it gives us a clue that the health outcomes (or health inequalities) as a result of austerity can vary between different places. When we consider the trio of austerity, health inequalities and geography, the interaction calls for a rigorous exploration of literature to ascertain the way they interact and the outcome they can bring.

The spatial health impacts of austerity are distributed unevenly among different segments of the population. As is the observation with the overall social impacts of austerity, health impacts are most pronounced within the most vulnerable groups in society. For example, a higher level of poor health has been seen between the northern and the southern regions of the UK, the so-called 'north-south divide'. It has been suggested that the coalition government's cuts to public spending are negatively skewed by local authority budget cuts and welfare reform disproportionately affecting the North (Bambra and Garthwaite, 2014). This has led to concern about widening deprivation and increases in health inequalities (Bambra and Garthwaite, 2014, Beatty and Fothergill, 2016, Pearce, 2013). However, there is little empirical assessment of the effects of austerity on geographical inequalities in health (Pearce 2013). The studies that do exist, however, have suggested a negative impact. For example, Niedzwiedz et al. (2016) found that reductions in spending levels and increased welfare conditionality adversely affected the mental health of disadvantaged social groups. Austerity measures have also affected vulnerable old-age adults as a study by Loopstra et al. (2016a) has noted, rising mortality rates among pensioners were linked to reductions in social spending and social care. Across England, there have been widening inequalities in mental health since 2010 (Barr et al., 2015) with the largest increases in poor mental health (including suicides, self-reported mental health problems and anti-depressant prescription rates) in the most deprived areas (Barr et al., 2016).

Taylor-Robinson et al. (2013) in their analysis found that North England received systematically larger budget cuts compared to the south. Furthermore, local authorities with higher premature mortality were the ones receiving the largest share of budget cuts (see Figure 2.4).

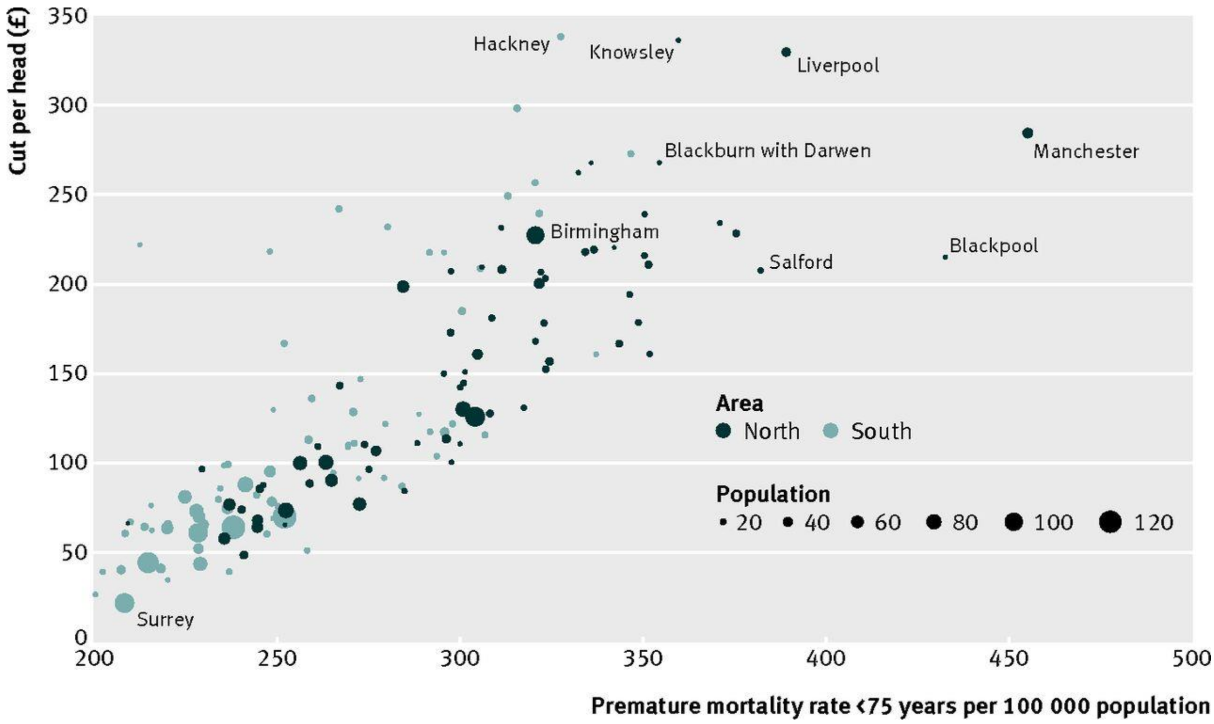

Figure 2.4: Local authority budget cuts 2010-11 to 2014-15 versus premature mortality (Taylor-Robinson et al., 2013)

The prevailing North-South divide on socio-economic differences has been cited as the cause of existing health inequalities in England, with the North experiencing more deprivation and hence poor health (Whitehead and Doran, 2011). A report published by Whitehead (2014) found health inequality based on the social gradient to be worse in the North compared to the rest of the country. Furthermore, health inequalities on grounds of geographical divisions show a clear correlation with 'rapid deindustrialisation', for example in the North East region of England (Norman and Bambra, 2007).

The constant increase in socio-economic inequalities over the recent decades has accompanied the 'spatial polarisation' of the UK population, which has a prominent role with the prevailing geographical health inequalities (Dorling and Thomas, 2009). Stuckler and Basu (2013) argue that the imposition of austerity has again helped worsen the situation of geographical health inequalities. The majority of the studies in the UK conducted to explore the extent of geographical health inequalities have been on a national scale and by utilizing national level datasets. Criticisms of national level statistics direct the failure in the representation of the proximal area level situation or even the inequalities that persist between areas (Cummins et al., 2005, Shouls et al., 1996). Hence, smaller area-based approaches are the crucial tools which can address geographical health inequalities and precisely measure the contributions of the place bringing out the differential outcomes (Graham, 2000). This identifies a clear need for studies at the local level with an application of geographical theories to better understand the causes of spatial health inequalities.

Analysis of the data from England and Wales conducted by Bennett et al. (2015) shows the widening gap of life expectancy based on the geographical and temporal component. Based on 'Bayesian spatiotemporal forecasting models'[1], they have projected the widening inequalities of life expectancies at Stockton-on-Tees after the imposition of austerity, which is expected to widen compared to the national average (see Figure 2.5). Bennett et al. (2015) included geocoded mortality and population data between 1981 to 2012 and related them to age, birth cohort, time and space in their models to forecast the gap. Widening inequalities at a local authority level point to the need for an exploration of inequalities within a local context, which is one of the primary objectives of this study.

[1] The models included components that accounted for mortality in relation to age, birth cohort, time, and space. The models used geocoded data on population and mortality between 1981 and 2012.

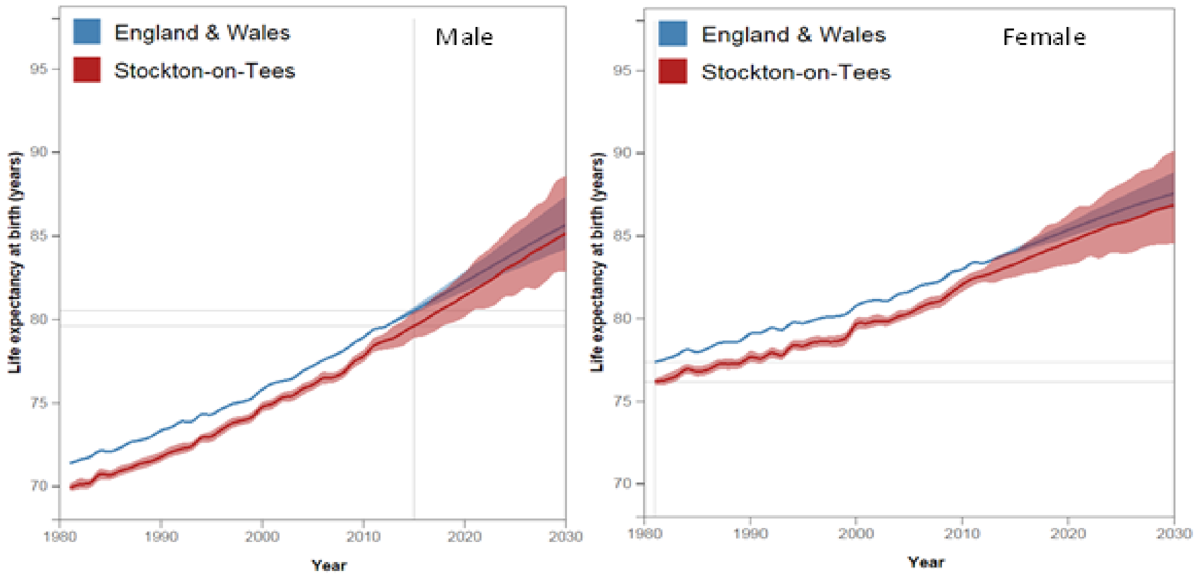

Figure 2.5: Estimates for life expectancy in Stockton-on-Tees and England and Wales between 1981 and 2030 based on Bennett et al. (2015)

Placing inequalities: Stockton-on-Tees

Considering the historical as well as current circumstances, Stockton-on-Tees is an ideal place to study the impacts of recession, austerity and health inequalities. In the initial part of this section, I will discuss the historical aspect of industrialisation and deindustrialisation in the area. In the latter part, I will discuss the current health inequalities and will also explore the impacts of recession and austerity in the borough.

The historical context of Stockton-on-Tees

Stockton-on-Tees, as a place, has a long-standing history of trade and economic prosperity The market at Stockton started from as early as 1310 and has always been central to the town from social as well as economic perspective (Stockton-on-Tees Borough Council, 2015). It was the industrial revolution that started from the later part of 18th century that changed the name, and scope of Stockton—from a small market town to a thriving hub of heavy industries (Beynon et al., 1994). Shipbuilding was an established industry in Stockton even before the industrial revolution (Sowler, 1972). Sowler (1972) argues that all other major industries established afterwards were to support the booming shipbuilding industries. The opening of the railway between Darlington and Stockton in 1825 further boosted the industrialisation process (Beynon et al., 1994). With the road, rail and water transportation facilities, iron, steel and chemical industries developing throughout the 19th and early 20th centuries.(Beynon et al., 1994, Sowler, 1972).

The Borough of Stockton was seriously affected by the economic crises of the 1920s, 1930s and that of 1980s. Beynon et al. (1994) argue that though other industrialised cities have also been impacted by these economic downturns, the impacts ‘were felt particularly keenly there (Teesside)’ (p. 1). After the financial recession of the 1980s, manufacturing industries such as steel, chemical and heavy engineering were displaced from Stockton-on-Tees. The recession resulted in the loss of high proportion of manufacturing and engineering jobs in Stockton-on-Tees (Bambra, 2016). The decline also resulted in the decline in the capacity and output in the manufacturing sector (Hudson, 2011). In the same context, Margaret Thatcher visited a derelict site in Stockton-on-Tees in 1987 (famously known as “*walk in the wilderness*”) in a bid to boost the regeneration process, which was not successful (Stewart, 2015). This is the same location where the present day Queen’s Campus of Durham University is located. Queen’s Campus was established in partnership with the Teesside development corporation (Melhuish, 2015). The health impacts of economic downturns and deindustrialisation are unequally distributed, with the vulnerable groups and deprived areas having the most of its share (Hudson, 2013).

> *"…with an increasingly differentiated regional geography of wellbeing, with poor health disproportionately concentrated in those regions suffering from deindustrialisation and economic decline".*

(Hudson, 2013; p. 70)

Stockton-on-Tees today

Stockton-on-Tees has the highest health inequalities in England. The borough of Stockton-on-Tees was chosen as the site for analysis because it has the highest health inequalities between LSOAs within a local authority in England both for men (at a 17.3 year difference in life expectancy at birth) and for women (11.4 year gap in life expectancy) (Public Health England, 2015). Life expectancy though is only a headline indicator, signifying the need to explore the extent and determinants of other aspects of health inequalities in that area (Bambra, 2016). This makes it a particularly important site to analyse health inequalities during austerity – and I wanted to unpack the headline life expectancy gap by looking in more detail at other underpinning health issues as well as their determinants. In 2013 Stockton-on-Tees had a population of 191,600 residents (Office for National Statistics, 2013) in a total area of 78.7 square miles and with a density of nearly 2,435 persons per square mile (Office for National Statistics, 2011) (Figure 2.6, below).

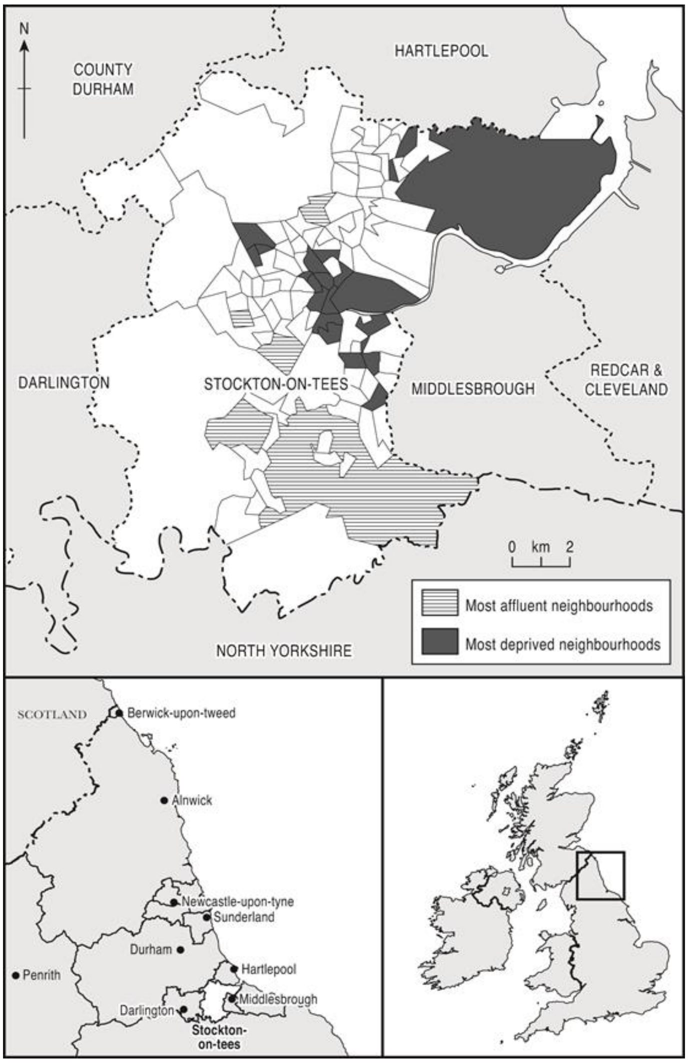

Figure 2.6: Maps of Stockton-on-Tees including most and least deprived neighbourhoods

Deprivation overall is higher than the national average and about 30 percent of the people living in Stockton-on-Tees are in the most deprived quintiles, which is significantly higher than the national average of 20 percent (Public Health England, 2015). Data from Public Health England for years starting from 2007 show that the gap in life expectancy between the most and least deprived areas continuously increased after the financial crisis and has continued after the introduction of austerity policies (see Figure 2.7, below).

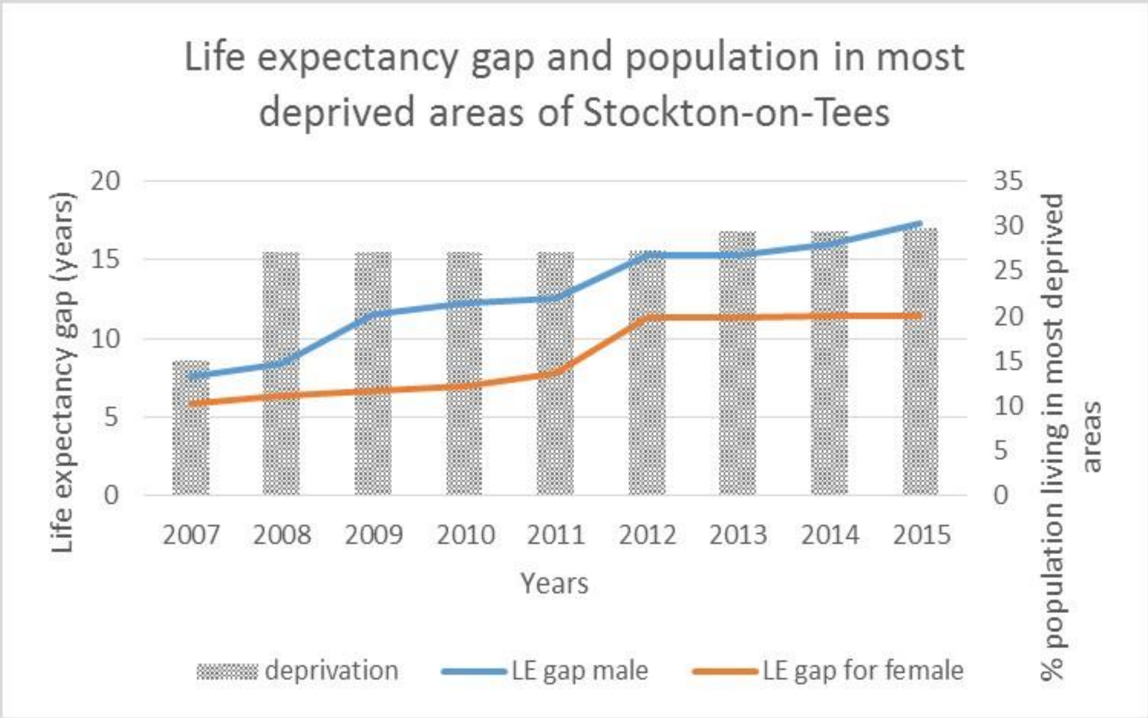

Figure 2.7: Gap in life expectancy and percentage of population living in most deprived areas of Stockton-on-Tees

Stockton has high levels of social inequalities, with some areas of the local authority with very low levels of deprivation (e.g. Ingleby Barwick) and others with high levels of deprivation (e.g. Hardwick, Stockton-on-Tees Town centre). These areas are often in close proximity to one another (as shown in Figure 2.6 above). Figure 2.8 shows the deciles of area-level deprivation, as measured by the index of multiple deprivation (IMD) for Stockton-on-Tees for the three time periods—2007, 2010 and 2015 (Dept for Communities and Local Government, 2011, Dept for Communities and Local Government, 2015). Bambra (2016) argues that "*all cities have a north*" (p. 85), which indicates there are areas within a city which are more deprived than the others. The figures below show a north-south divide in the status of deprivation, with neighbourhoods in the north being most deprived compared to those in the south. Considering the IMD scores of 2007 as the baseline, the majority of the LSOAs remained in the same national deciles of IMD scores in 2015. During this time, deprivation deciles worsened for 29 out of the 120 LSOAs, remained constant in 68 areas and 23 areas moved to better performing deciles. Figure 2.9 below shows how the deprivation deciles changed between 2007-2010, 2010-2015 and 2007-2015.

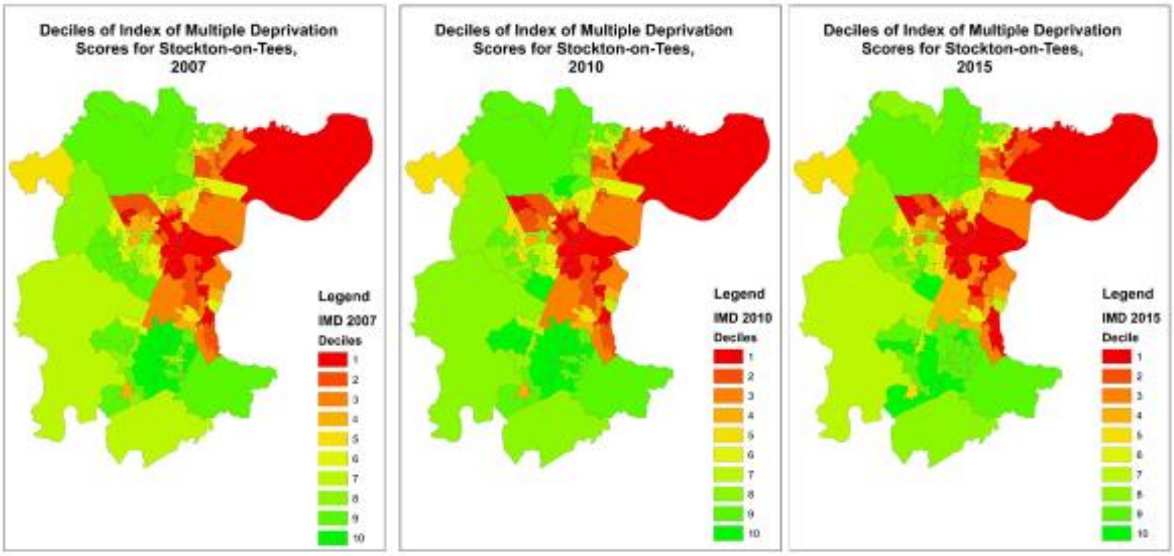

Figure 2.8: Deciles of IMD for Stockton-on-Tees between 2007 and 2015

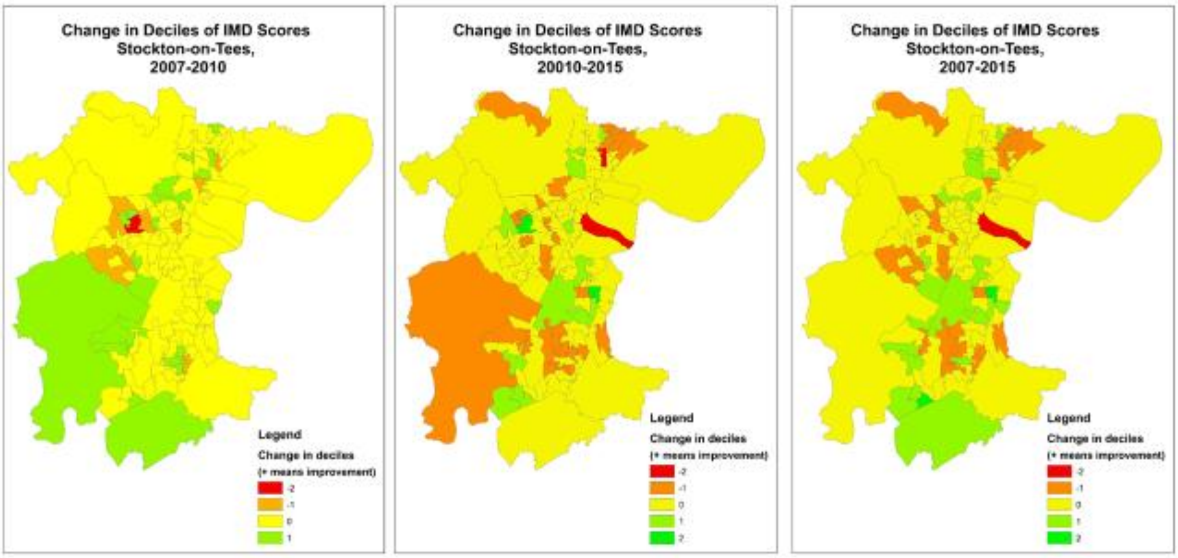

Figure 2.9: Pattern of the change in national deciles of IMD

The global financial crisis of 2007/8 had a negative impact upon Stockton-on-Tees, with increased rates of unemployment and financial cuts (Edwards, 2012). The welfare cuts for Stockton-on-Tees are estimated to result in the loss of between £13 million and £21 million by 2020 (ibid). About 22 percent of children in Stockton-on-Tees were living in poverty in 2012 (Stockton JSNA, 2013). As highlighted by Hudson (2013), the impacts of the financial crisis were unequally distributed, deprived areas being the worst hit. Following the welfare cuts, the number of people claiming benefits increased and they were mostly found in a high concentration in the most deprived neighbourhoods of Stockton-on-Tees (Edwards, 2012).

Job density (defined as number of jobs to the population aged 16-64 in the area) in Stockton-on-Tees is 0.76, which lower than the national average of 0.83 (Nomis, 2016). Almost one in five households in Stockton-on-Tees are workless households, which is again higher than the national average of 15 percent (ibid). Following the welfare cuts, the use of foodbanks has significantly increased in Stockton-on-Tees, with people from the most deprived areas using them the most (Garthwaite, 2016). Garthwaite (2016) and (Mattheys et al., 2016) have argued that austerity policies are aggravating people's ill health in Stockton-on-Tees, and are particularly damaging to the mental health conditions. It can thus be argued that recession and austerity are increasing the geographical health inequalities gap in Stockton-on-Tees, and the area therefore provides a good background to conduct this research.

Summary

This literature review has explored the existing evidence in the fields of health, wellbeing and health inequalities. The review has highlighted the complex nature of health and wellbeing and discussed different aspects of the social determinants that shape the health and wellbeing of an individual. The chapter discussed the different theories of health inequalities and in doing so the role of neighbourhoods and place were also explored. Most significantly, the chapter reviewed the role of individual-level compositional and area-level contextual factors in creating health inequalities. The chapter has also highlighted a need for a collective dimension, a shift from the conventional approach of focusing only on the contributions of compositional or contextual factors is required. The chapter then reviewed the impact of austerity imposed by the coalition government following the financial recession of 2008. Austerity has had far-reaching impacts, leading to social and health inequalities. Local authorities have received unequal funding cuts, and evidence show these to be more prominent in the North, where the study site is located. The chapter has also highlighted that health inequalities based on social and geographic contexts have become more prominent, where the most vulnerable are those most affected. Moving on to Stockton-on-Tees, the chapter has highlighted the relevance of the research by looking into its historical and current position. Finally, the chapter concluded by arguing that the exploration of the composition and context of the places where health is most unequal can give us a clue to understanding why place matters in creating the differences. In the next chapter, I move on to outline the methodological approach deployed in the research.

Chapter 3: Methodology

Introduction

The focus of this doctoral research is to examine and explore geographical health inequalities and how they change during a period of austerity. This study is based upon data collected for a prospective cohort study, conducted over the period of two years. The previous chapters have highlighted the significance in the health geography literature around compositional and contextual factors in explaining the health inequality gap. In this chapter, the research approaches adopted to explore and explain health inequalities in Stockton-on-Tees are presented.

It is important to note that the data analysis included in this thesis is solely my work, although the longitudinal survey design and data collection was part of the wider project.

Aims and research questions

The primary aim of my doctoral research is to examine the relationship between place and health inequalities during a period of austerity. This research aims to provide an understanding of the determinants that lead to inequalities in general and physical health. Adopting a critical realist perspective, I am looking at the role of the individuals (agency) and the neighbourhood context (structure) and how they influence the general and physical health outcomes. Much of the health inequalities research done is focused on larger geographies, such as at a regional or at a national scale. Less has been done at a local level. The borough of Stockton-on-Tees has the highest level of health inequalities in England as measured by life expectancy at birth, with a gap of 17.3 years for men and 11.4 years for women between the most and least deprived neighbourhoods (Public Health England, 2015), which provides an appropriate case study. The study design and the research approach explored the connection and relationship of individual social determinants and their interaction with the local environment to produce inequalities in general and physical health. The use of longitudinal cohort study enables me to investigate the temporal aspect of inequalities and provides an insight into the relationship of health inequalities and austerity over time

The key objectives of my research were to investigate if there is a difference in general and physical health outcomes between the most and least deprived neighbourhoods of Stockton-on-Tees and what explains those differences. Assuming time is equivalent to austerity, the next objective of my research was to investigate the role of time in the health divide. The existing evidence indicates that there are disproportionate impacts from austerity and welfare reform, and people living in deprived areas are those worst affected (Hastings et al., 2015). I wanted to investigate the link between health inequalities, the social determinants and austerity. I wanted to explore if any relationship existed between the characteristics of an individual (the compositional factors), the neighbourhood characteristics (the contextual factors) and the health outcomes. Therefore, I used the composition-context lens to answer the following research questions:

a) What is the extent of health inequalities in physical and general health in Stockton-on-Tees?
b) How do compositional and contextual factors explain the gap?
c) How have health inequalities in Stockton-on-Tees changed during austerity?
d) How does the role of compositional and contextual factors change in Stockton-on-Tees during the period of austerity?

Research design

This study adopts a quantitative approach to identify the determinants of geographical health inequalities and estimate their relative contribution in creating the gap. This research presents Stockton on Tees as a case-study, it compares the effects of austerity upon the most and least deprived areas of the local authority. Existing evidence shows that the least wealthy are more likely to have poorer health and be most affected by cuts in welfare and social care (Hastings et al., 2015). The research is focused on examining the extent and nature of health inequalities between residents of the most and least deprived Lower Super Output Areas (LSOAs) of Stockton-on-Tees.

Several approaches have been used to try to understand and explain differences in health outcomes between population subgroups, but these perspectives often say little about the role of the wider political context in causing the gap. But work done by Beckfield and Krieger (2009) and Bambra (2016) have highlighted the increasing importance of political processes. As a health geographer, I wish to better understand how these macro-level structures (including politics) ‘shape the lives’ of people and places and result in health inequalities. As a researcher, the standpoint, I have used and that has helped me to understand this complex phenomenon is the critical realist perspective. This offers a position, from where I could understand how the social structures interact with the individuals and how it shapes the geographical health divide.

There is an ongoing debate on the role of composition and context in health inequalities research, Cummins et al. (2007) argue that composition and context should be looked at from a relational perspective as they are not mutually exclusive but are mutually reinforcing. This perfectly fits into the structure and agency attributes of the critical realism, as Bhaskar (1979) has highlighted their interaction: *'what properties do societies and people possess that might make them possible objects for knowledge?'* (p. 15). From this standpoint, we can now argue, agents (the individuals) enter into some specific social relationship (as defined by the social structures) that can impact the health outcomes. Critical realism views society as 'inseparable from its human components because the very existence of society depends in some way upon our activities' (Archer, 1995, p. 1). In the same line, Fleetwood and Ackroyd (2004) have argued that 'social structure is relational: it exists in virtue of agents entering into relations' (p. 42). When linking this argument with the composition and context debate in health inequalities, we could find a milieu of compositional and contextual factors, which is relational in nature and indicate their possible interactions to produce different health outcomes.

In social science, facts are conceptually developed with an attempt to 'define real entities'. These real entities can either be materially real entities such as the physically present infrastructures. Alternately, these could be socially real, for example, unemployment, social structures, systems, organisations and the services offered.

Now, with critical realism, the focus of my research is to understand the relation between the 'real world' and the concepts and knowledge that can be built out of it, by means of 'retroductive' inference (Meyer and Lunnay, 2013). Danermark et al. (2001) and Meyer and Lunnay (2013) have highlighted five strategies of retroductive inferences: counterfactual thinking (using a priori knowledge to answer questions), social and thought experiments, studies of pathological cases, studying extreme cases, and comparative case studies.

With this approach, I had to use a priori knowledge and move beyond and ask the question on the existence of 'structure' and 'agency' in health inequalities research. My question then was, "Do structure and agency interact to produce 'the condition' of health inequalities?" Danermark et al. (2001) have suggested how we can structure our enquiry. For example, if we are interested in investigating geographical health inequalities, we as researchers need to ask, what are the conditions under which geographical health inequalities occur? What makes it possible? Schrecker and Bambra (2015) argue that we also need to ask "what is the role of political economy in creating the gap?"

From an epistemological point of view, critical realism focuses on uncovering the causal mechanisms. While exploring the causal mechanisms, we need to consider the power relations between the structures and agencies and in some cases, 'between people in different social ranks throughout society' (Wilkinson, 1999). The critical realist perspective allows me to investigate the role of agency and structure. It also provides me with an opportunity to seek insight into the causal mechanism of how health inequalities are produced. Critical realist perspective will also help me look into the political nature of health inequalities, this includes but is not limited to financial crisis and welfare cuts.

Longitudinal cohort study

Prospective cohort studies provide an important opportunity to explore and understand the link between the health outcomes and the determinants associated with these outcomes, and also offer understanding how these change over a course of time. As the aim of the research project is to examine whether and if the health inequalities and their determinants changed during the financial crisis and in an age of austerity, a longitudinal cohort study provides a way to explore the situation and to make a plausible inference.

The baseline survey and its recruitment strategy

Sampling Strategy

The survey used a probability based sampling strategy. Probability sampling is an ideal approach in quantitative research, whereby each individual meeting the set criteria and from the population of interest has a chance of being randomly selected. Randomisation in probability sampling avoids the 'unnecessary assumptions about the population and the sample' (Hansen et al., 1983, p. 776). Probability sampling is also important to ensure the validity of sample size calculation and ensure that an inference can be made from the findings and generalised to the wider population. In their work, Barlett et al. (2001) have argued that the foundation which determines the sample size include i) information on primary variables of measurement, ii) margin of error allowed (error estimation) and iii) variance estimation. Variance estimation is usually based on the results from pilot studies or the data from previous similar studies. In longitudinal studies like ours, the possible rate of attrition is also a determinant of the final sample size (Goodman and Blum, 1996).

Figure 3.1 shows the sampling strategy for the survey. To identify the lowest and highest areas of deprivation in Stockton, we looked at the 120 Lower Super Output Areas (LSOA) in the local authority of Stockton on Tees, selecting the 20 with the lowest Index of Multiple Deprivation (IMD) scores from 2010 and the 20 with the highest IMD scores (IMD range 1.54-74.5) (Department for Communities and Local Government, 2011).

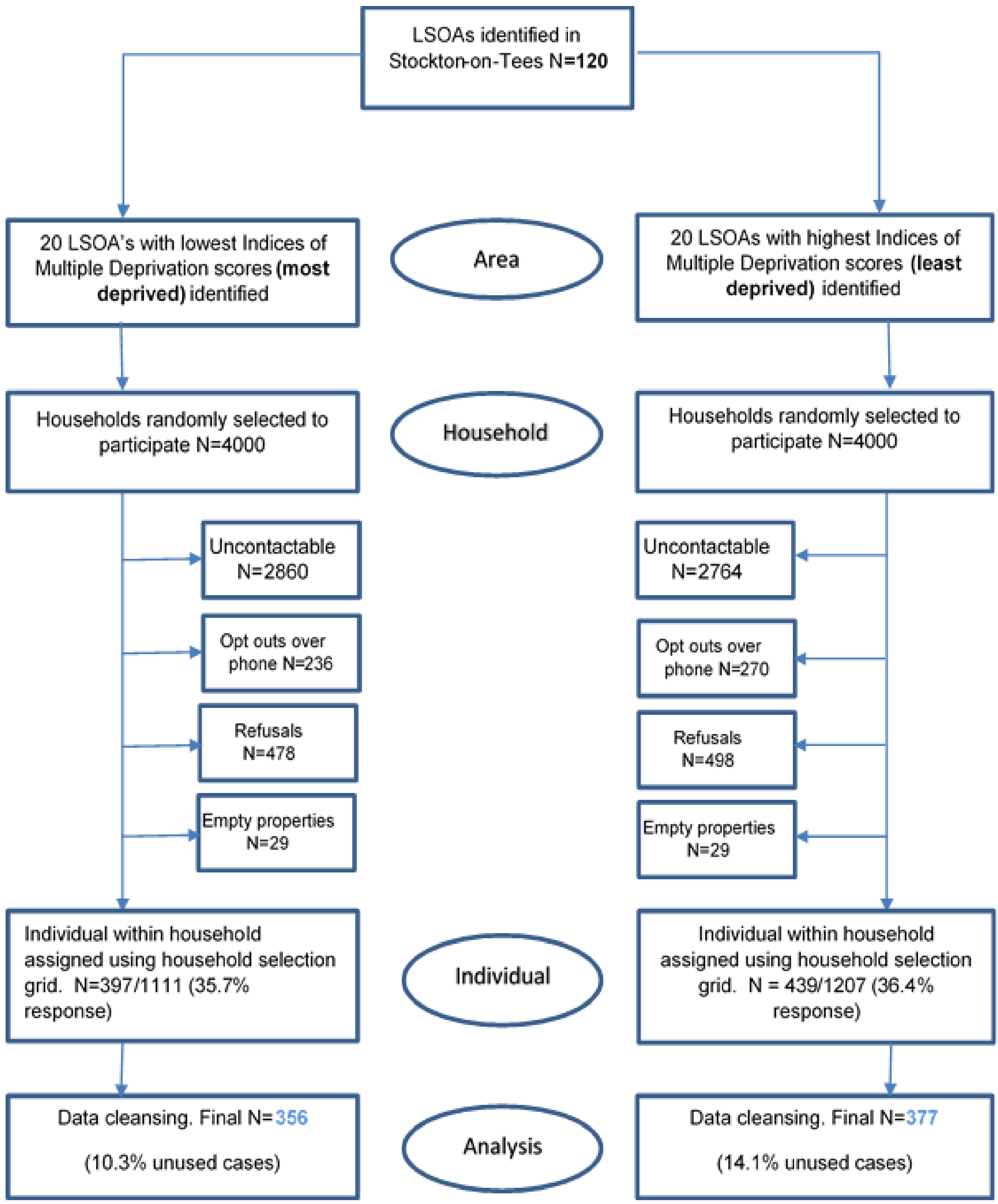

Figure 3.1: Sampling Strategy for the Baseline Survey

The sample size for the prospective cohort study was estimated based on the conservative power calculation, utilising the experiences from previous health surveys in the same region of the UK (Warren et al., 2013). The final estimated sample size was 800 (400 in each group). The sampling process assumed a 5 percent difference in health outcome between the least and most deprived areas. This calculation also allowed an attrition of 20 percent between the baseline and the first follow-up study and further five percent between each of the follow-up surveys. 20,013 eligible addresses and phone numbers were identified from the 40 study LSOAs, using the most recent Office for National Statistics (ONS) postcode lookup tables. The number of eligible addresses ranged from 313 to 1380 addresses per LSOA. Using a stratified random sampling technique (using "R" statistical software programme), 200 target households were randomly selected in each of the 40 LSOAs.

Representativeness of the sample is a key factor behind the generalisability of the findings. To make a valid generalisation, we emphasise that the sample is a true representation of the study population. Selection of a representative sample minimises the possibilities of bias and ensures the accuracy of the results. The following statement by Bar-Hillel highlights the significance of representativeness while conducting researches.

> *"There is another excellent reason why representativeness, even in its original sense shouldn't be abandoned. The world, in many important senses, abides by it - mathematically and empirically speaking."*
>
> (Bar-Hillel, 1984, p. 105)

Kahneman and Tversky (1972) have highlighted that the representativeness of a sample 'is easier to assess than to characterize' (p. 431). They have argued that representativeness indicate that the sample is 'similar in essential properties to its parent population' (p. 431). Likewise, randomness is another aspect of the representative data. To try and represent the people living in the most and the least deprived areas of Stockton-on-Tees, a stratified random sample was selected for the baseline survey and followed up for two years. However, it should be noted at this point that this case study was focused only in the areas at the extreme ends of deprivation. So, the primary approach of representation and randomness was relevant to the most and least deprived neighbourhoods of Stockton-on-Tees. All the households and all the individuals aged 18 and above and living in the most and least deprived areas of Stockton-on-Tees had equal chances being sampled for the survey. Therefore, the sample we mobilised can only be representative of those areas and may not represent the whole of Stockton-on-Tees.

Survey recruitment

Assuming a 10 percent response rate, 8000 randomly selected households (4000 each from the most and least deprived LSOAs) were sent study invitation letters by post in April 2014. The assumption of a 10 percent enrollment rate was because the survey used a postal initial recruitment approach and so the response was expected to be lower than for other recruitment methods (Eriksen et al., 2011, Sinclair et al., 2012). Recipients were asked to contact the research team to indicate if they would be willing to participate in the study and arrange a time for a face-to-face interview and also to indicate if they did not want to participate. Research staff attempted to contact the households who did not respond to the letter by visiting the address and returning on up to four occasions at differing times of the day. Additionally, up to five attempts were made to contact households by phone and at differing times of the day, when phone numbers were available.

An additional letter was also sent to households who had not responded, four weeks into the initial field period. 976 people did not wish to participate, there were 58 empty/derelict properties, and 5624 households were uncontactable (not responding to five phone calls, and four physical visits to the property, and repeated invitation letters).

In total, we contacted 2318 households of which 836 participated in the study giving a total response rate of just over 10 percent and ‘contactable’ response rate of 36 percent. I discuss the response rate in the limitations section later in the chapter. LSOAs were first stratified into least and most deprived categories then households were randomly sampled from the selected LSOAs. At the individual level, eligible participants were sampled by the use of a household selection grid, this was a multi-stage randomised sampling strategy (Devaus, 1991) (See Appendix B-1: Grid for selecting individuals, page 282). Face-to-face interviews were conducted between April and June 2014: 397 in the most deprived areas and 439 in the least deprived areas. Participating individuals were sent a £10 high street voucher as a thank you for taking part. Figure 3.1 (above) shows the sampling strategy adopted for the study.

Follow-up surveys

There were 3 follow up waves after the baseline survey. In chapter 5, I will present the attrition curve (survival rate) and the implications of the dropout rates for this study. Table 3.1 presents a total number of survey participants in each wave and the dropout rates for each wave. In reaching the final wave, about half of the participants from the baseline cohort were retained, there was a higher rate of dropout in the most deprived areas which is typical of a longitudinal study (Eysenbach, 2005).

Table 3.1: Total number of survey participants in each wave (prior to data cleaning for analysis).

	Least Deprived		Most Deprived		Total	
	N	Percentage*	N	Percentage*	N	Percentage*
Baseline	439	-	397	-	836	-
6m	286	65	229	58	515	62
12m	260	59	218	55	478	57
18m	234	53	176	44	410	49

* The percentages (%) in the table represent the percentage of participants retained in the study relative to the number at baseline.

During the baseline survey, the participants were told that they would be contacted later for the follow-up after six months (see Appendix B-3: Information sheet: Survey, page 284). All three rounds of follow-up surveys were conducted by telephone interviews. The interviews lasted for no more than 30 minutes. Consent was sought during the baseline survey and for the participants involved in the follow-up surveys, they were free to refuse to answer any question or opt out of the research at any point.

Methodological issues with the survey

In setting up a research project for evaluating the impacts of the government's actions such as the welfare reform programmes, one of the main concern is the timing of such evaluation. It is a difficult choice to make because "*there is no single answer to this question that can be applied to every regulation*" (Coglianese, 2012` p. 50). Coglianese (2012) further argues a standard time period, such as five years is most often the preferred choice. In the case of this research, collecting the baseline data in 2014 could therefore be an ideal period to look into the impact of financial crisis. But, as the welfare reform programmes were rolled out in a phased manner (see

Table 2.7, page 58), it is not possible to have a holistic evaluation in a single time period.

Questionnaire

A comprehensive questionnaire was mobilised in this survey for both the face-to-face and telephone interviews. Questionnaires can ‘offer an objective means of collecting information’ and are often used as the only research tool (Boynton and Greenhalgh, 2004, p. 1312). A valid and reliable questionnaire requires rigorous planning and design. A well-designed and efficiently organised questionnaire can be a cost-effective means of conducting research. A well-designed questionnaire is the one that consists the appropriate types of questions (e.g. closed or open ended) which are logically ordered and clustered properly to minimise ambiguity and confusions (Boynton and Greenhalgh, 2004). Likewise, a consideration is made not to include misleading and sensitive questions. Questionnaires are efficient in collecting a large amount of information in a fairly short period of time and cost. The data generated from questionnaires are easier and more convenient to ‘scientifically’ and ‘objectively’ analyse. For studies like this, the questionnaire is an ideal choice as it produces quantifiable data and provides scope to make a reasonable comparison between the groups of interest. Likewise, use of the same questionnaire on several occasions over time can help understand the trend.

In health inequalities research, use of findings validated and standard self-reported questionnaire is a common practice, (Maheswaran et al., 2015, Malmström et al., 1999, Szende et al., 2014). As the Stockton-on-Tees project is an inter-disciplinary case study and to cater for the need of the project team, the survey was expected to gather a wide range of information, such as the mental health outcomes and the wider social determinants of health. For my research, I only used a selection of data based on the relevance. I contributed to the revisions made to the questionnaire for waves 2, 3 and 4, with questions on locality and transport being added.

The survey included questions on health, demographics and the compositional and contextual determinants of health. Questions were designed in a way that they could be matched with other surveys (such as the General Household Survey) and a comparison could be made with national and regional level studies (see Table 3.2). In their work, Boynton and Greenhalgh (2004) have highlighted the benefits of using the previously validated tools—for example, it saves time and resources. This was also done to ensure and maintain validity and reliability of the research and to compare with other research (Boynton and Greenhalgh, 2004).

Table 3.2: National survey questions used in the project

Survey	**Questions Used**
Health Survey England 2011	Income scale questions and show card; marital status questions; national identity and ethnic background; caring responsibilities; if the respondent is cared for by others; social network questions; general health questions; smoking and alcohol questions; physical exercise questions.
General Lifestyle Survey 2010	Accommodation type; residents at the address; transport questions; benefits show card (although this needed to be amended to include recent welfare changes); monthly outgoings questions; questions about paid work, training/education courses and unpaid voluntary work; educational qualifications show card.
Poverty and Social Exclusion UK 2012	Household features and goods; psycho-social work questions; food poverty question.

English Longitudinal Survey of Ageing 2010	Loneliness questions
European Social Survey 2013	Happiness scale
National Travel Survey 2013	Questions related to transportation and commute
Place survey 2008	Satisfaction, belongingness, neighbourhood safety perception

In this survey, I used three standard validated physical and mental health outcome measures: EuroQol (EQ5D-VAS and EQ5D score) to measure general health outcomes and ‘quality metric short form (SF8) PCS Physical component score for physical health. I will discuss these instruments in more details in the later part of this chapter.

The questionnaire was designed as a structured face to face or telephone interview. The questionnaire was comprehensive in nature, which included multiple validated health measures and a wide range of determinants of health. Although this process requires more time and resources than a self-administered questionnaire, it has advantages, for example, the interviewer gets to introduce the research topic, explain the questions and can help the participants to give as accurate information as possible (Holbrook et al., 2003).

In the questionnaire, all the health measures used were self-assessed and self-rated. The survey participants were either asked to rate their current health status or were asked to choose an option that best represents their situation for the several dimensions included. Self-rated measures often face criticisms and the researchers face ‘scepticism’ while reporting their work (Spector, 1994). Use of self-rated questions can result in two types of bias; firstly, misclassification is the situation when the participants provide inaccurate responses. Recall bias is a usual shortfall for self-rated measures if it seeks information from the past, which is the case with SF8PCS scores. In this case, the participants fail to correctly remember things from the past. Research participants responding to a questionnaire are often times influenced by 'social desirability', whereby people give information what they think is socially desirable, which might compromise the accuracy of the data (Fisher, 1993). This is the case especially for sensitive questions or for situations leading to stigma. Secondly, selection bias or '*missingness'* of information can be an issue when the participants refuse to answer certain questions (Myrtveit et al., 2013). Despite these flaws, a validated and well-organised questionnaire with self-rated measures is the most widely deployed research tool. As a researcher, we need to consider ways and techniques to ensure the information we obtain is accurate and we need to believe that the participants are honest.

Using self-rated measures to assess health situation is not always free of complications because it is linked to the perception of the people. There can be a significant difference between the perceived and the 'actual' health status of the people. Perceived health is a relative condition usually associated with the person's individual characteristics (composition) or the environmental determinants (context). Though self-rated health measures are subjective in nature, several types of research have now found their strong relationship with objective health status; see for example Kuhn et al. (2006) and Wu et al. (2013).

Asking indirect questions is an approach to minimise the bias associated with 'social desirability'; it can help the participants to 'disengage themselves from the social implications of their responses' (Fisher, 1993, p. 305). Studies such as Conner-Spady and Suarez-Almazor (2003) and Witney et al. (2006) have shown a strong correlation of objective health with indirect measures, such as EQ-5D. Furthermore, Witney et al. (2006) argue that these 'population-based indirect measures' of health outcomes are 'less complex' to administer and 'more reflective' of the health status (p. 979). Two of the health measures included in my research (EQ5D and SF8) are indirect measures, the details of which is included in the latter part of this chapter.

Investigating health inequalities

As the focus of my research was to assess inequalities in general and physical health among the most and least deprived neighbourhoods of Stockton-on-Tees. As I have already mentioned the survey used the EuroQol (EQ5D-VAS and EQ5D score) to measure general health outcomes and 'quality metric short form (SF8) PCS Physical component score for physical health. As discussed in the previous section, these measures are well-validated and are particularly relevant for use in the general population. Using the averages of these outcome measures, a comparison was made between the most and least deprived neighbourhoods of Stockton-on-Tees.

The EuroQol measure consists of two parts: EQ5D questionnaire and the 'Visual Analogue Scale' (EQ5D-VAS), also known as "health thermometer" (EuroQol Research Foundation, 2016). The EQ5D is a simple and generic health measure used in the clinical and economic appraisal. This is the 'world's most widely applied generic multi-attribute utility instrument (MAUI)' (McCaffrey et al., 2016, p. 2), in a review conducted by Diane et al. (2003), 63% of the studies using MAUI had employed EQ5D. Furthermore, EQ5D has been translated into more than 170 languages (EuroQol

Research Foundation, 2016). The EQ5D questionnaire asked participants about their mobility, self-care, ability to carry out usual activities, pain and discomfort and level of anxiety and depression on the day of enquiry. The responses of these items are categorised into three response levels: ‘no problems’, ‘some problems’ and ‘severe problems’. With these options, it results in 243 different combinations, which are then converted to a scale between – 0.594 and 1.00, the latter being better health (Marra et al., 2005).

EQ5D-VAS is the second part of the EQ5D questionnaire and represents the perceived health status of the participant on the specific day of enquiry, which is measured on a scale of 0-100, 0 being the worst, 50 representing the midpoint and 100 the best health state they can imagine (Warren et al., 2014). This measure is recorded on a 20 cm ‘thermometer-like’ scale, which provides researchers with a quantitative measure of perceived health. Though EQ5D-VAS is criticised for having ‘scaling biases’ or ‘end-of-scale bias’, whereby the respondent tend to focus on the extreme ends of the scale (Whitehead and Ali, 2010). However, the simple and easy-to-understand nature of the scale makes it a useful tool in population surveys.

Using eight questions that focus on the health status of the participants during the last four weeks, SF8 produces two health scores: physical component summary (SF8-PCS) and mental component summary (SF8-MCS) (Warren et al., 2014). However, in this thesis, the analysis is limited to SF8-PCS only and a linked study has used the SF8-MCS (see Mattheys et al. (2016)). SF8 is a utility instrument, which is shorter and condensed version of SF-36. Under the SF8-PCS, questions were asked on six dimensions: general health; physical functioning; limitation in the daily role due to physical condition; bodily pain; energy/vitality; and physical health. The SF8 is a reliable, practical and efficient instrument to be used in population health surveys (Daly and Taylor, 2003, Diane et al., 2003). The scores for this measure ranges between 0 and 100: the higher the score, better is the physical health state. These scores were clustered into two categories based on deprivation status and the differences of the average values between these clusters indicated the presence of an unequal health outcome.

Piloting

A pilot study of the questionnaire was carried out in December 2013 and January 2014 with a random sample of 48 households in two non-study areas: the 21st most (26% response rate) and 21st least deprived (35% response rate) lower super output areas (LSOAs) which were not part of the study area. These LSOAs were chosen as their deprivation status was almost similar as of those selected for the study and piloting on them would prevent cross contamination (see sample size section for more details on the sampling technique, page 80). Following the pilot study, some questions were refined. The most important output, however, was the demonstration of the feasibility of the health measures.

Though pilot studies are ‘under discussed, underused and under-reported’, they are an important part of the research projects—they are crucial in justifying the particular methods and tools used (Prescott and Soeken, 1989, p. 60). In their paper, Van Teijlingen et al. (2001) have argued that the reporting of the practical issues during a pilot study is helpful to other researchers to manage similar situations in the future. They have also highlighted the need to encourage researchers to report the main findings of the pilot studies and what changes, if any, were considered in the project.

Variables considered to have potential associations with health inequalities

My doctoral research is guided by the composition-context debate of health inequalities, as was discussed in Chapter 2. In line with this theory, I grouped the explanatory variables into two broad categories of composition and context. Within the compositional category, the variables were further subclassified to the material, psychosocial and behavioural variables. Table 3.3 provides a summary of variables included in the research.

Table 3.3. Overview of variables

Classification	**Variables**
Variables of interest	
Demographic factors	Age, sex**
Health dimension	General and physical health outcomes (EQ5D, EQ5D-VAS and SF8PCS)
Covariates	
Compositional	
Material	Household income, worklessness, paid job, damp house, cold house, housing benefits, household benefits,
Psychosocial	Lack of companionship, feeling eft out, happiness, isolation
Behavioural	Alcohol use, alcohol units per week, smoking, frequency and amount of exercise, fruit and vegetable intake
Contextual*	Neighbourhood pollution, noise, safety perception, crime, belongingness
Time factors	Period effect, cohort factor**

* Contextual variables from secondary sources are listed in Table 3.4

** Time independent variables

Data extraction and construction of final dataset and strategy for analysis

The core data used in this research as I have explained came from the longitudinal study which was part of the "Local Health Inequalities in an Age of Austerity: The Stockton-on-Tees Study". Whilst all of the individual level compositional data came from the cohort study, some of the relevant neighbourhood level contextual data were obtained and added from the secondary sources (see Table 3.4, below)

Data from secondary sources

The scale and availability of secondary data on neighbourhood related attributes were the major challenges for my research. But, whenever possible, contextual data was obtained for smaller geographical units such as post codes. The selection of the contextual factors was thus determined by the availability of data at the geographical scale of my analysis. Variables were chosen to cover the four main contextual domains of geographical theory as explored in the previous section (see page 43): social-interactive, environmental, geographical and institutional (Bernard et al., 2007, Galster, 2010). These domains broadly represent what are thought to be the key mechanisms of neighbourhood effects on health and well-being. Galster (2010) has highlighted the significance of these domains in understanding and quantifying the causal relationship between contextual factors and health outcomes.

Table 3.4 summarises the contextual data directly obtained or generated using ArcGIS along with their source and geographical scale. Relevant data from sources such as Index of Multiple Deprivation (IMD) and Office of National Statistics (ONS) were readily available at an LSOA level and could simply be borrowed and combined with the dataset. Some data needed computation using ArcGIS and this process relied upon the secondary data sources such as Ordnance Survey and Open Street Map. This process of computation using ArcGIS involved techniques such as ‘network analysis’ and ‘density analyses’. Assuming an average person walks 1.6 kilometres (1 mile) in 20 minutes, a buffer of that distance was placed around each type of service outlet while measuring their access or while computing their densities (The Urban Task Force, 1999). Network analysis was used to compute the shortest network distance from a survey participant’s postcode. This process sums up the distance of each section of the street/road (Apparicio and Séguin, 2006). An alternative to this approach would be the use of ‘Euclidean distance’, which measures the air distance between the two nodes. Compared to the Euclidean distance, network distance provides more accurate and practical measure of distance and access (Apparicio et al., 2008). The Network Analyst Extension of ArcGIS was used to complete this analysis. The postcodes of the participants were then attached to the buffer areas. An average value was then extracted for the respective LSOA and the data was merged with the survey data set by matching it with the LSOA of the survey participants.

Table 3.4: Secondary contextual data and their sources

Contextual variables		Definition	Source	Geographical unit for the data	Time Point
Geographical					
1	Air quality	Air quality indicator as a sub-domain of living environment score	Index of Multiple Deprivation (IMD)	LSOA	2015
2	Geographical barriers	Geographical Barriers Sub-domain Score	IMD	LSOA	2015
Physical environment					
3	Domestic Garden	Proportion of area covered by domestic garden	CORINE land cover map	LSOA	2012
4	Green Space	Proportion of area covered by green space	CORINE land cover map	LSOA	2012
5	Indoor environment	Indoor environment Sub-domain Score	IMD	LSOA	2015
6	Outdoor environment	Outdoor environment Sub-domain Score	IMD	LSOA	2015
7	Road traffic accident	Road Traffic Accident indicator as a sub-domain of living environment score	IMD	LSOA	2015
8	MEDIx score	Multiple Environmental Deprivation Index (MEDIx score) (+3 being most deprived)	Centre for research on environment, society and health (CRESH)	LSOA (retrieved from Ward)	2015

9	MEDIx class	MED Class	CRESH	LSOA	2015
10	Walkability score	Walkability score using techniques identified by Leslie et. Al (2007)	Computed with ArcGIS using data from Ordnance Survey (OS), Open Street Map (OSM)	Post code (6-7 character)	2014-15
Social Environment (Institutional)					
11	Alcohol outlet density	Density of (all) alcohol outlets	Computed with ArcGIS using data from OS and OSM	Post code (6-7 character)	2014-15
12	Fast-food outlet density	Density of fast food outlets	Computed with ArcGIS using data from OS and OSM	Post code (6-7 character)	2014-15
13	Access/distance to nearest GP	Nearest GP as obtained from Inverse care law research	Computed with ArcGIS using Fuse Geo-HealthCare Database	Post code (6-7 character)	2014
14	Nearest pharmacy	Nearest Pharmacy as obtained from Inverse care law research	Computed with ArcGIS using Fuse Geo-HealthCare Database	Post code (6-7 character)	2014
15	Access to recreation sites	Density of recreation sites within 20 minutes' walk	Computed with ArcGIS using data from OS and OSM	Post code (6-7 character)	2014-15
16	Sporting facilities	Density of sports facilities within 20 minutes' walk	Computed with ArcGIS using data from OS and OSM	Post code (6-7 character)	2014-15
17	DWP Benefit Rate	% individuals receiving DWP benefits May 2014	NOMIS	LSOA	2014
18	Cars/vans possession	% Households with no cars or vans in LSOA	NOMIS	LSOA	2014
19	Employment rate	% Economically active/in employment in LSOA	NOMIS	LSOA	2014
Social interactive (sociability)					

20	Social grade AB	Approximate proportion of social grade AB in the LSOA	ONS	LSOA	2014-15
21	Social grade DE	Approximate proportion of social grade DE in the LSOA	ONS	LSOA	2014-15
22	Crime scores	Crime Score for the LSOA	IMD	LSOA	2015
23	Household overcrowding	Proportion of overcrowded households	ONS	LSOA	2014-15
24	Social Fragmentation Index	Social Fragmentation Index as explained by Fagg et. al. (2008) and updated with 2011 census data by Curtis et. al. (2015)	Updated with 2011 census data by Curtis et. al. (2015)	LSOA	2011

Why use data at the LSOA level?

The health status of an individual is not just a result of his/her personal attributes, but is an outcome of the interactions between the attributes which are within the individual and those are without. The hierarchical structuration of an individual nested within the wider neighbourhood calls for an enquiry that can explore and explain the nature and relationship of such interactions. In light of this, health inequalities gap is an outcome of the interactions of the compositional and contextual factors at various spatial scales (Cummins et al., 2007). This tells us why health geographers should be sensitive in selecting a particular scale to better understand the role of place in creating health gaps (Schuurman et al., 2007). Selection of an appropriate spatial scale is based on the theory adopted,

> *"In trying to collect data on local material infrastructure and the social context in areas, three major methodological issues are—what spatial scales are appropriate for meeting different needs, at what spatial scale or level of aggregation information is actually available, and what might be the appropriate time interval between environmental exposures and any effects on health"*

(Macintyre et al., 2002; p. 134)

As identified by Macintyre et al. (2002), the availability of spatial data is one of the major issues directing the level of geographical analysis. Geographical boundaries are usually defined based on political and administrative relevance, hence bear the potentiality of variability. Spatial data in the UK context are readily available at higher geographic and administrative scale (e.g. regions and districts), while for local authorities, it is often scarce.

When studying deprivation status and relating it to health inequalities, LSOA is usually a preferred smallest spatial unit (Cairns, 2013). LSOA in the case of England and Wales are formed of contiguous output areas (typically 4-6) and they have a minimum population of 1000 and an average of 1500 people. The National Health Service (NHS) uses LSOA to improve the reporting of small area statistics in England. Likewise, in England, LSOA is the smallest geographical unit for which measures of deprivation (Index of Multiple Deprivation-IMD) are computed. For the survey, this measure of deprivation was the basis of identifying the 20 most and 20 least deprived neighbourhoods of Stockton-on-Tees. In this research, participants were clustered based on the deprivation status of the LSOA and the health inequalities gap was assessed at the same scale. Furthermore, compared to other geographical units such as wards, LSOAs have a relatively even population size (unlike wards) making it more comparable (Norman, 2015). I have presented earlier most of the current health inequalities research have been carried out at a national or regional scale. I argue that it is crucial to consider smallest possible geographical units to conduct research so that a more fine-grained understanding of the situation at a local level can be gained.

Preparing and cleaning the dataset

Apart from cleaning the data, two of the outcome measures had to be computed from the multi-attribute utility instrument: EQ5D scores and SF8PCS scores. Using the standard technique set by EuroQol, values (also called weights) were assigned to the specific health state. For the EuroQol and SF8PCS measures, the final values were computed using software from their respective licensing organisations.

After all the data was compiled and the secondary data was merged into the database, data cleaning process was carried out. Cases with missing data on health outcome measures and the explanatory variables were excluded from the analysis. This was done to prepare a completed dataset, which was a requirement for the analytical strategy adopted for the research. A complete dataset allows making a comparison between the different models when variable selection is required. Variables such as individual income had high missing data and had to be removed, but it was highly correlated with household income, which filled the gap, to some extent. For the baseline survey, 836 participants had completed the survey, however when handling the missing data only 733 participants had complete data for the health outcomes and the relevant covariates (See Appendix C-2: Data cleaning process for EQ5D-VAS, EQ5D and SF8PCS analysis, page 286)

Statistical analysis

The data used in this research was hierarchical in nature and with repeated data nested within individual participant. The analysis plan was to use both of these components. As discussed in the previous section, my research is guided by the composition-context theory of health inequalities, which emphasises the importance of interactions between the individual compositional characteristics and the area level contextual factors. In their book, Leeuw and Meijer (2008) have argued that the failure to consider the hierarchical structure and complex nature of the data in standard models can result in inappropriate inferences. The use of multilevel analysis is an ideal approach of handling this type of dataset and for understanding the micro-macro relationship of health inequalities (Hox, 2010). When individual data is nested or stratified into clusters, in my case under deprivation status of the LSOAs, multilevel analysis can present the relationship between the health outcomes and the explanatory variables in the form of 'relative contribution'. When we are studying the role of place and health, Kearns and Moon (2002) argue that the use of multilevel models are 'more faithful to external reality and effective as an empirical means of capturing place' (p. 611). This form of analysis requires the contextualisation of regression to quantify the correlation between the individual and area level characteristics. The coefficients of regression explain the nature and strength of association between the health outcomes and the contributing factors. The following statement by Leslie et al. (2007) highlights the acceptance and significance of multilevel analyses in research like mine.

> *"[T]he notion of regressing regression coefficients, or using slopes-as-outcomes, is an appealing way to code interactions and to introduce a particular structure for the dependencies within groups."*
>
> (Leeuw and Meijer, 2008, p. 3)

For my research, I used two analytical approaches:

1) Analysis of the contribution of composition and contextual factors
2) Exploration of the role of time in general and physical health inequalities gap.

The two chapters that follow present the findings from these analytical approaches separately.

Analysis of the contribution of composition and contextual factors

Using the data from the longitudinal survey and from secondary sources, multilevel modelling was applied to explore the mean gap in general and physical well-being between the most and least deprived areas of Stockton-on-Tees. In doing so, potential clustering effects of the LSOAs was controlled for. To measure the relative contributions of compositional and contextual factors, a complete data set was used, which was generated after removing missing data. The main focus of the first approach was to measure the change and to establish:

1) The magnitude of inequalities in general health and physical well-being (as measured by EQ5D, EQ5D-VAS and SF8PCS);
2) The associations between compositional and contextual variables and the health outcomes;
3) The relative explanatory contribution of the compositional and contextual variables;
4) The 95% confidence interval, which was obtained from nonparametric bootstrapping (Politis, 2014).

The whole process of building multilevel model was carried out after the pre-selection of variables. The results were then reinforced by the bootstrap analysis.

Pre-selection of variables

Separate bivariate analysis for the three health outcomes was performed with the key explanatory variables to get rid of the less important ones. The variables were grouped into the composition-context categories and used statistical analysis techniques such as analysis of variance (ANOVA), t-test and simple linear regression to screen the association. While ANOVA was used for continuous variables, linear regression was used for ordinal variables and t-test was used for binomial variables. The detail process of pre-selection is presented in chapter 4 and the results are summarised in the appendix (See Appendices C-2 through C-4; page 287).

Model building

Once the important variables were identified, they were then subjected to the multilevel modelling process. The process involved step-wise removal of the less significant variables. Once the final model was identified, separate as well as a combination of different multilevel models (based on the categories of explanatory variables) were tested against the 'reference model' to investigate the relative contribution of each category individually and the combination with other categories. A reference model for each health outcome measure was built by adjusting for deprivation status, age and gender. This model estimates the gap in health measures between the participants from the most and the least deprived LSOAs of Stockton-on-Tees Borough. A total of 14 multilevel models were fitted to the data and compared with the reference. The details of this process and the findings from the analysis is presented in Chapter 4.

Bootstrap analysis

When presenting the point estimates of effect size (percentage contribution), it should always be supported by a confidence interval (Kirby and Gerlanc, 2013). Unlike regression coefficients, there is no simple standard formula that can be used to quantify confidence interval associated with relative contribution of the different contextual and compositional factors to health gap between least and most deprived areas. Bootstrapping is the preferred approach to calculate confidence intervals for such indirect effects or estimates (Shrout and Bolger, 2002). Bootstrapping is a process of creating an empirical sample by resampling with replacement from the original sample (Mackinnon et al., 2004). Fritz et al. (2012) argue when dealing with percentile bootstrapping, the iterations should be more than 2500 to correct the elevated Type I error[2]. For this research, the data was bootstrapped 10,001 times with replacement and 95 percent confidence intervals were created to generate uncertainty bounds for the percentage contributions of various factors using 2.5th and 97.5th percentile. The nonparametric bootstrapping was done in the statistical application "R". The whole process was carried out for all the three health outcomes and for all waves of the survey.

Time trend analysis in general and physical health inequalities gap

With the second approach, the relationship of austerity with health inequalities gap was explored using the longitudinal dataset. The main analyses performed under this approach were:

1) Individual growth modelling analysis was implemented, mostly to explore the rate of change and the role of time. Individual growth curve (IGC) is an advanced technique capable of modelling and assessing the within-person systematic change and the differences between the groups over a period of time. Under this approach, analysis was done considering time as a continuous variable (0, 6, 12 and 18), indicating the months of surveys
2) Analysing the role of time and considering time as a categorical variable (1, 2, 3, 4), indicating the waves.

[2] Elevated Type I error rates occur when the sample size is small and the effect size of the nonzero path is medium or larger.

3) Exploring the ‘missingness’ of the data by analysing the pattern of missing data and by performing multiple imputations.

Strengths and limitations of the methodological approaches

When there is an ongoing scholarly debate about the composition and context of geographical health inequalities, this study makes an important contribution on this issue. The study uses data from the detailed health and social determinants survey that mobilised a stratified random sample to compare the health status of people living in the most and least deprived neighbourhoods of Stockton-on-Tees. The survey was designed to capture a wide range of information at a micro level yet have an opportunity to link with data at a macro scale. While the majority of the studies conducted to explore the role of austerity on health inequalities either are on a national scale or utilise national level datasets, this survey comes to answer the questions of health inequalities from a localised perspective.

Along with the strengths of the study, it is subject to a number of limitations. The major limitation remains with the sample size, despite multiple contact attempts, the response rate for baseline and all follow-up waves remains relatively low. This was partly because of the approach adopted, with opt-in and postal requests the response could be low. The assumption of a 10 percent enrolment rate was because the survey used a postal initial recruitment approach and so response was expected to be lower than for other recruitment methods (Eriksen et al., 2011, Sinclair et al., 2012). Although a random sampling technique was used and all households living in the most and least deprived areas had equal chances of participating, the sample ended up being older and with more female (as compared to the census data). Both age and gender were adjusted for in the multilevel models to account for this - but these factors may still effect the generalisability of the findings.

In chapter 2, I presented the historical and current context of Stockton-on-Tees (see 65), where I have highlighted what makes Stockton-on-Tees an ideal place to conduct a localised case study. Stockton-on-Tees provides a unique location for doing health inequalities research when we consider its industrial past and the 'partially' successful post-industrial service economy. The most recent recession had a negative impact upon Stockton-on-Tees, with increased rates of unemployment and a significant welfare cuts (Edwards, 2012). The financial crisis and resulting austerity policies have been linked with the poor health outcomes of the people living in Stockton-on-Tees, with more pronounced effects in the deprived neighbourhoods (Garthwaite, 2016, Mattheys et al., 2016).

The use of localised case study approach offers many advantages: it draws upon inter-disciplinary insights; focuses on a specific place, community or issue; and is able to produce a detailed and rich account of the case. This approach makes it easy to understand the multi-faceted complex issues (Crowe et al., 2011), such as the impact of financial crisis and austerity. As Emmanuel and Barry (2003) "sought to embrace all the richness and complexity of a real setting" in their work (p. 1159), the Stockton-on-Tees case study provides the scope of a more 'responsive' data source, which represents the true picture of the local context since not all places are exactly alike. Yin (1999) argues that application of localised case study approach is particularly effective to investigate contemporary topic of research as it puts "intense focus on a single phenomenon within its real-life context" (p. 1211). Furthermore, Crowe et al. (2011) argues that the use of localised case study approach can indicate the causal links, by asking the ‘what’ and ‘why’ questions. In the Stockton-on-Tees’ case, this approach is ideal to describe the situation of health inequalities, explore the gap and explain what is causing it. Using the localised case study approach, it is expected that the diverse impacts of financial crisis and the resulting austerity policies can be traced.

There are several limitations of using a localised case study approach. A key limitation is the issue of generalisability as the study is based on a small geographical scale. However, the intention of this research was to have a detailed picture of health inequalities within the local context. As Darke et al. (1998) argue, case studies can offer space for bias from the researchers—while designing, conducting and interpretations of the findings. This, therefore, calls for a careful interpretation of the research findings. However, Yin (1999) makes a point that bias is an important issue with the other established forms of research as well.

Spatial heterogeneity is a condition that indicates the existence of sufficient variation of ‘exposure’ variables within the study area. This ensures that local level factors are the key and determining factors for the outcome variables. While applying a localised case study approach in a geographical research, spatial autocorrelation of the ‘exposure’ or independent variables is an important issue to be taken into consideration because this generate possible bias (Hawkins, 2012). Even when an attempt is made to get a local picture of the context, there could always be an influence of the factors at a higher geographical scale (such as the socio-political context), also known as spatial dependency. As highlighted by Arthur (2008), “local statistic outcomes are influenced by the degree of spatial autocorrelation in the global statistic” (p. 307). There is always an ‘uncertainty’ when analysing the complex relationship of these ‘exposure’ or independent variables and health outcomes (Thomas, 2013).

My research adopted the health gap approach and was focused on the LSOAs in the extreme ends of deprivation. The Stockton-on-Tees project focused on the 20 most and 20 least deprived areas and not the whole of the borough of Stockton-on-Tees. This means my sample, which was randomly selected from the two extreme ends expected to represent the people living in those areas only and may not possibly represent the whole of Stockton-on-Tees. However, with longitudinal studies, a representative sample at baseline can become less representative in the follow-ups, which can be a result of several reasons such as the population change and 'healthy responder effect', whereby people with health problems are less likely to respond to research requests (Manuel et al., 2016).

In setting up a research project for evaluating the impacts of the government's actions such as the welfare reform programmes, one of the main concern is the timing of such evaluation. It is a difficult choice to make because *"there is no single answer to this question that can be applied to every regulation"* (Coglianese, 2012` p. 50). Coglianese (2012) further argues a standard time period, such as five years is most often the preferred choice. In the case of this research, collecting the baseline data in 2014 could therefore be an ideal period to look into the impact of financial crisis. But, as the welfare reform programmes were rolled out in a phased manner (see Table 2.7, page 58), it is not possible to have a holistic evaluation in a single time period. Furthermore, the duration of data collection (two years) could be insufficient to detect all effects of austerity on health and inequalities, considering the phased implementation and also the lag period between the actions and possible impacts. The findings are thus indicative of association and are not indicative of causal links.

However, it is worth noting at this point that there could be issues with representativeness of the sample - even though the random approach meant that everyone living in each of the sampled LSOAs had an equal chance of participating in the survey, the sample ended up being older and more female than would be expected based on census estimates of the general population. Missing data is an important, yet unavoidable condition with the surveys, more pronounced with longitudinal studies like mine. An important limitation of this research was the inability to draw the profile of the participants who were lost between the waves. The research is unable to show if this group is the most affected by austerity measures (e.g. obliged to move house due to change to housing benefit). Schmidt and Teti's statement below best reflects the issue of attrition with the longitudinal research design.

> *"Sample attrition is probably one of the most common and frustrating problems faced by longitudinal researchers."*
>
> (Schmidt and Teti, 2005, p. 9)

As presented in Table 3.1 (page 86), the high level of attrition and missing data can bias the sample. In this context, Goodman and Blum (1996) argue that "subject attrition can lead to the violation of the assumption of random sampling in subsequent data collection in longitudinal research" (Goodman and Blum, 1996, p. 628). Along with the attrition, proper assessment of missing data along with the adoption of appropriate measures can help address the biases. This is because "studies excluding individuals not answering specific questions might experience a drastic decline of power" (Myrtveit et al., 2013, p. 9).

Appropriate and adequate planning of longitudinal cohort studies is a crucial issue. This type of research involves the strenuous organisation and administration of the survey and results in the collection of a large amount of data. As Schmidt and Teti (2005) have highlighted, the number of measurements is an important component of longitudinal studies—two observations can also make a longitudinal survey but this is less helpful in determining the role of time. Use of multiple measurements and growth curve data are thus the best approaches to examine the trajectories of individual growth. Considering this, the longitudinal survey was initially planned for a baseline survey and another six rounds of follow-ups. As indicated in the previous section, a higher than expected attrition rate was observed in the follow-up surveys, which resulted in the finalisation of the longitudinal study after four waves. Despite the early termination of the research, I still have enough data points to make and support the argument.

This research is based on a hierarchically structured data and the multilevel analysis was performed but this approach can have the crucial problem of 'dependence of the observations at the lower levels', whereby factors at lower levels seem to make more contribution than the level nesting it (Hox, 2010). The number of spatial units under which the participants are nested is an important factor to identify the role of place on the study outcomes, in my case the health inequalities gap. Maas and Hox (2005) have argued that in practice, 50 or more geographical units are recommended when performing any spatial analysis. Jones and Duncan (1996), however, argue that the ideal number of geographical units to perform an effective spatial analysis is 100. They further highlight the role of a number of geographical units by saying:

> *"to get reliable estimates of place differences we need lots of places. Having many individual respondents provides information…within a place, but many places are needed to assess the differences between places."*
>
> (Jones and Duncan, 1996; p. 85)

Another limitation was with the contextual or neighbourhood data. As presented in chapter 2, neighbourhood factors influence the health of the people from different mechanisms (see page 43). The longitudinal survey had limited option of collecting neighbourhood level factors, which could have introduced some level of residual confounding. There was also a limited availability of contextual data from secondary sources at an LSOA level. Whenever possible, the data was transformed into the LSOA level, such as from ward level[3]. This, however, may have introduced large-scale clustering effects into the analysis (Rezaeian et al., 2007). As argued by Rezaeian et al. (2007) spatial dependency (a tendency in which geographically close areas are more highly related than the distal ones) is a common issue with neighbourhood-level data that results in clustering effects.

Although the baseline data were collected on a face-to-face basis and follow-ups over the telephone by trained interviewers, the outcome measures are still all self-reported and these measures may have limited precision and reliability (Mathews and May, 2007). Although the health outcome measures used in this research were validated ones, other measures could also have been used (Meltzer, 2003).

Another limitation is that the relative contribution of contextual and compositional factors of health inequalities is done separately for each wave. The justification for this

[3] The ward is the primary unit (simply the building blocks) of English electoral geography for civil parishes and borough and district councils.

approach is that the nature of health measures and the contributing factors change over time. However, the limitation is that the role of time in the relative contribution of the different factors is not directly captured.

Despite these limitations, the research and the methodological approaches adopted are crucial in exploring the relationship between compositional and contextual factors with prevailing health inequalities in Stockton-on-Tees. The multilevel modelling helped analyse the hierarchical and complex data set and has provided enough evidence to make some generalisable arguments.

Summary

In this chapter, I have presented the methodological approaches used in my research and have given justifications for using them. Starting with the aims and objectives, I discussed the research design, the survey tools used and how the secondary data were collected and used in the research. I also discussed the different statistical analyses approaches adopted and the strengths and limitations of the whole approach. The next chapter will present the findings from the composition and context analysis of the local health inequalities using data from the longitudinal cohort survey.

Chapter 4: Health Gap: The Composition and Context Exploration of General and Physical Health Inequalities

Introduction

This chapter presents the findings from the cohort study, and explores the gap in general and physical health between the participants from the most and least deprived neighbourhoods of Stockton-on-Tees. As discussed in the methodology chapter, this longitudinal cohort study took place between 2014 and 2016. During the baseline survey, 836 participants were involved and the final follow-up ended up with 410 participants.

The underlying argument of this chapter is that individual level compositional factors and area level contextual factors make significant direct contributions and they interact with each other and produce indirect contributions in determining the health gap. The chapter also provides empirical evidence to support existing theoretical assertions that composition and context should therefore be looked at from a relational perspective. Over the study period, the gap remains almost constant for EQ5D-VAS and EQ5D scores but is increasing for SF8PCS scores. Apart from explaining the baseline characteristics and the preparatory work for the analysis, the findings are divided into three main sections.

1) The magnitude and trend of inequalities in general and physical health;
2) The associations between the health outcomes and compositional and contextual factors for all waves.

3) The relative contributions of the compositional and contextual factors to the health inequalities gap.

In the initial part, I present the data cleaning process involved and the assumptions made during the model building process. I then explore the characteristics of the sample during the baseline survey. I explore the demographic characteristics of the sample and compare it between the most and least deprived areas. I also explore the differences in key variables relating to individual compositional and contextual determinants of physical and general health.

I then present the inequalities in health outcome measures and also trends in the gap in general and physical health outcomes. Next, I explore the compositional and contextual factors that are associated with the health outcomes and assess how they change over the study period. Finally, I conclude the chapter by presenting the relative contributions of the compositional and contextual factors towards the gap in physical and general health. In doing so, I explore how these contributions changed over time during austerity.

Data cleaning and pre-selection of variables

For all the findings presented in this chapter, a data set with complete information was developed, which was the prerequisite of the analyses performed. This was done by removing cases with missing information. The basic approach to dealing the missing data was:

1) Deleting the cases if the data was missing for a small number of cases

2) Deleting the entire variable if the data were missing for a relatively larger number of cases. Certain variables, such as the classification of the current employment (with 536 missing cases) were excluded from the entire analyses. Appendix C-2 (page 285) presents the details of the cases and variables excluded from the model building process in full.

Selecting which variables to retain was a difficult choice that I had to make. Some of the variables related to job experiences had a larger volume of data missing, such as job security (535 cases missing), job-related stress (534 cases missing) and job satisfaction (535 cases missing), for which the entire variables were deleted. This left some conceptual problems because the existing literature suggests a strong link between health effects and job control through the psycho-social mechanisms (Bambra et al., 2007, Siegrist and Marmot, 2004). Having said that and considering the sample size I had, I decided to exclude the missing data for the selected variables. This was done to prevent any unnecessary inferences based on the incomplete dataset. Income was another variable with high missing data (57 cases), but considering its importance (in terms of study objectives) and its association with the health outcome measures during the initial bivariate analysis, the variable was retained and the cases with missing data were removed from the analysis.

Table 4.1 (below) summarises the number of participants that were included in the final analysis for each wave after dealing with the missing data. The rate of missing data was slightly over 12 percent for the baseline survey but it was 10 percent or less for all the follow-ups.

Table 4.1: Total number of cases with complete data used in the multilevel modelling

	Least Deprived			Most Deprived			Total		
	Total cases	Complete data	%	Total cases	Complete data	%	Total cases	Complete data	%
Baseline	439	356	81.1	397	377	95.0	836	733	87.7
6m	286	257	89.9	229	220	96.1	515	477	92.6
12m	260	238	91.5	218	205	94.0	478	443	92.7
18m	234	214	91.5	176	155	88.1	410	369	90.0

The model building process

As discussed in **Chapter 3**, multilevel models were fitted to explore the health inequality gap in Stockton-on-Tees. When building any statistical model, assumptions are made. One of the benefits of using multilevel modelling is that assumptions can be weaker and the models can be more flexible in terms of the assumptions made (Greenland, 2000).The data used in this research was hierarchical in nature and it was clustered within the categories of geographical areas. Hierarchical, because the data was collected at an individual level but at the same time, data was also collected for the household and the neighbourhood. The assumptions were thus made to address the nature of the data and the planned analysis.

The first assumption was related to the *independence* of the health outcome measures and the independence of the residuals or the *independent errors*. The survey participants were clustered by Lower Super Output Areas (LSOAs) and it was likely for the people from the same area to have a similar health outcome compared to those from other areas. This violates the assumption of independence as the cluster of observations are correlated with each other. The multilevel models presented in this chapter take this into consideration and controls for the possible clustering effects within the LSOAs.

The second assumption made was the *normal distribution* of the dependent variables. To assess the *normality,* it is assumed that the error terms at every level of models are normally distributed. Goldstein (2011) argues that this assumption is flexible and allows a convenient parameterisation for complex covariance structures at several levels. In this research, it was done by looking at the point estimates and their standard errors (Goldstein, 2011).

The third assumption of *multicollinearity* indicates that there is not any form of linear or nonlinear relationship among the explanatory variables included in the analysis. Presence of such relationship can influence the outcome measures. The existence of multicollinearity can make it difficult to determine the contribution of a certain explanatory variable towards the outcome measure. As indicated by Shieh and Fouladi (2003), 'higher' multicollinearity requires a cautious interpretation of the coefficients and the findings obtained. Being based on these assumptions, there was no need to perform sensitivity analysis for this research.

Baseline characteristics of the participants

After preparing a complete dataset, a descriptive analysis was performed to explore the baseline characteristics of the survey participants. This was done to make a general comparison between the participants from the most and the least deprived areas of Stockton-on-Tees. The analysis was done for the key compositional and contextual variables—including sociodemographic, material, behavioural, psychosocial and the neighbourhood factors.

Socio-demographic characteristics

Table 4.2 shows the baseline information of the study participants that remained in the final analysis after excluding the missing data. These show that in terms of gender the sample has a higher proportion of women (60%) compared to the census data for Stockton for 2011 (51%). The sample also has an older population with 29 percent of the sample aged over 65 compared to about 16 percent in the census (Office for National Statistics, 2013). In further analyses, I have therefore controlled for age and gender. Almost two in five participants from the most deprived areas were single compared to almost three in five being married in the least deprived areas. Participants were asked to rate their health during the last four weeks into five categories: excellent, very good, good, fair, poor and very poor. Participants from the most deprived areas were more likely to report having poorer general health and having a mental health problem compared to the least deprived areas. Almost 18 percent of participants from the most deprived areas reported having poor health (poor and very poor health were combined for this purpose) compared to less than five percent in the least deprived areas. Similarly, 12 percent of the participants from the most deprived areas reported having a mental health problem compared to the seven percent in their counterparts. This could be linked with the idea of the health gaps (Graham and Kelly, 2004).

Table 4.2: Characteristics of the baseline sample: Socio-demographic characteristics

Variables Categories	Number (%)	
	Least Deprived	**Most Deprived**
Age		
Under 25s	15 (4.0)	37 (10.4)
25-49	130 (34.5)	131 (36.7)
50 to 64	110 (29.2)	95 (26.6)
65 and over	122 (32.4)	94 (26.3)
Gender		
Male	162 (43.0)	146 (41.0)
Female	215 (57.0)	210 (59.0)
Marital status		
Married	221 (58.6)	90 (25.3)
Single	67 (17.8)	142 (39.9)
Divorced	39 (10.3)	58 (16.3)
Widowed	39 (10.3)	41 (11.5)
Ethnicity		
White	360 (95.5)	340 (95.8)
Asian or Asian British	10 (2.7)	0 (0.0)
Self-reported general health		
Good	280 (74.3)	174 (48.9)
Fair	79 (20.9)	119 (33.4)
Poor	18 (4.8)	63 (17.7)
Self-reported mental health problem	26 (6.9)	43 (12.0)

Compositional characteristics

Following the health inequalities literature, the compositional variables are separated into the material, psychosocial and behavioural categories. Table 4.3 outlines the compositional characteristics of the baseline sample. As expected, there was a distinct pattern of educational attainment, with more people having higher degrees in the least deprived areas and more people with entry level/no formal qualifications in the most deprived areas. The existing research base suggests an inseparable relationship of deprivation and the educational attainment, this is reflected in the characteristics of the survey participants (Department for Children Schools and Families, 2009).

In terms of socioeconomic status, the participants were broadly in keeping with the census as around 88 percent of households in the least deprived areas were owner occupied compared to 91 percent in the census. In the most deprived areas, 28 percent of the sample were owner occupiers compared to 38 percent recorded in the 2011 census (Office for National Statistics, 2013). A significant proportion of households from both areas were receiving some form of benefits (71% for least deprived areas compared to 87 percent in most deprived areas). In the same way, more than half of the participants (54%) from the most deprived areas were receiving housing benefit compared to less than five percent in the least deprived areas. See Appendix C-1 for a comparison of the socio-demographic indicators from the survey with the 2011 census findings for Stockton-on-Tees, the North East region of England and the whole of England (page 285). The proportion of participants reporting housing issues was significantly higher in the most deprived areas (inadequate heating—20% vs. 7%, dampness—26% vs. 3%, darkness—17% vs. 8% and lack of double glazing—5% vs. 2%).

More than two third of households in the most deprived areas had at least one member who was not currently working, which was slightly less than two fifth for the least deprived areas. Likewise, almost 44 percent participants from the most deprived areas described themselves as unemployed compared to only 14 percent in the least deprived areas. However, at this point, we should make a note that this was an older sample which was reflected in the proportion of retired people (38% in the least deprived areas and 31% in most deprived areas). Of those employed, more people were in professional jobs in the least deprived areas (11% vs. 3%). There was a large difference in median net household income between the two areas, which was £10400-£13000 for the most deprived areas and £26000-£28600 for the least deprived areas (Mode for the net income was £10400-£13000 vs. £36400-£41600). Likewise, ownership of motor vehicles(s) was significantly higher in the least deprived areas (94% vs. 43%).

Among the psychosocial factors, participants from the most deprived areas were more likely to report lacking companionship, almost one-third of them reported having the issue at least at some point, compared to 24 percent among their counterparts. Similar findings were obtained for feeling left out (30% vs. 16%) and feeling isolated (28% vs. 18%). The average happiness score (scale of 0-10) was also higher among the participants from the least deprived areas (8 vs. 7.4); with a higher dispersion as measured by standard deviation in the most deprived areas.

While smoking was more prevalent in the most deprived areas (37% vs. 10%), the use of alcohol was higher in the least deprived areas (79% vs. 59%). In Stockton-on-Tees, the overall prevalence of smoking among the adults was 20 percent (Public Health England, 2015). The average units of fruit and vegetables consumed were slightly higher in the least deprived areas (4 units vs. 3 units). More participants from the most deprived areas reported being active on a daily basis (36% vs.30%). In contrast, 32 percent of the participants from the most deprived areas reported of never doing any physical exercise compared to one-fourth among their counterparts.

Table 4.3: Characteristics of the baseline sample: Compositional factors

Variables Categories	**Number (%)**	
	Least Deprived	**Most Deprived**
Material		
Highest Educational Level		
Higher or First Degree	100 (26.5)	17 (4.8)
Higher Diplomas/A-Levels or Equivalent	106 (28.1)	39 (10.9)
GCSE or Equivalent	87 (23.1)	138 (38.8)
Entry Level/No Formal Qualifications	84 (22.3)	162 (45.5)
Housing Tenure		
Own outright	193 (51.2)	61 (17.1)
Mortgage or loan	138 (36.6)	37 (10.4)
Rent	44 (11.7)	254 (71.3)
Live rent free	2 (0.5)	4 (1.1)
Household Receipt of Benefits	266 (70.6)	311 (87.4)
Household Receipt of Housing Benefit	16 (4.2)	193 (54.2)
Workless Household (at least one member out of work)	142 (37.7)	237 (66.6)
Current Job Skill Type		
Professional	43 (11.3)	10 (2.8)
Unskilled	27 (7.1)	42 (11.8)
Work Status		
Participant in Paid Employment	183 (48.5)	89 (25.0)
Retired	142 (37.5)	112 (31.4)
Unemployed*	53 (14.0)	156 (43.7)
Household Annual Income (Mode)	£36400-£41600	£10400-£13000
Problems with Damp in the Home	10 (2.7)	94 (26.4)
Home is too Dark	31 (8.2)	62 (17.4)
Home is not Warm enough in Winter	27 (7.2)	72 (20.2)
Home without double glazing	6 (1.6)	19 (5.3)
Own motor vehicle(s)	353 (93.6)	153 (43.0)

Psychosocial		
Lacking Companionship		
Hardly ever	286 (75.9)	239 (67.1)
Some of the time	70 (18.6)	76 (21.3)
Often	21 (5.5)	40 (11.2)
Feeling Left Out		
Hardly ever	318 (84.4)	249 (69.9)
Some of the time	47 (12.4)	66 (18.5)
Often	12 (3.2)	41 (11.5)
Feeling Isolated		
Hardly ever	310 (82.2)	255 (71.6)
Some of the time	54 (14.3)	60 (16.9)
Often	13 (3.4)	41 (11.5)
Happiness scale: mean (std. deviation)	8 (1.6)	7.4 (2.1)
Behavioural		
Respondents who smoke	39 (10.3)	132 (37)
Respondents who drink alcohol	297 (78.8)	210 (59.0)
Fruit/vegetable intake: average units (standard deviation)	4 (2.0)	2.8 (1.9)
Frequency of physical exercise		
Every day	113 (30.0)	128 (36.0)
Most days	65 (17.2)	44 (12.4)
Couple of times a week	78 (20.7)	42 (11.8)
Once a week	14 (3.7)	15 (4.2)
Less than once a week	13 (3.4)	14 (3.9)
Never	94 (24.9)	113 (31.7)

*Unemployed incorporates all individuals of working age who are not in employment, including those classed as unemployed, unable to work due to ill-health or disability, or looking after the home/family

Contextual characteristics

Table 4.4 presents the neighbourhood related factors reported by the survey participants from both areas. A higher proportion of participants from the most deprived areas reported problems with noise (24% vs. 11%), pollution (13% vs. 3%) and crime (29% vs. 6%) in their neighbourhood. More than 12 percent of people from the most deprived areas felt unsafe walking alone in their neighbourhood after dark compared to less than two percent in the least deprived areas. It is however worth noting at this point that these contextual data were reported by the survey participants and are mostly physical and psycho-social in nature.

Table 4.4: Characteristics of the baseline sample: Contextual factors

Variables Categories	**Number (%)**	
	Least Deprived	**Most Deprived**
Problems with Neighbourhood Noise	42 (11.1)	85 (23.9)
Problems with Pollution	13 (3.4)	45 (12.6)
Problems with Crime	24 (6.4)	105 (29.5)
Feeling unsafe walking alone after dark		
Very safe	207 (54.9)	107 (30.1)
Safe	141 (37.4)	132 (37.1)
Unsafe	23 (6.1)	73 (20.5)
Very unsafe	6 (1.6)	44 (12.4)

Exploring the gap

One of the objectives of my research was to examine if there was a difference in health as measured by physical and general health outcome measures. The question was to address if there was a gap? What was its scale and did it change over time? In this research, general health was measured using EQ5D-VAS and EQ5D scores whereas physical health was measured using SF8PCS scores. The longitudinal data were used to make an initial comparison between the two areas to see if the health gap depended upon place.

The magnitude and trend of inequalities

I started with descriptive analyses and by building boxplots to see if there was a gap in health outcomes between the two areas. This was done for all three health measures used in the research.

EQ5D-VAS

The boxplots below (Figure 4.1) show that for all waves there was a larger range of EQ5D-VAS scores for people living in the most deprived areas compared to those living in the least deprived areas. This suggests the existence of a constant and greater variation of EQ5D-VAS scores in the most deprived areas. The difference in median values between the two areas was five in wave two and 10 for all other waves. As seen in Figure 4.1, even the lower values of EQ5D-VAS scores from most deprived areas fell within the interquartile range but such values became suspected outliers (less than 1.5 times inter-quartile range—indicated by circles) and outliers (more than 1.5 times inter-quartile range—indicated by stars) for the least deprived areas.

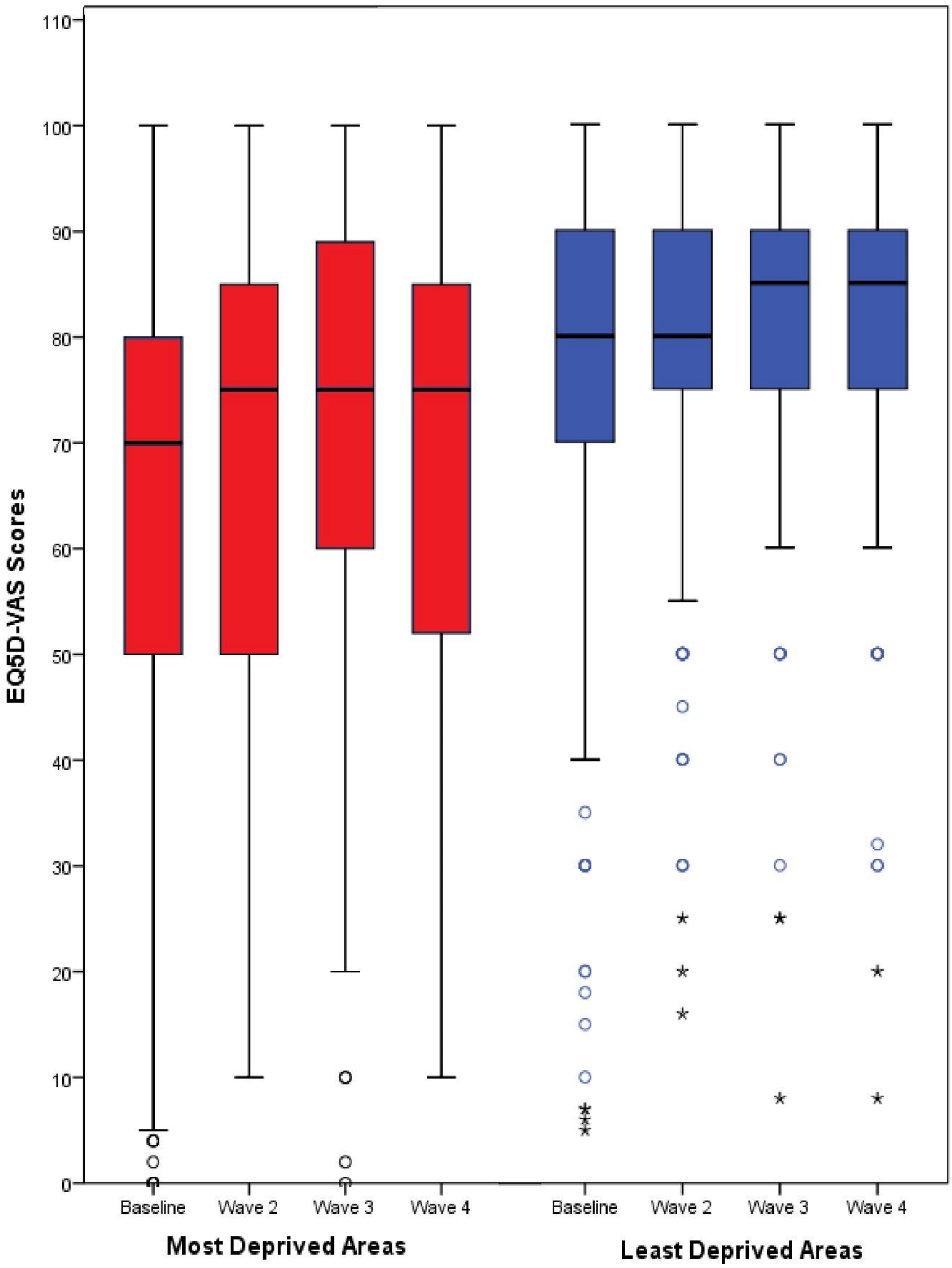

Figure 4.1: Boxplots of EQ5D-VAS for all waves by most and least deprived areas

There was a constant gap in the average values of EQ5D-VAS for both the areas as these values increased by almost the same rate during the study period. The level of variability in these scores, as measured by standard deviation was higher for the most deprived areas (see Table 4.5).

Table 4.5: Descriptive analysis of EQ5D-VAS scores

Area	Measures	Baseline	Wave 2	Wave 3	Wave 4
Most Deprived	Mean	64.71	69.45	70.85	70.01
	N	356	220	205	155
	Std. Deviation	23.36	22.22	21.44	20.91
	Minimum	0	0	0	0
	Maximum	100	100	100	100
	Median	70	75	75	75
Least Deprived	Mean	75.37	79.47	80.67	80.77
	N	377	257	238	214
	Std. Deviation	18.05	16.20	15.36	14.32
	Minimum	5	16	8	8
	Maximum	100	100	100	100
	Median	80.00	80.00	85.00	85.00

EQ5D Scores

Figure 4.2 presents the boxplots for EQ5D scores for both areas for the survey waves. The range of EQ5D scores was relatively larger for participants from the most deprived areas, indicating a higher variation in the scores. There was a noticeable difference in the median scores between the two areas. As seen in the figure, even the lower EQ5D scores from most deprived areas fell within the interquartile range or were suspected outliers (less than 1.5 times inter-quartile range—indicated by circles) but there were significant numbers of outliers (more than 1.5 times inter-quartile range—indicated by stars) for the least deprived areas.

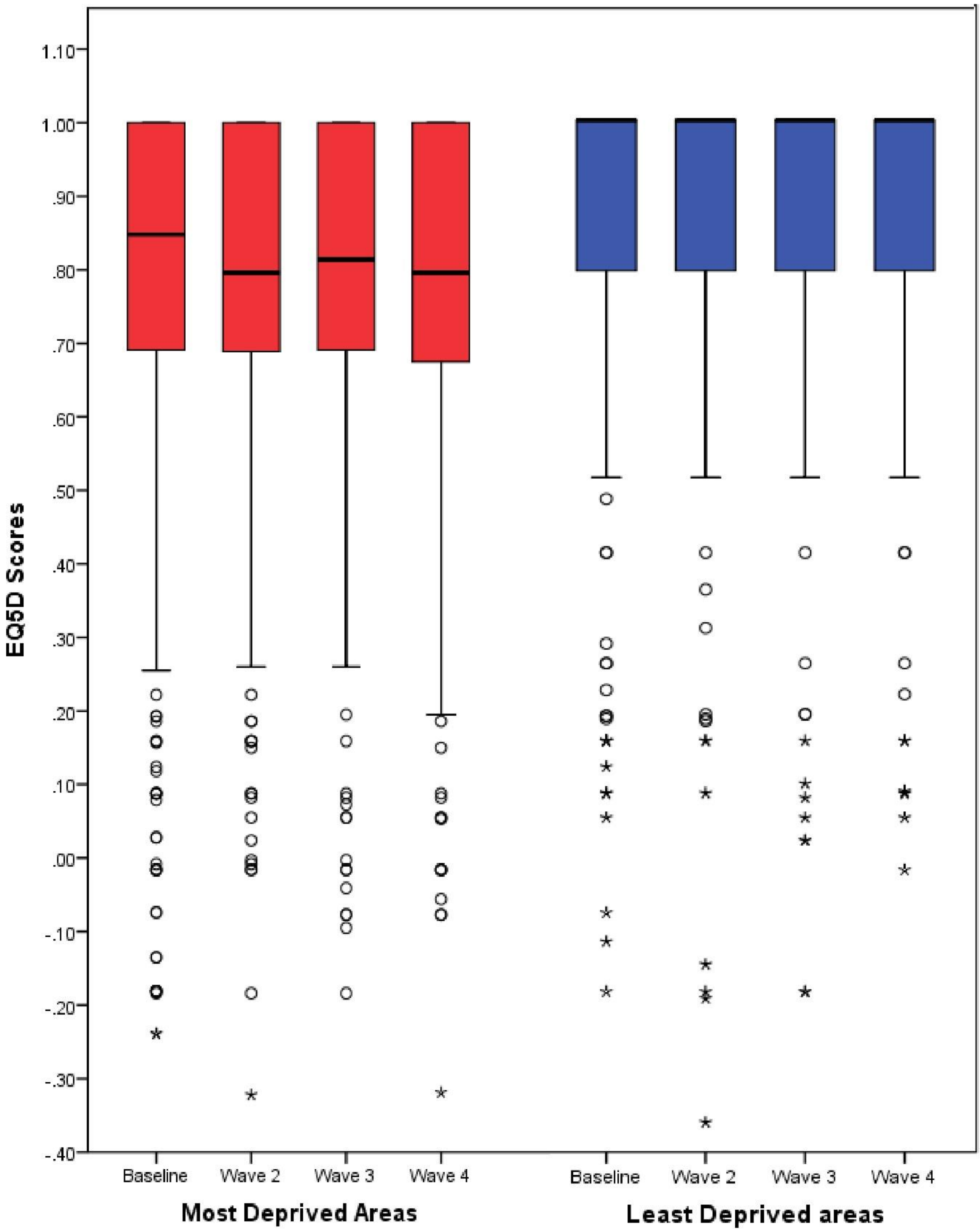

Figure 4.2: Boxplots of EQ5D scores for all waves by most and least deprived areas

The results of the descriptive analysis presented in Table 4.6 reinforces the information presented in the boxplots, with higher average scores for the least deprived areas for all survey waves. The average EQ5D scores remained almost constant for both the groups. The lower standard error of the mean for both the areas indicates that the people from least deprived areas are more likely to have higher EQ5D scores compared to those living in the most deprived areas.

Table 4.6: Descriptive analysis of EQ5D Scores

Area	**Measures**	**Baseline**	**Wave 2**	**Wave 3**	**Wave 4**
Most Deprived	Mean	0.76	0.75	0.78	0.73
	N	356	220	205	155
	Std. Deviation	0.02	0.02	0.02	0.02
	Minimum	-0.24	-0.32	-0.18	-0.32
	Maximum	1	1	1	1
	Median	0.85	0.80	0.81	0.80
Least Deprived	Mean	0.87	0.87	0.85	0.86
	N	377	257	238	214
	Std. Deviation	0.01	0.01	0.01	0.01
	Minimum	-0.18	-0.36	-0.18	-0.02
	Maximum	1	1	1	1
	Median	1	1	1	1

SF8PCS

As with the measures of general health, the boxplots for SF8PCS showed a similar trend, with a wider range of scores for the participants from the most deprived areas compared to those from the least deprived areas. In addition, there were no outliers in the most deprived areas, indicating all lower scores in the group were within the interquartile range, which was not the case with the least deprived areas (see Figure 4.3).

Unlike the findings of the other general health measures, the average scores of SF8PCS follow a different trend. The average scores of SF8PCS scores for the most deprived areas constantly decreased during each wave from 46 to 44, while the scores remained almost constant for the least deprived areas. Variability of the average scores, as measured by standard deviation did not change considerably for both the areas (see Table 4.7).

Table 4.7: Descriptive analysis of SF8-PCS scores

Area	**Measures**	**Baseline**	**Wave 2**	**Wave 3**	**Wave 4**
Most Deprived	Mean	45.95	44.59	44.55	44.18
	N	356	220	205	155
	Std. Deviation	11.79	11.54	12.29	11.83
	Minimum	15.37	17.08	15.94	19.47
	Maximum	63.71	62.43	62.79	60.98
	Median	49.20	47.79	48.26	48.92
Least Deprived	Mean	50.18	50.03	50.64	50.38
	N	377	257	238	214
	Std. Deviation	9.93	9.16	8.60	9.12
	Minimum	16.75	11.95	16.39	15.58
	Maximum	61.96	61.13	65.75	65.35
	Median	54.32	52.88	53.70	53.10

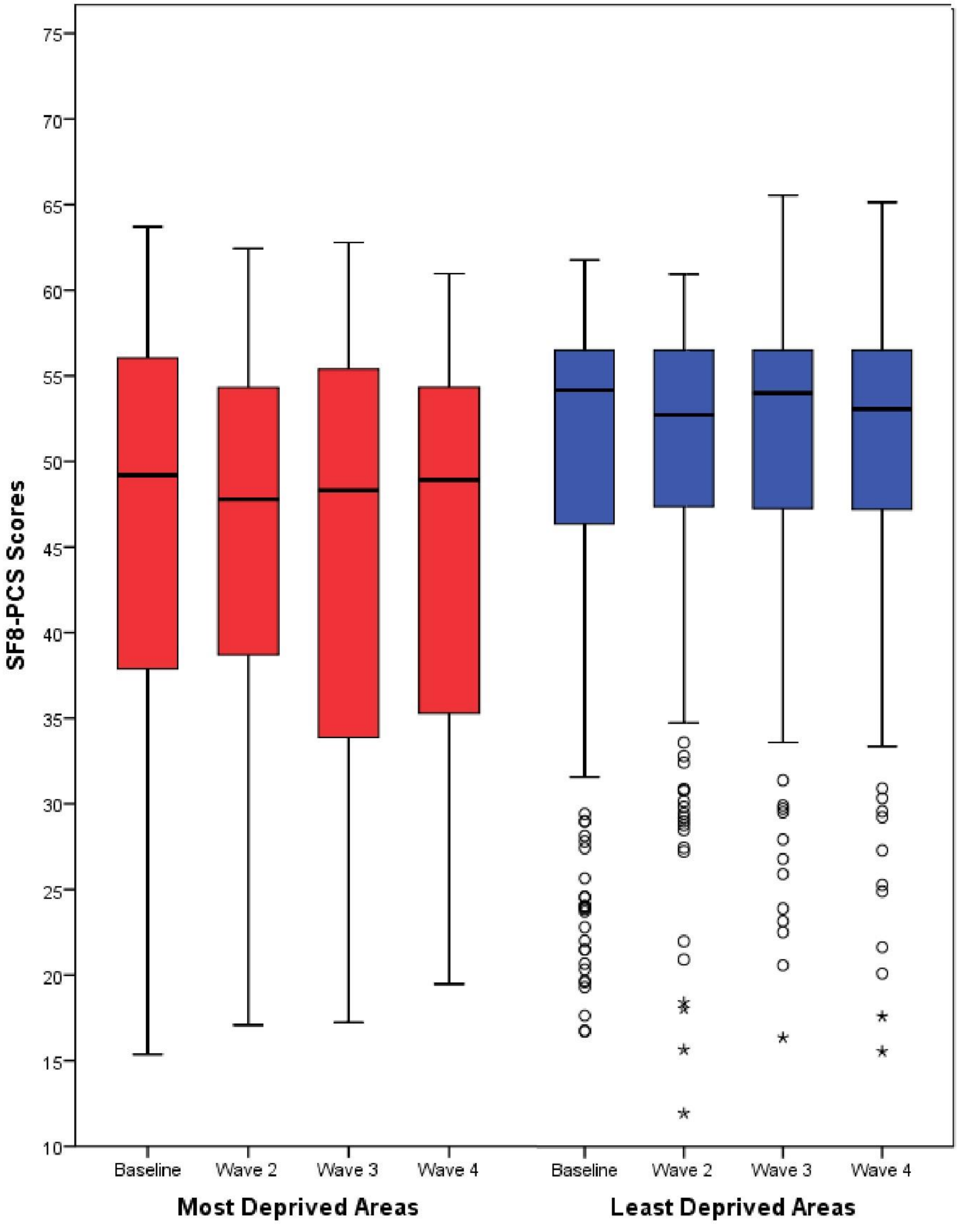

Figure 4.3: Boxplots of SF8-PCS for all waves by most and least deprived areas

The gap in health outcome measures

To explore the gap and relationship between place and the health outcomes, several multilevel models were produced and fitted. Of the different models, the reference model (see Table 4.8) estimates the gaps in EQ5D-VAS, EQ5D and SF8PCS between the participants from the most and the least deprived LSOAs of Stockton-on-Tees Borough. The modelling process was applied to all waves of the survey to examine if there was any change in the relationship. While doing so, age and gender were adjusted as the existing literature base suggest a significant association of these factors with health inequalities (Graham, 2009). This was also done because of the nature of our sample (older population). The people living in the least deprived areas have significantly better general and physical health scores compared to those living in the most deprived areas of the borough.

Table 4.8: The trend of health inequalities in Stockton-on-Tees: Estimates of fixed effects

Health measures	**Parameter**	**Estimate (95% Confidence Interval)**			
		Baseline	**Wave 2**	**Wave 3**	**Wave 4**
EQ5D-VAS	Intercept	71.85(66.2,77.47)	77.37(71.1,83.65)	77.02(70,83.33)	76.91(70,83.72)
	Deprivation	10.86(5.89,15.82)	10.41(6.57,14.26)	10.1(6.69,13.59)	10.96(7.38,14.5)
	Gender	-0.14(-3.15,2.87)	0.09(-3.42,3.59)	-1.93(-5.44,1.58)	-3.47(-7.05,0.12)
	Age	-0.15(-0.24,-0.06)	-0.15(-0.25,-0.04)	-0.1(-0.20,0.01)	-0.1 (-0.21,0.01)
EQ5D	Intercept	0.95 (0.88,1.01)	0.84(0.75,0.93)	0.81(0.72,0.90)	0.78(0.68,0.88)
	Deprivation	0.12(0.07,0.17)	0.13(0.07,0.18)	0.07(0.01,0.13)	0.14(0.09,0.19)
	Gender	0.03(-0.01,0.07)	0.01(-0.04,0.05)	-0.05(-0.09,-0.01)	0.02(-0.03,0.07)
	Age	-0.01(-0.05,-0.03)	-0.002(-0.03,0)	0(-0.02,0.01)	-0.01(-0.03,0.01)
SF8PCS	Intercept	54.1(51.51,56.78)	51.1(47.68,54.4)	50.3(46.79,53.86)	50.36(46,54.38)
	Deprivation	4.76(2.8,6.73)	5.84(3.71,7.97)	6.48(4.55,8.42)	6.53(4.42,8.64)
	Gender	0.99(-0.56,2.54)	0.37(-1.49,2.23)	0.90(-1.07,2.87)	1.002(-1.12,3.12)
	Age	-0.17(-0.2,-0.13)	-0.12(-0.18,-0.07)	-0.11(-0.17,-0.05)	-0.12(-0.18,-0.05)

Figure 4.4 (below) shows the trend in estimated inequality gap in general and physical health between the areas. On average, people from the least deprived areas are likely to score more than 10 points higher on the EQ5D-VAS. While the people from least deprived areas were more likely to have significantly better EQ5D scores, there was a fluctuating trend when we look at the longitudinal data. Though no particular trend was observed with the general health measures, a steady increase in the gap between the two areas was observed with the physical health measure (SF8PCS). The estimate for SF8PCS increased from 4.76 (2.8, 6.73) during the baseline to 6.53 (4.42, 8.64) during the final wave, which is a 37 percent increase in the gap. When we correlate the findings presented in Table 4.7, Table 4.8 and Figure 4.4, we can see that, over time, the people from the most deprived areas are not doing as well in physical health measures as their counterparts.

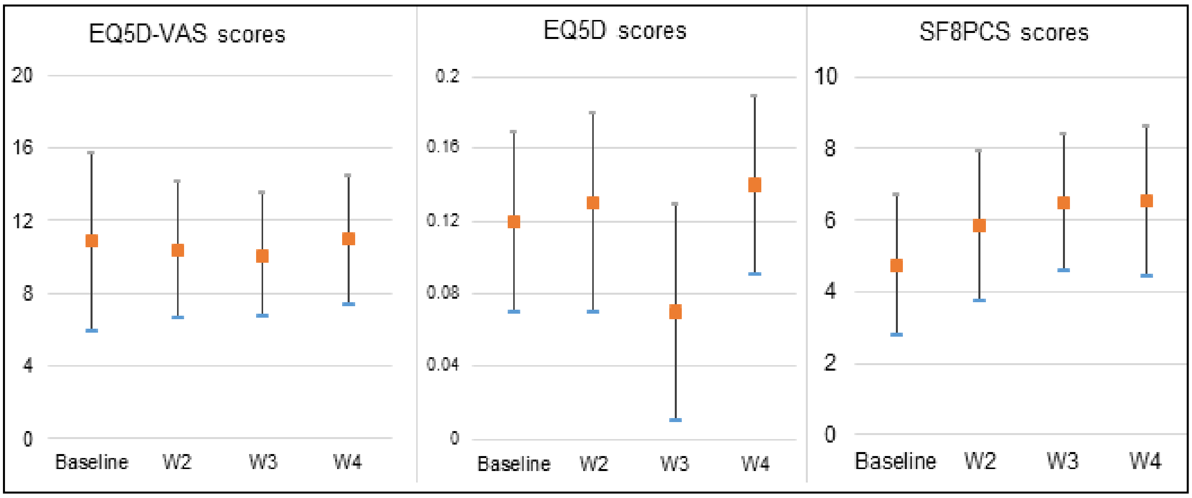

Figure 4.4: Trend of estimated inequality gap in EQ5D-VAS, EQ5D and SF8PCS scores between most and least deprived areas with 95 percent confidence interval

The association between the health outcomes and the compositional and contextual factors

After analysing the gap in general and physical health outcomes between the most and least deprived areas of Stockton-on-Tees, the next step was to explore the key compositional and contextual factors associated with this gap. Multilevel models were fitted for EQ5D-VAS, EQ5D and SF8PCS and for each wave. In doing so, the models were adjusted for age and gender and controlled for the potential clustering within the LSOAs.

Table 4.9: List of predictors fitted into the first model

Compositional	Contextual
Material	Is there crime, violence or vandalism in the area
Are there problems with damp in the home	Are there problems with noise in the neighbourhood
Is the home too dark, not enough light	Is there pollution, grime or environmental problems in the neighbourhood
Is the household warm enough in winter	Is there pollution, grime or environmental problems in the neighbourhood
Highest educational level	How safe would the participant feel walking alone after dark
Is the participant in paid employment	% individuals receiving DWP benefit
Is anyone in the household in receipt of benefits	Outdoor environment Sub-domain Score-IMD
Household income	% Households with no cars or vans in LSOA
Housing tenure	Alcohol outlet density for the neighbourhood
Is this a workless household	Fast-food outlet density for the neighbourhood
Vehicle ownership	Approximate proportion of social grade AB in the LSOA
Is the household in receipt of housing benefit	Approximate proportion of social grade DE in the LSOA
Does the house have double glazed windows	Crime scores for the LSOA from IMD
Psychosocial factors	Social Fragmentation Index for the LSOA
Happiness scale	Nearest GP as obtained from Inverse care law research
How many people live in the house	Nearest Pharmacy as obtained from Inverse care law research
How often does the participant feel isolated from others	Does the participant feel the neighbourhood had changed
How often does the participant feel isolated from How often does the participant feel they lack companionship	Does the participant feel they feel belonging to the neighbourhood
How often does the participant feel left out	Walkability scores for the neighbourhood
How often does the participant meet socially with friends, family or work colleagues	Is the participant satisfied with their neighbourhood
Behavioural factors	
Does the participant drink alcohol	
Weekly alcohol consumption	
Frequency of physical exercise	
Daily portions of fruit and vegetables	
Does the participant smoke	

The analysis started with the univariate analysis of the individual variables to filter out redundant variables (Agresti, 2015, Hosmer et al., 2013). Final models were obtained using likelihood ratio test to ensure no substantial information was lost due to variable selection (Verbeke and Molenberghs, 2000). Significant variables during the initial screening and pre-selection process were entered into the first model (see Table 4.9, above). Compositional factors were classified into material, psychosocial and behavioural factors.

As the sampling was done at the LSOA level, a correlation between the participants residing in the same area was expected. By treating LSOAs as random effects, the within LSOA correlation was accounted for. After fitting the significant variables into the first model, a step by step model deduction was carried out. Variables which were not significant at $p<0.500$ were removed and the remaining variables were fitted into another model. Likewise, the step was carried out at $p<0.20$, $p<0.10$ and then finally at $p<0.05$. The overall fit of the model was assessed at each stage to make sure the important variables were not lost during the model reduction process. A sensitivity analysis with likelihood ratio test ensured no information was lost. In the next section, I present the association of the different compositional and contextual factors with the health measures.

EQ5D-VAS

The associations between EQ5D-VAS and compositional and contextual factors are presented in Table 4.10 (below). During the baseline survey, one material, two each of psychosocial and behavioural and three from the contextual factors were associated with EQ5D-VAS. A significant and positive association between EQ5D-VAS and household income and happiness scale was found. Likewise, use of alcohol had a positive association, indicating people who drank alcohol had higher EQ5D-VAS scores compared to the non-drinkers. In terms of psychosocial factors, people who are happier had higher EQ5D-VAS scores and those who felt left-out had significantly lower scores. In terms of behavioural factors, compared to people who exercise daily, those exercising less frequently had lower EQ5D-VAS scores. Among the contextual factors, feeling unsafe walking alone after dark, neighbourhood noise and pollution were all negatively associated with EQ5D-VAS scores.

Household income and neighbourhood pollution, which were associated with EQ5D-VAS during the baseline were no longer associated during the second wave. In terms of the material factors, worklessness was found to be negatively associated, compared to the people who had a job, workless people had significantly lower EQ5D-VAS scores. As with the baseline survey, happiness and alcohol use had positive associations, while the feeling of being left-out, feeling unsafe walking alone after dark and neighbourhood noise had negative associations with EQ5D-VAS scores.

During the third wave being in paid employment and belonging to the neighbourhood where you live were the factors positively associated with EQ5D-VAS scores. People from households receiving benefits, increasing the feeling of lacking companionship, increasing frequency of feeling isolated, lesser involvement in physical exercises, feeling unsafe walking alone after dark were all negatively associated with EQ5D-VAS scores.

People from households with double glazed windows, those who drank alcohol and who felt belonging to their neighbourhood had better EQ5D-VAS scores. People lacking companionship and having an increasing frequency of feeling isolated had lower EQ5D-VAS scores. Likewise, people living in the neighbourhoods where noise, pollution and prevalence of crime were of problems, had lower EQ5D-VAS scores.

There was an intra-LSOA correlation of 24.21/ (324+24.21) = 7 percent during the baseline survey. This indicates that there was a seven percent chance of people having similar EQ5D-VAS scores if they are from the same LSOA. This also means that most of the variability in the outcome are between individuals rather than between the LSOAs. However, for rest of the waves, the random effects results suggested that the variability in the data was mostly between the individual participants and there was little influence of area. This also showed that the inter-LSOA variation was negligible for the follow-up surveys.

Table 4.10: Association between EQ5D-VAS and the explanatory variables. Point estimates and 95% Confidence Intervals

Factors	**Variables***	**Baseline**	**Wave 2**	**Wave 3**	**Wave 4**
	Deprivation	3.02(-1.88,7.91)	4.37(1.1,7.65)	5.16(1.62,8.7)	7.2(3.57,10.83)
	Age	-0.11(-0.19,-0.02)	-0.11(-0.21,-0.01)	-0.04(-0.16,0.07)	-0.11(-0.21,0)
	Gender	-3.02(-5.9,-0.14)	-2.1(-5.16,0.96)	-3.23(-6.62,0.15)	-4.29(-7.74,-0.83)
Material	Household income	0.36(0.07,0.66)			
	Household worklessness (Yes/No)		-4.5(-7.98,-1.02)		
	Paid employment (Yes/No)			4.16(0.05,8.28)	
	Household benefits (Yes/No)			-3.81(-7.95,0.33)	
	The house has double glazing (Yes/No)				9.56(-0.74,19.87)
Psycho-social	Lacking companionship			-2.99(-5.81,-0.16)	-3.91(-7.62,-0.21)
	Happiness scale	2.24(1.43,3.05)	3.06(2.11,4.01)		
	Frequency of feeling left out	-4.69(-7.22,-2.16)	-5.55(-8.37,-2.73)		
	Frequency of feeling isolated from others			-5.71(-9.14,-2.27)	-5.95(-9.79,-2.12)
Behaviou-ral	Frequency of physical exercise**	-1.51(-2.2,-0.83)	-2.48(-3.4,-1.56)	-2.54(-3.58,-1.49)	
	Alcohol use (Yes/No)	4.58(1.58,7.58)	4.27(1.19,7.35)		5.25(1.72,8.78)
Contextual/ Neighbour-hood	Feeling unsafe walking alone after dark (Yes/No)	-1.87(-3.56,-0.18)	-2.42(-4.13,-0.72)	-2.03(-3.87,-0.19)	
	Neighbourhood noise (Yes/No)	-1.37(-5.15,2.42)	-1.79(-5.73,2.16)		-4.26(-9.77,1.26)
	Pollution/Environmental problems (Yes/No)	-5.14(-10.47,0.19)			-1.33(-9,6.34)
	Neighbourhood crime (Yes/No)				-0.29(-5.56,4.97)
	Belongingness to the area (Yes/No)			0.25(-2.44,1.94)	0.31(-1.85,2.48)
Random effects	Covariance parameter	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)
	Residuals	324(17.37)	254.23(16.46)	278.78(18.75)	253.66(18.67)
	LSOA	24.21(10.05)	0.00(0.00)	0.00(0.00)	0.00(0.00)

* For the Yes/No response variables, ‘No’ was the reference group **Daily exercise was the reference category

EQ5D Scores

Table 4.11 shows the point estimates and 95 percent confidence limit for the factors associated with EQ5D scores. During the baseline, in material terms, households which had at least one workless member and houses with heating and dampness issues were the material factors and all were negatively associated. In terms of psychosocial factors, while happiness was positively associated, the feeling of being left-out and isolated had a negative association with EQ5D. Higher frequency of physical exercise and use of alcohol were significantly associated with higher EQ5D scores. Among the contextual factors, feeling unsafe walking alone after dark, pollution/environmental problems and presence of crime and vandalism in the neighbourhood were negatively associated with the EQ5D scores.

During the second wave, having a paid job was the only material factor associated with EQ5D, which had a significant positive association with EQ5D scores. Alike the baseline survey, happiness scale had a positive association and feeling isolated had a negative association. Similarly, the frequency of physical exercise and units of alcohol consumed had a significant positive association with EQ5D scores. Among the contextual factors, feeling unsafe walking alone after dark and presence of crime and vandalism in the neighbourhood were negatively associated with the EQ5D scores.

Multilevel models for EQ5D scores were not fitted for the wave 3 dataset because none of the psychosocial factors were found significant during the initial selection. There was a fluctuation in the EQ5D scores during the wave (see Figure 4.2, above). In addition to this, the percentage explanation of the final model did not improve compared to the reference model. The models developed in such case would be incomparable with other waves.

In the final wave, households receiving benefits were significantly associated with lower EQ5D scores. Alike the baseline and the first follow-up survey, happiness scale had a positive association while feeling isolated had a negative association. Similarly, the frequency of physical exercise had a significant positive association with EQ5D scores. Feeling unsafe walking alone after dark, the presence of neighbourhood noise and crime and vandalism in the neighbourhood were negatively associated with the EQ5D scores.

The random effects results for all waves suggest that the variability in the data was mostly between the individual participants and there was little influence of area. This indicates that the data for all waves can be treated as independent and the inter-LSOA variations were negligible.

Table 4.11: Association between EQ5D scores and the explanatory variables. Point estimates and 95 percent Confidence Intervals

Factors	**Variables***	**Baseline**	**Wave 2**	**Wave 4**
	Deprivation	0.01(-0.03,0.06)	0.027(-0.024,0.079)	0.053(-0.006,0.111)
	Age	0.0003(-0.004,-0.002)	-0.001(-0.002,0)	-0.002(-0.003,0)
	Gender	0(-0.03,0.03)	-0.031(-0.072,0.009)	0.01(-0.04,0.06)
Material	Household benefits (Yes/No)			-0.093(-0.164,-0.022)
	Household worklessness (Yes/No)	-0.06(-0.1,-0.02)		
	Paid job (Yes/No)		0.07(0.023,0.117)	
	The house is damp (Yes/No)	-0.05(-0.1,0)		
	The house is warm (Yes/No)	0.05(0,0.1)		
Psycho-social	Lacking companionship	0.04(0,0.07)		
	Happiness scale	0.03(0.02,0.04)	0.023(0.01,0.035)	0.035(0.017,0.053)
	Frequency of feeling left out	-0.05(-0.09,-0.01)		
	Frequency of feeling isolated from others	-0.07(-0.11,-0.02)	-0.073(-0.11,-0.036)	-0.052(-0.099,-0.005)
Behavioural	Frequency of physical exercise**	-0.02(-0.03,-0.01)	-0.047(-0.059,-0.035)	-0.011(-0.024,0.002)
	Alcohol use (Yes/No)	0.05(0.02,0.09)		
	Alcohol units		0.003(0.001,0.005)	
Contextual/ Neighbour-hood	Feeling unsafe walking alone after dark (Yes/No)	-0.03(-0.05,-0.01)	-0.034(-0.057,-0.012)	-0.014(-0.039,0.011)
	Neighbourhood noise (Yes/No)			-0.093(-0.17,-0.015)
	Pollution/Environmental problems (Yes/No)	-0.04(-0.1,0.03)		
	Neighbourhood crime (Yes/No)	-0.02(-0.07,0.03)	-0.044(-0.097,0.01)	-0.014(-0.088,0.06)
Random effects	Covariance parameter	Estimate (Std. Error)	Estimate (Std. Error)	Estimate (Std. Error)
	Residuals	0.048(0.0026)	0.044(0.003)	0.05(0.003)
	LSOA	0.0008(0.0007)	0.001(0.001)	0.001(0.001)

* For the Yes/No response variables, ‘No’ was the reference group
**Daily exercise was the reference category

SF8PCS

Relationship between different attributes and SF8PCS scores is presented in Table 4.12. The baseline findings suggest that having a workless member in the household or having a damp house was associated with lower SF8PCS scores. In terms of psychosocial factors, people who stayed happier were more likely to have better physical health. The frequency of exercise was positively and significantly associated with SF8PCS scores. A significant association was found with feeling unsafe walking alone after dark and SF8PCS scores. Finally, ‘outdoor living environment deprivation scores’ (a sub-domain of living environment deprivation domain) for IMD 2015 (Dept for Communities and Local Government, 2015) was significantly associated with lower SF8PCS scores.

During the second wave, having a paid job was the only material factor positively associated with SF8PCS scores. Among the psychosocial factors, while happiness scale had a positive association, increasing frequencies of feeling left out had a negative association. Compared to those doing exercises regularly, people who were less active had significantly lower SF8PCS scores. In contrast, the amount of alcohol consumed were positively associated with SF8PCS scores. In line with the baseline survey, a significant association was found between feeling unsafe walking alone after dark and SF8PCS scores. In addition, neighbourhood noise and ‘crime scores’ (a sub-domain of IMD) were associated with lower SF8PCS scores.

The multilevel modelling for Wave 3 dataset suggests that receiving housing benefit have a significant negative association with SF8PCS scores. People who felt isolated from others were more likely to have poorer physical health scores. Drinking alcohol above the recommended limit (14 units a week) was positively associated with the physical health scores. Similarly, people reporting feeling unsafe walking alone after dark and presence of neighbourhood noise were more likely to have lower SF8PCS scores.

In the final wave, household income had a significant positive association with physical health scores. While happiness scale was positively associated people feeling left out and isolated were significantly likely to have poorer physical health status. The frequency of physical exercise was positively associated with SF8PCS scores. As in wave 3, associations were obtained for feeling unsafe walking alone after dark and presence of neighbourhood noise.

Similar to the findings for the EQ5D scores, the random effects results for all waves suggest that the variability in the data is mostly between the individual participants and there is little influence of area. This indicates that the data for all waves can be treated as independent and that the inter-LSOA variations are negligible.

Table 4.12: Association between SF8PCS scores and the explanatory variables. Point estimates and 95 percent Confidence Intervals

Factors	**Variables***	**Baseline**	**Wave 2**	**Wave 3**	**Wave 4**
	Deprivation	0.22(-1.77,2.22)	0.57(-2.71,3.85)	2.31(0.05,4.57)	2.74(0.3,5.17)
	Age	-0.12(-0.17,-0.08)	-0.07(-0.12,-0.01)	-0.13(-0.18,-0.07)	-0.1(-0.17,-0.04)
	Gender	-0.07(-1.58,1.45)	-1.3(-3,0.39)	-0.37(-2.28,1.55)	-0.67(-2.79,1.44)
Material	Household income				0.23(0.01,0.44)
	Paid job (Yes/No)		3.83(1.86,5.81)		
	Household worklessness (Yes/No)	-3.93(-5.57,-2.29)			
	Housing benefit (Yes/No)			-3.65(-6.12,-1.18)	
	The house is damp (Yes/No)	-2.32(-4.5,-0.13)			
Psycho-social	Happiness scale	1.09(0.7,1.48)	0.55(0.03,1.07)		1(0.26,1.74)
	Frequency of feeling left out		-2.65(-4.22,-1.08)		-3.48(0.9,6.06)
	Frequency of feeling isolated from others			-2.58(-4.19,-0.97)	-2.84(-5.26,-0.43)
Behavioural	Frequency of physical exercise**	-0.81(-1.15,-0.46)	-1.64(-2.14,-1.13)		-0.63(-1.15,-0.1)
	Alcohol units	0.06(0.01,0.11)	0.11(0.03,0.19)		
	Alcohol above recommended limit (Yes/No)			3.44(1.15,5.73)	
Contextual/ Neighbour-hood	Feeling unsafe walking alone after dark (Yes/No)	-1.01(-1.9,-0.13)	-1.86(-2.8,-0.92)	-1.53(-2.58,-0.48)	-0.97(-1.99,0.05)
	Neighbourhood noise (Yes/No)	-0.59(-2.58,1.39)	-0.33(-2.49,1.83)	-2.59(-5.16,-0.03)	-2.5(-5.68,0.69)
	Outdoor environmental score-IMD	-2.86(-5.34,-0.37)			
	Crime score- IMD		-0.94(-2.52,0.63)		
Random effects	Covariance parameter	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)
	Residuals	92.43(4.94)	76.96(5.18)	90.6(6.09)	87.88(6.47)
	LSOA	0.05(1.05)	0.04(1.44)	0.0(0.00)	0.00(0.00)

* For the Yes/No response variables, ‘No’ was the reference group **Daily exercise was the reference category

The relative contribution of explanatory variables in the health gap

The second part of the model building process involved the exploration of the relative contribution of the variable categories from the final model. Direct (sole contribution) and indirect (interactions) contributions of the explanatory variable categories were computed to explain the inequalities. In this section, I will look into the percentage reduction, percentage change and percentage contribution of the various compositional and contextual factors to the health gap in Stockton-on-Tees, and explore how this contribution has changed over time.

Percentage reduction and percentage change for the specific model were computed using **Equation 1**. In addition, **Equation 2** was used to explore the percentage contribution of the categories of explanatory factors. To examine the indirect or interactive contributions of these categories, I used **Equation 3**. This process was carried out for all three health outcome measures and for all the survey waves, excepting for EQ5D scores for the second follow-up (wave 3).

Equation 1. Equation to determine percentage change between models

$$\%\, Change\ for\ Model\ Mx = 100 * \frac{Reference\ Model\ (M0) - Adjusted\ Model\ (Mx)}{Reference\ Model\ (M0)}$$

Equation 2. Equation to determine percentage contribution

$$\begin{aligned}&\%\ contribution\ of\ category\ X \\ &\qquad = Total\ \%\ change\ (M15) - \%\ change\ of\ model\ without\ category\ X\end{aligned}$$

Equation 3. Equation to determine indirect contribution

$$\begin{aligned}&Indirect\ contribution \\ &\qquad = Total\ \%\ change\ (M15) - (\%\ contribution for\ material \\ &\qquad + \%\ contribution\ of\ psychosocial + \%\ contribution\ for\ behavioural \\ &\qquad + \%\ contribution\ of\ contextual)\end{aligned}$$

In multilevel modelling, bootstrapping is the preferred approach to calculate confidence intervals for the indirect effects (Shrout and Bolger, 2002). For this study, the data was bootstrapped 10,001 times and 95 percent confidence intervals were calculated as 2.5 percent quantiles of the bootstrapped estimates to generate uncertainty bounds for the percentage contributions of various factors. The nonparametric bootstrapping was done in R. The whole process was carried out for all three health outcomes, separately.

The next stage of the modelling process involved the identification of the percentage contributions of the individual category and also the combinations of the different determinants of general and physical health gap. To find the relative contributions of these determinants, 14 different models were fitted to the longitudinal data.

The models were:

M0 (reference model): Deprivation

M1: Deprivation + Material

M2: Deprivation + Psychosocial

M3: Deprivation + Behavioural

M4: Deprivation + Contextual

M5: Deprivation + Material + Psychosocial

M6: Deprivation + Material + Behavioural

M6: Deprivation + Material + Contextual

M7: Deprivation + Psychosocial + Behavioural

M8: Deprivation + Psychosocial + Contextual

M9: Deprivation + Behavioural + Contextual

M10: Deprivation + Psychosocial + Behavioural + Contextual

M11: Deprivation + Material + Behavioural + Contextual

M12: Deprivation + Material + Psychosocial + Contextual

M13: Deprivation + Material + Psychosocial + Behavioural[4]

M14: Deprivation + Material + Psychosocial + Behavioural + Contextual

EQ5D-VAS

Table 4.14 presents the estimate and its 95 percent confidence interval; the percentage change of the specific model; and the percentage contribution of the model along with its 95 percent confidence interval which was obtained from the bootstrap analysis. Using **Equation 1**, the percentage explanation of the final models were computed for each survey wave. For example, controlling for age and gender, the

[4] M13 is the model with all the compositional factors

estimate for the reference model during the baseline was 10.86 and for the final model, it was 3.02. The calculation was 100*(10.86-3.02)/10.86 = 72.2 percent, which means the full model accounts for 72.2 percent of the gap in EQ5D-VAS scores (see Table 4.14). During the subsequent follow-up surveys, the explaining power of the full models dropped to 58, 49 and 34 respectively.

The same calculation process was repeated for each model to explore the percentage change of that specific model. For instance, the percentage change of Model 1 (M1: D+M) for baseline was calculated by 100*(10.86-6.36)/10.86 = 41.4 percent. After the calculation of the percentage change for each model, direct and indirect contributions of a specific category were computed by comparing the different models. The direct contribution refers to the unique share of a specific category in explaining the health inequalities gap. On the other hand, the indirect effect is the shared contribution of all the categories in explaining the health gap. The relative contribution was computed from the percentage explanation of the full model and the percentage change for each model. The relative contribution of a category was calculated by using **Equation 2**, which subtracts the percentage change of the model without this specific category from the percentage change of the full model. For example, the direct relative contribution of material factors (M1: D+M) to the gap in EQ5D-VAS was calculated by subtracting the percentage change of the model without the material factors (M10: D+P+B+C) from the full model (M14: D+M+P+B+C). The calculation of direct contribution of material factors for the baseline survey was therefore 72.2-51.8= 20.4 percent. The indirect contribution or *clustering effect* was computed using **Equation 3**, in which the sum of the percentage contribution of each category was subtracted from the percentage explanation of the full model. For example, indirect contributions of the different categories to the gap in EQ5D-VAS for baseline was 32.2 percent, which was computed by subtracting the summed up relative contribution of M1, M2, M3 and M4 (20.4 + 0.7 + 4.3 + 14.6) from the total percentage explained by the full model (72.2). Table 4.13 (below) presents the standardised contribution of the specific category to the gap in EQ5D-VAS.

During the baseline, all compositional factors combined explained about 42 percent of the deprivation health gap but among its sub-categories, material factors were the most important contributor making 20 percent explanation. The gap was least explained by the psychosocial factors (0.7% and 95% CI: -9.13, 11.31) followed by behavioural factors (4.3% and 95% CI: -5.07, 11.03). Their insignificant contribution was reinforced by their 95 percent confidence intervals obtained from nonparametric bootstrapping. Likewise, the bootstrapped confidence interval for the model with both behavioural and psychosocial factors combined (M7) indicate its lack of contribution to explaining health inequalities. Contextual factors, on the other hand, explained the gap by about 15 percent. Meanwhile, the presence of high indirect/clustered effects (32.2%), which was almost 44 percent of the total explanation (see Table 4.13), indicates the important interaction of compositional and contextual factors in explaining the inequalities.

Likewise, during wave 2, the most important contributors were the contextual factors (18%) followed by psychosocial factors (8.7%) and behavioural factors (5.8%). Though the relative contribution of the material factors was the lowest, all compositional factors combined explained 20 percent of the gap. The bootstrapped confidence interval for material, psychosocial and behavioural models indicate their lack of contribution to explaining the gap. Like the baseline survey, the presence of high clustered effects

(22.3%), 38 percent of the total explanation, indicates the important interaction between the compositional and contextual factors to widen the gap in EQ5D-VAS.

During wave 3, contextual factors appear to contribute most of the gap (15%) in EQ5D-VAS, which was almost 29.5 percent of the total explanation of the full model (see Table 4.13). Although material factors were of secondary importance (14%), the bootstrapped confidence interval showed this was the only individual category making a significant contribution. The standardised clustered effect was almost 45 percent of the total explanation, which signifies the level of interaction between the study variables.

During the final wave, psychosocial and behavioural factors were the most important categories contributing to the gap in EQ5D-VAS, which was almost 10 percent each. Though the bootstrapped confidence interval for psychosocial factors was not significant, the confidence interval for the behavioural factors indicates their significant contribution towards the gap. The role of contextual factors in explaining the gap was slightly over five percent and about 3 percent for the material factors, the bootstrapped confidence interval for both of these categories were insignificant. Though the full model could only explain slightly over 34 percent of the gap, the standardised clustered effect was still about a fifth of the total explanation. This reiterates the findings from the initial waves, which showed the important clustered effects of the compositional and contextual factors.

Table 4.13: Relative contribution of different categories standardised to the total explained percentage of the full model for the gap in EQ5D-VAS

Category	**Baseline**	**Wave 2**	**Wave 3**	**Wave 4**
All Compositional	57.8	35.1	52.7	68.6
Material	28.3	5.7	28.2	8.2
Psychosocial	1.0	14.9	14.4	28.9
Behavioural	6.0	9.9	2.4	28.5
Contextual	20.2	31.0	29.5	15.3
Clustered	44.6	38.4	44.6	19.1
Total Explained	72.2	58.0	49.1	34.3
Total Unexplained	27.8	42.0	50.9	65.7

Table 4.14: Percentage contribution of compositional and contextual models to the inequality gap of EQ5D-VAS

	BL/Wave1			Wave2			Wave 3			Wave 4		
	Estimate (95% CI)	% Change	% contribution (95% CI)**	Estimate (95% CI)	% Change	% contribution (95% CI)**	Estimate (95% CI)	% Change	% contribution (95% CI)**	Estimate (95% CI)	% Change	% contribution (95% CI)**
M0: D	11 (5.9,15.8)			10.4 (6.6,14.3)			10 (6.7,13.6)			11 (7.4,14.5)		
M1: D+M	6.4 (1.2,11.5)	41.4	20.4 (3.2,36.2)	9.6 (5.9,13.4)	7.4	3.3 (-1.0,8.0)	8.3 (4.8,11.9)	17.7	13.8 (2.3,23)	10.7 (7.1,14.3)	2.3	2.8 (-0.9,6.5)
M2: D+ P	7.9 (3.3,12.4)	27.6	0.7 (-9.1,11.3)	8.1 (4.8,11.4)	22.2	8.6 (-6.1,26.1)	8.6 (5.3,11.9)	15.4	7.1 (-2.3,21.6)	9.3 (5.9,12.7)	15.2	9.9 (-2,25.3)
M3: D+B	9.7 (4.5,14.8)	11.1	4.3 (-5.1,11.0)	8 (4.5,11.5)	23.2	5.8 (-3.6,20.9)	9.3 (6,12.7)	8.2	1.2 (-4.7,15.7)	9.6 (6,13.2)	12.6	9.8 (0.8,19.3)
M4: D+C	7.5 (2.6,12.5)	30.5	14.6 (3.2,27.2)	6.5 (2.6,10.4)	37.6	18 (5.4,39.1)	7.8 (4.1,11.5)	23.3	14.5 (-3.9,29.3)	9.8 (6.0,13.5)	10.8	5.2 (-1.3,36.1)
M5: D+M+P	5.1 (0.4,9.9)	52.6	32.3 (12.6,50.9)	7.6 (4.5,10.8)	26.6	13.9 (-2.8,32.2)	7.3 (4,10.7)	27.5	25 (8.8,41.2)	8.9 (5.5,12.3)	18.7	12.1 (-0.9,26.4)
M6: D+M+B	5.9 (0.5,11.2)	46.0	29.1 (8.5,44.9)	8 (4.5,11.5)	23.2	9.8 (-0.7,25.3)	7.5 (4.1,10.9)	26.1	14.2 (2.8,33.2)	9.4 (5.8,13)	14.4	13.2 (1.7,22.6)
M6: D+M+C	3.5 (-1.6,8.6)	68.1	35.3 (14,54.2)	5.9 (2.1,9.7)	43.7	40.5 (7.4,43.2)	6 (2.3,9.8)	40.5	27.5 (3.8,43.2)	9.5 (5.7,13.2)	13.5	8.1 (0.9,39.5)
M7: D+P+B	6.8 (2.3,11.4)	37.0	4.1 (-9.8,16.2)	8.6 (5,12.2)	17.5	14.3 (-1.5,37.8)	7.9 (4.7,11.2)	21.6	8.6 (-2,28.4)	8.1 (4.6,11.6)	26.2	20.8 (5.5,36.6)
M8: D+P+C	6.2 (1.5,10.8)	43.2	26.2 (10.9,43.8)	5.4 (2.1,8.7)	48.2	34.8 (20.9,64.1)	6.6 (3.1,10.2)	34.9	23.1 (4.3,43.9)	8.6 (5.,12.2)	21.1	19.9 (9.8,55.0)
M9: D+B+C	6.5 (1.4,11.6)	40.0	19.6 (5.8,33.6)	5.8 (2.2,9.4)	44.1	31.5 (16.2,59.6)	7.7 (4.1,11.3)	24.1	21.6 (5.8,48.6)	8.5 (4.7,12.3)	22.2	15.6 (6,50.9)
M10: D+P+ B+C	5.2 (0.5,9.9)	51.8	30.8 (13.9,48.5)	4.7 (1.4,8.0)	54.7	50.6 (36,85.9)	6.6 (3.1,10.0)	35.3	31.4 (15,61.9)	7.5 (3.9,11.1)	31.5	31.9 (19.7,70.2)
M11: D+M+B+C	3.1 (-2.2,8.3)	71.5	44.6 (38.8,63.7)	5.3 (1.7,8.9)	49.4	35.8 (19.5,64.5)	5.9 (2.2,9.5)	42.1	33.7 (13.5,64.4)	8.3 (4.5,12.1)	24.4	19.1 (8.6,54.8)
M12: D+M+P+C	3.5 (-1.4,8.3)	68.0	61.2 (45.6,83.7)	5 (1.6,8.3)	52.3	34.8 (25.7,71.6)	5.3 (1.6,8.9)	48.0	40.9 (16.7,62.7)	8.3 (4.7,11.9)	24.5	21.7 (11.4,56.9)
M13. D+M+P+B	4.6 (-0.2,9.4)	57.6	41.7 (22.2,60.4)	6.3 (3.2,9.3)	40.0	20.4 (3,45.2)	6.6 (3.3,9.9)	34.6	25.7 (10.2,48.3)	7.8 (4.3,11.2)	29.1	23.5 (6.7,38.3)
M14: D+M+ P+B+C	3.0 (-1.9,7.9)	72.2	72.2 (53.1,98.8)	4.4 (1.1,7.6)	58.0	58 (42.4,94.5)	5.2 (1.6,8.7)	49.1	49.1 (28.8,82.3)	7.2 (3.6,10.8)	34.3	34.3 (21.9,73.1)
Indirect		32.2	32.2 (7.6,32.6)		22.3	22.3 (14.3,41)		12.6	12.6 (5,30.5)		6.6	6.5 (-1.0,21)

** 95 percent confidence interval computed by bootstrap analysis

Table 4.15: Percentage contribution of compositional and contextual models to the inequality gap of EQ5D score

	BL/Wave1			Wave2			Wave 4		
	Estimate (95% CI)	% Change	% contribution (95% CI)**	Estimate (95% CI)	% Change	% contribution (95% CI)**	Estimate (95% CI)	% Change	% contribution (95% CI)**
M0: D	0.12(0.07,0.17)			0.13(0.07,0.18)			0.14(0.09,0.19)		
M1: D+M	0.06(0.01,0.11)	51.5	23.3(12.91,38.27)	0.1(0.05,0.15)	19.25	8.26(1.74,16.29)	0.09(0.03,0.15)	36.54	24.05(0.21,47.07)
M2: D+ P	0.08(0.04,0.13)	33.76	0.5(-9.22,9.64)	0.08(0.03,0.13)	36.26	4.69(-7.72,16.67)	0.11(0.06,0.16)	19.71	4.51(-14.69,18.44)
M3: D+B	0.11(0.05,0.16)	13.48	6.7(-1.82,13.13)	0.1(0.05,0.15)	22.24	4.71(-6.28,21.05)	0.14(0.09,0.19)	1.83	0.78(-8.67,5.21)
M4: D+C	0.07(0.02,0.12)	43.07	18.3(2.83,31.15)	0.06(0,0.12)	51.8	29.39(9.2,46.07)	0.12(0.07,0.18)	12.18	15.13(-5.68,37.48)
M5: D+M+P	0.04(0,0.09)	65.2	23.3(16.47,47.75)	0.08(0.03,0.13)	36.26	17.65(2.78,32.14)	0.07(0.02,0.13)	48.45	35.6(6.75,58.03)
M6: D+M+B	0.05(0,0.1)	58.41	35.1(20.08,49.9)	0.08(0.03,0.13)	35.62	15.68(2.36,33.97)	0.09(0.03,0.15)	37.02	42.5(-1.06,47.25)
M6: D+M+C	0.02(-0.03,0.07)	83.25	45.4(26.56,65.74)	0.04(-0.02,0.1)	69.18	37.19(15.59,53.97)	0.07(0.01,0.13)	51.36	42.5(15.16,67.61)
M7: D+P+B	0.07(0.02,0.11)	44.68	6.9(-7.31,15.81)	0.07(0.02,0.12)	41.32	9.34(-6.77,30.9)	0.11(0.06,0.16)	21.27	35.6(-17.43,17.86)
M8: D+P+C	0.05(0.01,0.1)	56.1	31.7(10.42,44.42)	0.05(-0.01,0.11)	62.84	42.9(23.48,62.98)	0.1(0.05,0.15)	27.35	29.96(2.79,54.2)
M9: D+B+C	0.06(0.01,0.11)	55.03	24.9(7.57,38.81)	0.05(0,0.1)	60.86	42.26(19.07,61.25)	0.12(0.07,0.17)	13.81	16.19(-5.33,39.55)
M10: D+P+B+C	0.04(0,0.09)	66.81	38.6(15.71,50.05)	0.04(-0.02,0.09)	70.26	59.26(37.21,81.71)	0.1(0.05,0.15)	28.75	31.17(3.56,55.41)
M11: D+M+B+C	0.01(-0.04,0.06)	89.63	56.4(21.71,63.3)	0.03(-0.02,0.08)	73.82	42.26(27.83,72.03)	0.07(0.01,0.13)	51.66	44.9(16.98,70.7)
M12: D+M+P+C	0.02(-0.02,0.06)	83.46	76.6(45.61,87.24)	0.03(-0.02,0.09)	73.8	56.28(34.29,75.89)	0.06(0,0.12)	58.63	65.29(34.55,91.68)
M13. D+M+P+B	0.03(-0.01,0.08)	71.83	47.1(23.45,58.81)	0.06(0.02,0.11)	49.12	26.71(8.27,49.64)	0.07(0.02,0.13)	48.84	35.53(5.05,57.83)
M14: D+M+P+B+C	0.01(-0.03,0.06)	90.12	90.12(56.31,97.79)	0.03(-0.02,0.08)	78.52	78.52(52.19,98.04)	0.05(-0.01,0.11)	67.74	67.74(36.82,94.08)
Indirect		41.32	41.32(20.5,44.8)		31.46	31.46(17.19,46.8)		24.83	24.83(10.3,50.18)

** 95 percent confidence interval computed by bootstrap analysis

EQ5D Scores

Multilevel models to explore the gap in EQ5D scores were not fitted for the Wave 3 dataset as none of the psychosocial factors could get through the initial assessment. The analysis and use of equations to compute the relative contributions was similar to what is presented in the previous section for EQ5D-VAS scores. The findings from the multilevel and bootstrap analysis for the rest of the waves have been presented in Table 4.15. The final models explained 90 percent, 79 percent and 68 percent of the gap in EQ5D scores during the baseline, wave 2 and wave 4 respectively.

All compositional factors combined explained more than 47 percent of inequalities gap for EQ5D scores (95% CI: 23.45, 58.81) during the baseline. When considering compositional categories, the highest contribution to the inequality gap was from material factors (23.3%). The contribution of psychosocial factors was less than a single percentage point, and only 7 percent for the behavioural factors. The bootstrapped confidence intervals at 95 percent for these categories (M2: -9.22, 9.64 and M3: -1.82, 13.13) as well as their combination (M8: -7.31, 15.81) also indicated an insignificant contribution. More than 18 percent of the gap was explained by the contextual factors. The high percentage of indirect effects (41.32%) points out the significant interaction that was present between the factors within compositional and contextual categories. The standardised indirect contribution for EQ5D was highest during the baseline among the three waves for which multilevel modelling was applied (see Table 4.16).

In contrast to the baseline findings, the contribution of contextual factors (M4) was than all compositional factors combined (M13) (29.39% vs. 26.71%) during **wave 2**.

Among the compositional factors, the material factors (M1) had the highest contribution at 8.2 percent. The behavioural (M3) and psychosocial factors (M2) contributed about 5 percent each towards the gap in EQ5D scores between the most and the least deprived areas of Stockton-on-Tees. Similar to the findings from the baseline survey, the bootstrapped confidence interval at 95 percent for the behavioural, psychosocial and their combined models (M7) were insignificant. The standardised indirect contribution was decreasing compared to the baseline survey, it was still significantly high at 31 percent with a significant bootstrapped confidence interval (17.19, 46.8), which indicates the presence of an important interaction between the compositional and contextual factors.

Similar to the baseline findings, all compositional factors combined contributed most (33.53%) to the inequality gap in EQ5D scores (95% CI: 5.05, 57.83) during **wave 4**. Among the compositional factors, the highest contribution was from the material factors (24.04%). While psychosocial factors contributed less than five percent (4.51%; 95% CI: -14.69, 18.44) to the gap, the role of behavioural factors was the least at less than a percent (95% CI: -8.67, 5.21). The bootstrapped confidence intervals for these two categories indicate an insignificant contribution. The contribution of contextual factors was slightly over 15 percent but the bootstrapped confidence intervals for this category (M4: -5.68, 37.48) indicate the contribution was insignificant. The clustered effect of the compositional and contextual factors towards the gap in EQ5D scores during the wave 4 was significant at about 25 percent (standardised: 27.6%).

When comparing all the waves, though the role of material factors (M1) towards the gap fluctuated during the first follow-up (wave 2), it was the only individual category that remained significant (bootstrapped 95% CI). The role of psychosocial (M2) and behavioural (M3) factors were insignificant individually and when combined (M7) throughout the survey period. Though there was a significant and higher contribution of the contextual factors (M4) during the baseline and wave 2, its contribution was insignificant during the final wave. Despite the declining trend of the clustered effect, there was a significant indirect contribution of the compositional and contextual factors throughout the survey period (Table 4.16).

Table 4.16: Relative contribution of different categories standardised to the total explained percentage of the full model for the gap in EQ5D scores

Category	Baseline	Wave 2	Wave 4
All Compositional	52.3	29.6	39.4
Material	25.9	9.2	26.7
Psychosocial	0.6	5.2	5.0
Behavioural	7.4	5.2	0.9
Contextual	20.3	32.6	16.8
Clustered	45.8	34.9	27.6
Total Explained	90.1	78.5	67.7
Total Unexplained	9.9	21.5	32.3

SF8PCS

While Table 4.17 presents the standardised contribution of the different categories, Table 4.18 shows the overall findings from the multilevel modelling for SF8PCS for all survey waves. The analysis and use of equations to compute the relative contributions was similar to what is presented in the previous section for EQ5D-VAS scores. The overall explanation of the final model was over 95 percent during the baseline, which gradually dropped to slightly over 90 percent during wave 2, 64 percent during wave 3 and 58 percent during the final wave.

During the **baseline** survey, the overall contribution of compositional factors to the inequalities gap for SF8PCS was over 44 percent. Material factors explained about 32 percent of the gap followed by 5 percent by the behavioural factors and less than a percent by the psychosocial factors. The bootstrapped confidence interval for both psychosocial and behavioural factors, individually (-6.83, 9.8 and -6.3, 10.94 respectively), as well as their combination (-7.35, 16.35), indicate an insignificant explanation. Contextual factors, on the other hand, were able to explain 38 percent of the inequalities gap. The indirect effect for SF8PCS was 21 percent, which indicates the presence of significant interaction between the compositional and the contextual factors.

Unlike the baseline survey, the overall contribution of all compositional factors combined was 23 percent, lower than that of the contextual factors (52%) during **wave 2**. Among the compositional factors, psychosocial factors contributed more than 10 percent to the gap, which was seconded by material factors at five percent and behavioural factors contributed less than a percent towards the gap. In contrast to the baseline survey, the 95 percent bootstrapped confidence interval indicates an insignificant contribution of all the individual categories. A quarter of the total explanation was the result of clustered effects (see Table 4.17), which indicates the presence of interaction between the compositional and contextual factors to produce the gap in physical health.

During the second follow-up (**wave 3**), the overall contribution of the compositional factors was 35 percent. Material factors were the highest individual contributor to the inequality gap at 25 percent followed by five percent by behavioural and about three percent by the psychosocial factors. The bootstrapped confidence interval for material factors showed a significant contribution but for the psychosocial and behavioural factors, the contributions were insignificant (M2: -2.4, 10.5 and M3: -3.7, 13.3). In addition, the contribution of the behavioural and psychosocial factors combined was also insignificant (M7: -2.4, 19.7). Contextual factors contributed 20 percent towards the gap. The standardised results showed that 18 percent of the explanation was the result of clustered effects, which was lowest among the four waves, yet indicates the presence of significant indirect interaction of compositional and contextual factors in resulting the gap in physical health.

During the **final wave**, the overall contribution of the compositional factors was 35 percent (standardised: 54.8%). Among the compositional factors, material factors explained 19 percent of the gap, followed by 10 percent by behavioural and half a percent by psychosocial factors. The bootstrapped confidence interval for all the individual categories of compositional factors showed an insignificant contribution (M1: -3.1, 34.2; M2: -10, 11.4; and M3: -2.7, 21). Like all previous waves, the combination of psychosocial and behavioural factors had an insignificant contribution towards the gap (M7: -6.9, 23.4). On the other hand, contextual factors made a significant contribution of 11 percent (95% CI: 8.3, 48.2). The standardised clustered effects for the final wave was the highest at 27 percent, which is an indication of the importance of interaction between the compositional and contextual factors in producing the physical health gap.

When comparing all the waves, except for wave 2, the role of contextual factors (M4) was found important in explaining the physical health gap. Though material factors (M1) had significant contribution during the baseline and wave 3, its contribution was insignificant during wave 2 and the final wave. Similarly, the two EuroQol indicators

(EQ5D-VAS and EQ5D), the contribution of psychosocial (M2), behavioural (M3) and their combination (M7) were insignificant for all waves of the survey. For all waves, clustered effects were high indicating the importance of interaction between the compositional and contextual factors in explaining the gap in physical health between the people living in the most and the least deprived areas of Stockton-on-Tees.

Table 4.17: Relative contribution of different categories standardised to the total explained percentage of the full model for the gap in SF8PCS scores

Category	**Baseline**	**Wave 2**	**Wave 3**	**Wave 4**
All Compositional	46.6	25.7	54.2	54.8
Material	33.1	5.8	38.4	29.2
Psychosocial	0.4	11.4	4.3	0.8
Behavioural	5.1	0.3	8.1	15.8
Contextual	39.6	57.5	31.4	16.8
Clustered	21.7	25.0	17.9	27.5
Total Explained	95.4	90.3	64.4	58.1
Total Unexplained	4.6	9.7	35.6	41.9

Table 4.18: Percentage contribution of compositional and contextual models to the inequality gap of SF8PCS

	BL/Wave1			Wave2			Wave 3			Wave 4		
	Estimate (95% CI)	% Change	% contribution (95% CI)**	Estimate (95% CI)	% Change	% contribution (95% CI)**	Estimate (95% CI)	% Change	% contribution (95% CI)**	Estimate (95% CI)	% Change	% contribution (95% CI)**
M0: D	4.8(2.8,6.7)			5.8(3.7,8)			6.5(4.6,8.4)			6.5(4.4,8.6)		
M1: D+M	2.5(0.6,4.5)	46.6	31.6(15,43.5)	4.7(2.9,6.6)	19.1	5.2(-2.4,16.4)	4.8(2.5,7)	26.3	24.7(3.8,44.1)	4.6(2.1,7.1)	30.2	18.8(-3.1,34.2)
M2: D+ P	4.1(2.3,5.8)	14.7	0.4(-6.8,9.8)	4.9(2.8,6.9)	16.6	10.3(-2.3,27.4)	4.8(2.5,7)	26.3	2.8(-2.4,10.5)	5.9(3.9,8)	9.0	0.5(-10,11.4)
M3: D+B	4.3(2.3,6.4)	8.9	4.9(-6.3,10.9)	4.9(3,6.8)	16.7	0.3(-13.2,23.9)	5.6(3.7,7.5)	13.2	5.2(-3.7,13.3)	5.3(3.2,7.4)	18.2	10.2(-2.7,21)
M4: D+C	2.3(0.1,4.6)	50.8	37.8(4.5,50.3)	1.9(-1.9,5.8)	67.1	51.9(-10.4,63)	4.6(2.5,6.6)	29.5	20.2(6.2,38.5)	5(2.8,7.3)	22.8	10.8(8.3,48.2)
M5: D+M+P	2.2(0.4,3.9)	54.8	35.1(17.3,51.4)	4.1(2.2,6)	29.6	19.9(2.2,41.6)	4.4(2.2,6.6)	31.8	29.7(7.7,49.7)	4.4(1.9,6.8)	33.2	22.6(-3.5,38.5)
M6: D+M+B	2.4(0.4,4.4)	50.3	39.9(18.5,51.1)	4(2.3,5.8)	30.8	7.4(-9.9,37)	3.9(1.7,6.1)	39.9	29.2(6.3,49.2)	3.6(1.2,6.1)	44.2	31.4(3.7,47.1)
M6: D+M+C	0.5(-1.6,2.6)	89.2	74(34.2,80.7)	1.2(-2.3,4.8)	79.0	61.8(-1.2,72)	2.9(0.5,5.2)	55.9	44.5(17.9,69.5)	3.4(0.9,6)	47.7	31.8(19.3,68.7)
M7: D+P+B	3.8(1.9,5.6)	21.4	6.2(-7.4,16.4)	4.2(2.3,6.1)	28.5	11.3(-7,40.6)	5.2(3.3,7.1)	19.9	8.5(-2.4,19.7)	4.8(2.8,6.9)	26.3	10.4(-6.9,23.4)
M8: D+P+C	2.1(0.1,4.2)	55.4	45.1(10.9,59)	1(-2.7,4.7)	82.9	59.5(-1.5,70.8)	4.2(2.2,6.3)	35.2	24.5(9.5,44)	4.8(2.6,7)	26.7	13.9(10.4,52.5)
M9: D+B+C	1.9(-0.4,4.2)	60.3	40.6(5.8,52.6)	1.7(-1.8,5.2)	70.3	60.7(-1.6,71.9)	4.2(2.2,6.3)	34.7	32.6(15.3,54.9)	4.2(2,6.4)	35.5	24.9(19.5,63.9)
M10: D+P+ B+C	1.7(-0.4,3.9)	63.7	48.8(14,61.7)	0.9(-2.6,4.3)	85.1	71.1(11,83.1)	3.9(1.9,5.9)	39.7	38.1(19.6,61.6)	4(1.8,6.1)	39.2	27.9(21.6,68.1)
M11: D+M+B+C	0.2(-1.9,2.4)	94.9	80.7(38.8,86)	1.2(-2.1,4.4)	80.0	73.7(9.8,83.7)	2.5(0.2,4.8)	61.6	38.1(28,82)	2.8(0.3,5.3)	57.6	49.1(33,85.9)
M12: D+M+P+C	0.5(-1.5,2.4)	90.4	86.5(46,92.7)	0.6(-2.9,4.1)	89.9	73.6(11.8,83)	2.7(0.3,5)	59.2	51.1(23.8,76.7)	3.4(0.9,5.9)	47.9	39.9(26.1,76.8)
M13. D+M+P+B	2(0.2,3.8)	57.6	44.5(22.2,59.9)	3.6(1.8,5.4)	38.4	23.2(0.5,59.5)	3.6(1.5,5.8)	44.2	34.9(10.8,55.3)	3.4(1.1,5.8)	47.2	35.3(4.5,50.5)
M14: D+M+ P+B+C	0.2(-1.8,2.2)	95.4	95.4(53.1,98.8)	0.6(-2.7,3.9)	90.3	90.3(27.1,98.4)	2.3(0.1,4.6)	64.4	64.4(35.5,91.2)	2.7(0.3,5.2)	58.1	58.1(41,95)
Indirect		20.7	20.7(7.6,32.7)		22.6	22.6(-5.1,40.8)		11.5	11.5(0.4,23.7)		17.7	17.7(2.6,35.4)

** 95 percent confidence interval computed by bootstrap analysis

Summary

In this chapter, I have presented the findings of multilevel modelling which explored the gap in general and physical health between the most and least deprived areas of Stockton-on-Tees. The chapter also explored how this gap changed over 18 months between 2014 and 2016. Considering the social determinants of health, my approach was to explore the relative contribution of compositional and contextual factors in producing the health gap. Two EuroQol measures of general health (EQ5D-VAS and EQ5D scores) and a measure of physical health (SF8PCS) were used to assess the health outcomes of the survey participants. The results show the presence of a significant gap in all three health measures and in all waves of the survey, but this was more pronounced for the two EuroQol indicators: EQ5D-VAS and EQ5D. While the gap in general health remained almost constant throughout the survey period the gap in physical health widened with each follow-up survey. The findings suggest that where you live matters for your health; people living in the least deprived areas have a considerable advantage in regard to general and physical health. On average, people from least deprived areas had significantly higher general and physical health scores compared to those living in the most deprived neighbourhoods of Stockton-on-Tees.

The relationship between health inequalities and the social determinants of health has been well established. This chapter adds further to the e evidence on the role of individual/compositional (Marmot and Allen, 2014) and area level/contextual (Cummins et al., 2005) factors in creating the health gap. A significant association between these factors and inequalities in general and physical health has been found, which is consistent with previous research. These findings are discussed further in **Chapter 6** (page 207).

Chapter 5: Time Trend: Exploring the Role of Austerity in General and Physical Health

Introduction

This chapter investigates the role of ‘time’ in explaining the gap in general and physical health among the participants from the most and least deprived neighbourhoods of Stockton-on-Tees. This chapter examines whether ‘time’ has a differing effect on the health gap based on whether the survey participant lives in the most or the least deprived areas of Stockton-on-Tees. In doing so, I present the trajectories and explore the rate of change in the health outcome measures.

A central part of my thesis is to explain how austerity impacts geographical health inequalities. Thus, the findings presented in this chapter attempt to answer two of the research questions presented in ***Chapter 3 (page 75)***:

1) What is the extent of health inequalities in physical and general health in Stockton-on-Tees? (Research question a.)
2) How have health inequalities in Stockton-on-Tees changed during austerity? (Research question c.)

As discussed in ***Chapter 2*** (see: Austerity and health, page: 55), health is a cross-cutting issue, which is an outcome of the interaction of individual circumstances and the wider socio-political context. The financial adjustment programmes put direct and indirect pressure on the health outcomes. Direct impacts as a result of cuts in health care budget and indirectly by constricting social and welfare programmes (Bambra and Garthwaite, 2014). The main aim of this chapter is to explore if the gaps in general and physical health change over time, if they do, when and at what rate (linear, quadratic or cubic) do they change. The overarching reason for performing this analysis is to explore the effects of austerity. The impacts of welfare cuts could be delayed as the timeline for each event is different (See

Table 2.7, page 58). This is the case because it is likely to have a lag between implementation and any noticeable impacts of these welfare reform programmes (Barr et al., 2017). To disentangle the impacts of austerity on health inequalities between the geographical areas, time is used as an indicator of austerity. With time as a 'proxy', a detailed analysis of the impacts of austerity on the health divide can be conceptualised. It should, however, be acknowledged that 'time' cannot fully represent the impacts of austerity because, as Wolf (2013) argues, 'Britain's austerity is indefensible' and is far bigger than time. The existing research base suggests a dynamic relationship between austerity and health inequalities and the health divide widens with time (Karanikolos et al., 2013a, Stuckler et al., 2017). Barr et al. (2017) have argued that the increasing trend of inequalities is due to the 2008 financial crisis and the resulting politics of austerity. This research, attempts understand this complex relationship, with a model that represents the change in the health gap over time and also acknowledges the role of austerity.

It also helps reveal broader and more generalised patterns of health inequalities. While the use of cross-sectional study can only test the static effects of time, the use of panel data, however, can support the change hypothesis—the change process over time factor (Matthes, 2015). As Scheufle and Moy (2000) argue, 'time factor' represents the "process of formation, change, and reinforcement". Therefore, using time as an indicator of austerity will help me understand how austerity results in health inequalities and how this relationship changes over time.

However, the basic assumption of my analysis is that time is equivalent to austerity because the austerity-induced welfare reform programmes have been gradually implemented since 2010 (see ***Chapter 2*,**

Table 2.7**,** page: 58***)***. Wunsch et al. (2010) argue the need to understand causal relations to forecast social phenomena and devise necessary actions. Thus another assumption, as Wunsch et al. (2010) highlight was that the existing knowledge supports causal and temporal ordering: and austerity induces health inequalities. It is challenging, if not impossible to make a claim that there are 'true' causal links between austerity (as time) and health inequalities. My assumption is that causality of austerity can be interpreted in epistemic terms, by taking into consideration the framework used in the model.

This has enabled me to observe whether the effects of welfare reform on health divide varies across different time points in the two areas of research. This chapter empirically investigates whether there is a statistically significant change in the trend in health inequalities between the most and least deprived areas of Stockton-on-Tees during the study's time period. This chapter compared such a scenario within the current setting of austerity programmes.

However, as Talving (2017) argues, it should be noted that using data from certain waves of the survey may not be adequate to expose the impacts of rigorous austerity programmes. It is also important to acknowledge at this point that because of the delayed impact of implemented programmes, the results may not totally explain the impacts of welfare reforms in causing the health divide.

In the initial part of the chapter, I present and discuss the nature of the missing data and the results of multiple imputations performed for the health outcome measures. This chapter explores the change in inter-individual differences in health outcomes over time. I then present a growth curve for each health outcome measure and explore the rate and type of effects ‘time’ has on these measures.

Trends in survey participation

Table 5.1 presents a matrix of participation and drop-out in the longitudinal survey. While more than a third (34.5%) of the survey participants dropped out after the baseline survey, half of the initial sample participated in all of the waves. Slightly over two percent of the initial sample re-joined in wave 3 after dropping out during the second wave. The follow-up surveys were conducted over telephone, following the consent received during the baseline interview. Up to 5 attempts were made to contact households at different times point during the day. Attempts were made to contact the households who missed the first follow-up survey and it was possible to get 15 (2%) missing participants to re-join the survey at wave 3.

Table 5.1: Matrix of survey participation

Waves	Least deprived Number (%)	Most deprived Number (%)	Total Number (%)
BL only	118 (31.3)	135 (37.9)	253 (34.5)
BL & W2	24 (6.4)	24 (6.7)	48 (6.5)
BL and W3	0 (0)	7 (2)	7 (1)
BL, W3 and W4	0 (0)	8 (2.2)	8 (1.1)
BL, W2 & W3	21 (5.6)	29 (8.1)	50 (6.8)
BL, W2, W3 & W4	214 (56.8)	153 (43)	367 (50.1)
Total	377(100)	356 (100)	733 (100)

BL = Baseline; W2 = Wave 2; W3 = Wave 3 and W4 = Wave 4

Missing data analysis

The findings presented in Chapter 4 were from a complete dataset, produced after conducting pair-wise deletion of the missing data. This was part of the requirements of the data analysis approach which was adopted. In that chapter, the extent, nature and impact of missing data were not taken into consideration, this section fills that gap.

With high drop-out rates, there is a need to analyse the attrition rate and consider its nature. The use of methods such as survival analysis (using Kaplan-Meier estimates) to estimate the probability of dropping out can suggest the 'usability efficacy' of the study outcomes (Eysenbach, 2005). Along with the drop-out rate, there is also the issue of missing data in longitudinal surveys. Data related to a variable can be missing (during consecutive waves) for all cases, this is generally known as '*unobserved'* data or 'within-wave' *missingness*. On the other hand, due to drop-outs data related to a case can be missing for all variables, also known as '*non-response'* or *'whole-wave' missingness* (Allison, 2012). Among the different approaches to handling missing data, multiple imputations (MI) was used. Maximum likelihood (ML) and MI are both the techniques to handle missing data (missing at random) and unlike pairwise deletion, both these techniques give smaller missing data errors (Newman, 2003). These techniques have their own strengths and drawbacks. Though ML usually yields a smaller degree of bias compared to MI (Shin et al., 2017), but unlike ML, MI can include the 'auxiliary' variables into the imputation model that are not later included into the final analysis (Graham, 2012). Exclusion of these auxiliary variables in ML models often results in significant differences between the models (Collins et al., 2001).

Approach 1: Survival analysis

Using the Kaplan-Meier estimate method, survival analysis was performed to explore the probability of participants remaining in the follow-up waves. The survival function estimates the probability that the event happened, the participant dropped out after Time "*t*" (Goel et al., 2010, Hogan et al., 2004). Table 5.2 (below) summarises the status of survey participation, comparing the number during the baseline and those who dropped out before reaching the final wave. When conducting survival analysis, we need to consider a subset of survey participants who may fail to complete the study. They are usually considered to be a "censored" population and this labelling process as a whole is called censoring (Clark et al., 2003). In my analysis, all cases those who missed the final waves were considered censored. There were 15 cases that missed wave 2 but were recovered at W3 but out of them seven were again lost during the final wave (see Table 5.1, above). Overall, almost half (49%) of the participants were lost by the time the final wave of the survey was conducted. The proportion of drop-out was relatively higher in the most deprived areas compared to the least deprived areas. The value of time was assumed to correspond to the months of survey i.e. for baseline TIME=0; at Wave 2, TIME=6; at Wave 3, TIME=12; and at Wave 4, TIME=18.

Table 5.2: Status of survey participants during baseline and those censored during the final wave

Area Category	Total during baseline	Total during Wave 4	Censored		Median survival (months)
			N	Percentage	
Least Deprived	377	214	163	43.2	18
Most Deprived	356	161	195	54.8	12
Overall	733	375	358	48.8	18

There was a statistically significant difference in the survival distribution between the most and the least deprived areas. Though the median survival time of all survey participants was 18 months, participants from the least deprived areas had a higher median survival period (18 months) compared to those from the most deprived areas (12 months) (see Table 5.2, above). Three tests (log-rank, Breslow and Tarone-Ware test) were used and all these tests suggested the existence of significant difference ($p<0.05$) in the probabilities of survival based on the type of areas (see Table 5.3). The log-rank method tests the equality of survival function, with all the points in time-weighted equally. It tends to focus more on what happens later in time. The Breslow tests the equality of survival functions by weighting the Time points based on the number of cases at risk at each Time point. It tends to look at what is happening earlier in the Time course. The Tarone-Ware tests the equality of survival functions by weighting the points of Time by the square root of the number of cases. It tends to focus on the middle of the Time points (Collett, 2015). All three tests found a significant gap in survival based on the area of survey participants. These findings are reinforced by the survival curve presented in Figure 5.1 (below), which shows that the probability of surviving (being in the survey) is higher for participants from the least deprived areas compared to those from the least deprived areas, throughout all survey waves. While the median survival duration for the least deprived areas was 18 months, it was 12 months for the most deprived areas.

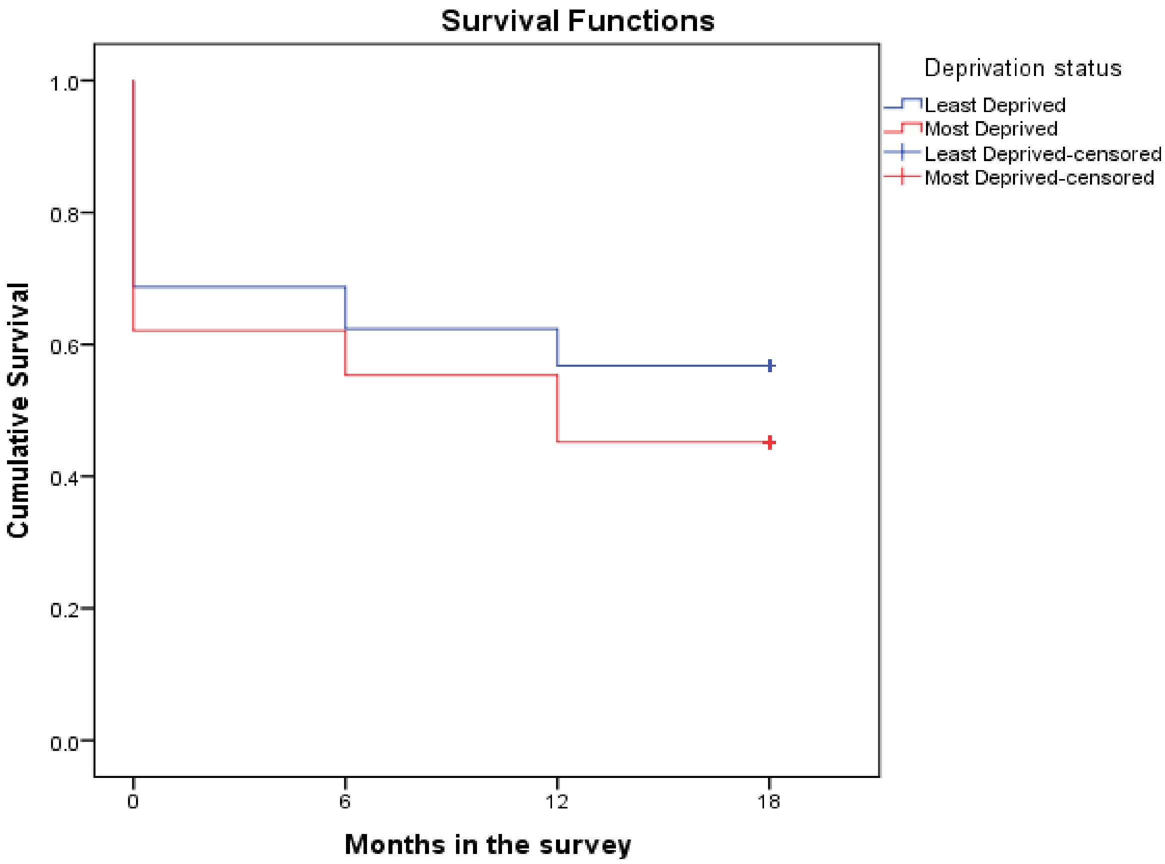

Figure 5.1: Survival curve by type of survey area

Table 5.3: Test of equality of survival distributions for the areas defined by the level of deprivation.

	Chi-Square	Sig.
Log Rank (Mantel-Cox)	8.95	0.003
Breslow (Generalized Wilcoxon)	7.37	0.007
Tarone-Ware	8.17	0.004

Approach 2: Multiple imputations

Multiple imputations were performed to explore if drop-out and missing values had impacted the research findings. An easy way to handle missing data is to delete the cases or variables with missing values or by not including them in the analysis. Though this sounds simple, it can result in bias and can impact the usability of the research findings. This section compares the health inequalities gap in Stockton-on-Tees by replacing the missing data by predicted values using the multiple imputation technique.

In this analysis, 10 imputations were carried out with 100 maximum iterations using sequential chained linear regression model and fully conditional specification or Markov chain Monte Carlo (MCMC) algorithm. Fichman and Cummings (2003) argue that: *"10 imputations are more than suitable for almost any realistic application"* (p. 291).

Maximum and minimum values were specified for each variable and rounded to the desired scale, which helped to reject all random imputations outside the range. The MCMC method imputes a missing value based on the previous observation and the multiple chains help stabilise the final imputed value by minimising the standard error (Barnes et al., 2016, Ni and II, 2005). Along with the MCMC method, other 'auxiliary variables' were also introduced into the model. As described in the previous section, auxiliary variables are those variables which are not included in the final analysis. As MCMC method imputes value based on previous observation, I used the same (complete) baseline dataset used for the composition-context analysis presented in the previous chapter. This makes the method suitable for handling missing data in longitudinal surveys.

To perform the multiple imputation, the longitudinal data was organised in the '*wide structure*' format for analysis—with each individual having a separate record containing information from all waves (Young and Johnson, 2015). Arranging data in this fashion facilitates the process of addressing and imputing missing data. Compared to '*long structure'* arrangement of the longitudinal data, '*wide structure'* yields more precise results (Allison, 2002). The details of the variables included in the multiple imputation procedure have been summarised in Appendix C-8 (page 296).

The multiple imputed dataset was then analysed to explore the pooled outcomes. The weighted average of the estimates, fraction of missing information (FMI), relative increase in variance (RIV) due to missing data and relative efficiency (RE) of the imputation process were computed. Both FMI and RIV are diagnostic measures to assess the impact of missing data on the estimates. FMI is the relative loss of efficiency while estimating a parameter as a result of missing data (Savalei and Rhemtulla, 2012). RIV measures the increase in error of the estimates because of the missing data. RE, on the other hand, indicates the efficiency yielded in the computation of estimates after replacing the missing values with imputed data. While it is idle to expect smaller values for RIV and FMI, the values closer to 1 are idle for RE. (Fichman and Cummings, 2003).

Table 5.4 presents the summary of the descriptive analysis of the health outcome measures from the multiple imputed dataset. The difference in average scores between the original dataset and the imputed dataset was considerably smaller for all health outcome measures. There was a significant gain in relative efficiency (RE) as a result of multiple imputation—with all health measures having more than 95 percent efficiency.

Table 5.4: Descriptive analysis of the multiple imputed dataset

		Original				Pooled				
		Mean	Std. Error	Std. Deviation	Variance	Mean	Std. Error	FMI	RIV	RE
EQ5D-VAS	BL	70.19	0.79	21.45	460.25					
	W2	75.47	0.89	19.19	368.08	74.06	0.79	0.26	0.34	0.97
	W3	76.81	0.90	18.73	350.78	74.83	0.77	0.23	0.28	0.98
	W4	76.25	0.92	17.73	314.49	74.16	0.77	0.33	0.46	0.97
EQ5D Scores	BL	0.82	0.01	0.27	0.07					
	W2	0.82	0.01	0.25	0.06	0.80	0.01	0.22	0.27	0.98
	W3	0.82	0.01	0.25	0.06	0.78	0.01	0.25	0.32	0.98
	W4	0.81	0.01	0.25	0.06	0.78	0.01	0.13	0.15	0.99
SF8PCS	BL	48.12	0.41	11.07	122.51					
	W2	47.81	0.48	10.40	108.21	48.64	0.36	0.09	0.10	0.99
	W3	48.08	0.52	10.77	116.07	49.07	0.38	0.16	0.18	0.98
	W4	47.99	0.56	10.75	115.64	48.95	0.37	0.15	0.18	0.98

Table 5.5 (below) compares the gap in EQ5D-VAS, EQ5D and SF8PCS between the participants from the most and the least deprived LSOAs of Stockton-on-Tees using the original and the multiple imputed dataset. While doing this, age and gender were adjusted for. Both datasets revealed that the people living in the least deprived areas have significantly better general and physical health scores compared to those living in the most deprived areas. The pooled estimates for deprivation were smaller than the estimates obtained from the original cleaned dataset for all health outcome measures.

For EQ5D-VAS, the difference in estimates (by deprivation) between the original and pooled dataset was 10 vs. 9 during wave 2, 10 vs. 9 during wave 3 and 11 vs. 8 during the final wave. There was a moderate relative loss of efficiency, as measured by FMI for the follow-up waves for which multiple imputation was performed. This was 22 percent during wave 2, which dropped to 15 percent in wave 3 and 19 percent in wave 4. RIV also showed a moderate increase in error of the estimates as a result of missing data. There was a 27 percent increase in the error during wave 2, 17 percent during wave 3 and 23 percent during the final wave as a result of missing data. There was a significant gain in RE following the multiple imputation which was 0.98, 0.99 and 0.98 for wave 2, wave 3 and wave 4 respectively.

The difference in estimates (by deprivation) between the original and pooled dataset for EQ5D scores was relatively low but the impact of missing data in the efficiency of the estimates was relatively higher compared to the other two health outcome measures. Almost 40 percent of the relative loss of efficiency while estimating the parameter for deprivation during wave 3 was due to the missing data. Also, 60 percent of the increase in variance was linked to missing data for the same wave. There was a high gain in efficiency in the computation of estimates after replacing the missing data with imputed values.

Compared to the two general health outcome measures, there was a smaller relative loss of efficiency while computing the estimates of the gap in the SF8PCS measures between the most and the least deprived areas. The pooled estimate could not indicate a specific trend in the gap in SF8PCS between the two areas, but in contrast, the original dataset suggested a widening gap between the areas. Relative efficiency of the imputation process was high for all follow-up waves.

Table 5.5: Comparison of the trend of health inequalities in Stockton-on-Tees using the cleaned and multiple imputed dataset

Health measures	Parameter	Baseline Estimate (95% CI)	Wave 2					Wave 3					Wave 4				
			Complete dataset; Estimate (95% CI)	MI Pooled				Complete dataset; Estimate (95% CI)	MI Pooled				Complete dataset; Estimate (95% CI)	MI Pooled			
				Estimate (95% CI)	FMI	RIV	RE		Estimate (95% CI)	FMI	RIV	RE		Estimate (95% CI)	FMI	RIV	RE
EQ5D-VAS	Intercept	71.8(66.2,77.5)	77.4(71.1,83.6)	75.3(69.9,80.7)	0.39	0.6	0.96	77.0(70,83.3)	74.9(70,79.7)	0.25	0.31	0.98	76.9(70,83.7)	75(69.7,79.5)	0.35	0.51	0.97
	Deprivation	10.9(5.9,15.8)	10.4(6.6,14.3)	8.5(5.5,11.6)	0.22	0.27	0.98	10.1(6.7,13.6)	8.7(5.8,11.6)	0.15	0.17	0.99	10.9(7.4,14.5)	8.34(5.5,11.1)	0.19	0.23	0.98
	Gender	-0.1(-3.15,2.9)	0.09(-3.4,3.6)	0.1(-2.9,3.2)	0.26	0.33	0.97	-1.9(-5.4,1.6)	-0.6(-3.6,2.3)	0.18	0.22	0.98	-3.5(-7.1,0.1)	-0.3(-3.5,2.9)	0.41	0.63	0.96
	Age	-0.15(-0.2,-0.1)	-0.2(-0.3,-0.04)	-0.1(-0.2,-0.01)	0.4	0.61	0.96	-0.1(-0.2,0.01)	-0.1(-0.2,0)	0.29	0.38	0.97	-0.1 (-0.2,0.01)	-0.1(-0.2,-0.01)	0.26	0.33	0.97
EQ5D	Intercept	0.9 (0.9,1.01)	0.84(0.75,0.93)	0.84(0.8,0.9)	0.19	0.22	0.98	0.81(0.7,0.9)	0.75(0.7,0.8)	0.2	0.24	0.98	0.78(0.7,0.9)	0.8(0.7,0.84)	0.35	0.51	0.97
	Deprivation	0.12(0.07,0.2)	0.13(0.07,0.2)	0.1(0.06,0.1)	0.2	0.25	0.98	0.07(0.01,0.1)	0.05(0,0.1)	0.39	0.6	0.96	0.14(0.1,0.2)	0.1(0.06,0.14)	0.19	0.23	0.98
	Gender	0.03(-0.01,0.1)	0.01(-0.04,0.1)	0.02(-0.02,0.1)	0.13	0.15	0.99	-0.1(-0.1,-0.1)	-0.04(-0.08,0)	0.34	0.47	0.97	0.02(-0.03,0.1)	0.02(-0.0,0.1)	0.41	0.63	0.96
	Age	-0.1(-0.1,-0.03)	-0.002(-0.03,0)	0(0,0)	0.26	0.34	0.97	0(-0.02,0.01)	0(0,0)	0.33	0.47	0.97	-0.01(-0.0,0.01)	0(0,0)	0.26	0.33	0.97
SF8PCS	Intercept	54.1(51.5,56.8)	51.1(47.7,54.4)	51.6(49.2,54)	0.23	0.28	0.98	50.3(46.8,54)	52(49.6,54.2)	0.15	0.18	0.98	50.36(46,54.38)	51.2(49,53.7)	0.35	0.51	0.97
	Deprivation	4.8(2.8,6.7)	5.8(3.7,7.9)	3.8(2.3,5.2)	0.07	0.07	0.99	6.5(4.5,8.42)	4(2.6,5.5)	0.11	0.12	0.99	6.53(4.42,8.64)	3.5(2.1,5)	0.19	0.23	0.98
	Gender	0.99(-0.6,2.5)	0.4(-1.49,2.2)	0.9(-0.5,2.3)	0.09	0.09	0.99	0.9(-1.07,2.9)	1.1(-0.5,2.7)	0.3	0.4	0.97	1.0(-1.12,3.12)	1(-0.7,2.8)	0.41	0.63	0.96
	Age	-0.17(-0.2,-0.1)	-0.1(-0.2,-0.07)	-0.1(-0.1,-0.1)	0.21	0.26	0.98	-0.1(-0.2,-0.1)	-0.1(-0.1,-0.1)	0.16	0.18	0.98	-0.12(-0.2,-0.1)	-0.1(-0.1,0)	0.26	0.33	0.97

Fitting the trajectories (growth curve modelling)

I used growth curve modelling to explore the within-individual systematic change and the difference between the individuals across the study waves. Though it is called individual growth curve (IGC), it examines the 'aggregates' of the individual curves, giving us a representative idea of the overall situation (Shek and Ma, 2011). The trends of health outcome measures are usually expressed as an intercept i.e. a slope, if the change over time is linear; and a curve if the change over time is polynomials (for example quadratic or cubic) (Webb and Bywaters, 2018).

Exploring the changes to the longitudinal data over time is mostly done using the generalised linear mixed modelling (GLMM) technique (Aktas Samur et al., 2014). There are issues with this technique when it comes to unequal sample size (be it due to drop-outs or due to missing values) and unequal time intervals between the survey points. One of the key assumptions of GLMM technique is the independence of the data—indicating observations are random and there is no relationship in space or time. The major criticism of this assumption is that the observations in longitudinal surveys are usually clustered under 'time' and these observations are mostly duplicated resulting in internal correlation. Growth curve models in their advanced forms can handle the shortcomings of GLMM technique and explain the role of Time in bringing about the observed changes (Shek and Ma, 2011).

Assumptions

Like any regression analysis, the growth modelling method has its own assumptions and the utility of the estimates obtained from this method depend mostly on the degree to which these assumptions are met. The key assumptions with growth curve modelling are:

1) The functional form of each individual curve is similar—'equivalence of the model parameters across all individuals' (Curran et al., 2010; p. 127).
2) The data is hierarchical in nature.
3) The assumption of normality—normality of outcome variables and normality of residuals at level 1 (Hox and Stoel, 2014).
4) The changes seen in the individual participant's health outcome is related to the time component.

Regarding the first assumption, all individual survey participants have the same growth curve but if there are two or more groups, their separate parameters may result in different curves (Hox and Stoel, 2014). The hierarchical structure of data is related to 'time' as the level-1 unit which is nested under the individual survey participants—the level-2 units for analysis (Bernier et al., 2011).

Preparation for the analysis

To perform growth curve modelling, the dataset was prepared in a univariate staked format (person-period format), where one record was created for each study period for an individual participant. A new variable "Time" was created, which was based on the measurement occasions. The schedule of data collection was tentatively at 6, 12 and 18 months of the baseline survey. Time was included in the growth curve models to test the linear effect of "time" on the health outcome measures. An assumption was made that the average Time of contact was according to the plan.

Value of Time was assigned according to the months of survey i.e. for baseline TIME=0; at Wave 2, TIME=6; at Wave 3, TIME=12; and at Wave 4, TIME=18. To test the non-linear relationship of time, higher order parameters were also included in the dataset. Time was squared to test its quadratic effect and cubed to test the cubic effect. Time was squared (for example 6^2=36 for Wave 2) to create TIME_SQ variable and Time was cubed (for example 6^3=216 for Wave 2) to create TIME_CUB variable. Least deprived areas were coded as "1" and most deprived areas were coded as "-1", this was done as the area was considered as a predictor. Using the grand mean centring method, a centred age of each participant was computed by subtracting the mean age from the baseline survey (55.29 years).

The relationship of each health outcome measure for each measurement point are shown in Table 5.6. When EQ5D-VAS and SF8PCS scores were significantly correlated at 0.01 *p*-values for each measurement point, correlation of EQ5D scores was not uniform, with special issues in wave 3.

Table 5.6: Correlations of the health outcome measures across survey waves

		Baseline	Wave 2	Wave 3	Wave 4
EQ5D-VAS	Baseline	1			
	Wave 2	0.589**	1		
	Wave 3	0.577**	0.646**	1	
	Wave 4	0.559**	0.634**	0.610**	1
EQ5D	Baseline	1			
	Wave 2	0.717**	1		
	Wave 3	0.045	0.114*	1	
	Wave 4	0.598**	0.670**	0.043	1
SF8PCS	Baseline	1			
	Wave 2	0.689**	1		
	Wave 3	0.670**	0.700**	1	
	Wave 4	0.675**	0.710**	0.732**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Model building process

While developing the growth curves for each health outcome measures, eight different steps were adopted as explained by Shek and Ma (2011). These steps are grouped into two levels: steps 1-4 are grouped to the level 1 models and the remaining steps are associated with level 2 models. The levels of models are explained in later part of this section.

1) **Model 1**: This is an unconditional model that examines the inter-individual mean difference in health outcome measures. In this step, a one-way ANOVA technique is used to compute intercept and random effect without including Time into the model.

2) **Model 2:** This is an unconditional growth model, which is the baseline to examine the role of 'time'. It tests the significance of the linear effect of Time on the health outcome measures. In conditions where the role of Time was not significant, no further modelling was required and the process stopped here.

3) **Model 3:** This is an unconditional growth model to determine if quadratic growth is the case. If the model-fit improved during this step, it indicates the existence of quadratic curve and further analysis for potential cubic trajectories was performed. Alternately, if the model fit did not improve during the step, linear growth curve parameters were retained and step 4 was skipped.

4) **Model 4:** unconditional growth model to determine if cubic growth is the case

5) **Model 5:** This model is an unconditional growth model with 'predictors' to determine if they are related to the growth parameters. Age, gender and deprivation were introduced during this step. This step examined if deprivation status was a predictor of the parameters obtained from the previous models.

6) **Model 6, 7 and 8:** testing of three different covariance structure models to assess the error covariance.

Levels of the models

Within the growth curve modelling, the eight models discussed above are grouped into two levels: the level 1 models are related to the exploration of within-person or intra-individual change and the second level models explore the pattern of between-person or inter-individual change. The models at level 1 provide an indication of the corresponding models for level 2 for the different level of the data. The important function of growth curve modelling is to identify and establish the exact trajectory of change over time—whether it is linear, quadratic or cubic in nature. While the linear curve suggests a constant rate of change over time, quadratic and cubic trend suggest a varying rate of change within the given timeframe. The models are then expanded to include other components of analysis, such as the predictors.

Level 1 models

The level 1 models help explore the within-person or intra-individual change in health outcome measures (i.e., repeated measurements over time). The level 1 models are of the most basic forms, that take into account the random intercept only (Curran et al., 2010). As part of the growth curve modelling process, level 1 models identify the pattern/trajectory of the curve. While Equation 4 examines if there is a linear trend, Equation 5 and Equation 6 look for quadratic and cubic trend respectively.

$$Y_{ij} = \beta_{0j} + \beta_{1j}\,(Time) + r_{ij} \tag{4}$$

$$Y_{ij} = \beta_{0j} + \beta_{1j}\,(Time) + \beta_{2j}\,(Time^2) + r_{ij} \tag{5}$$

$$Y_{ij} = \beta_{0j} + \beta_{1j}\,(Time) + \beta_{2j}\,(Time^2) + \beta_{3j}\,(Time^3) + r_{ij} \tag{6}$$

- Y_{ij} is the repeatedly measured health outcomes for individual *i* at time *t*
- β_0 is the initial status (i.e., Wave 1) of the health outcomes for individual *i*
- β_1 is the linear rate of change for individual *i*
- β_{2j} is the quadratic slope for individual *i*
- β_{3j} is the cubic slope for individual *i*
- r_{ij} is the residual in the outcome variable for individual *i*

Level 2 models

After determining the trend of the trajectory for the individuals from level 1 models, the level 2 models capture whether the rate of change varies across individuals (whole sample) in a systematic way. In this level, predictor variables are added into the equation to explore their effects on inter-individual variation in the health outcomes. For example, if the analysis found that the individual trajectories followed a quadratic (Equation **5**) and not cubic (Equation **6**) rate of change, in this level of modelling, predictor variables are added to the quadratic equation skipping the linear model. The assumption of normality of errors is applied at this stage. Equations 7, 8 and 9 are for linear, quadratic and cubic curves respectively with predictor variables.

$$Y_{ij} = \gamma_{0i} + \gamma_{1i}(Time) + \gamma_{4i} W_j + \cdots + r_{ij} \tag{7}$$

$$Y_{ij} = \gamma_{0i} + \gamma_{1i}(Time) + \gamma_{2i}(Time^2) + \gamma_{4i} W_j + \cdots + r_{ij} \tag{8}$$

$$Y_{ij} = \gamma_{0i} + \gamma_{1i}(Time) + \gamma_{2i}(Time^2) + \gamma_{3i}(Time^3) + \gamma_{4i} W_j + \cdots + r_{ij} \tag{9}$$

- Y_{ij} is the grand mean for the health outcome for the whole sample at Time t.
- Υ_{1i} is the initial status of the health outcome for the whole sample at Time t.
- Υ_{1i} is the linear slope of change relating to the health outcome for the whole sample at Time t.
- Υ_{2i} is the quadratic slope of change relating to the health outcome for the whole sample at Time t.
- Υ_{3i} is the cubic slope of change relating to the health outcome for the whole sample at Time t.
- Υ_{4}i is used to test whether the predictor (e.g., deprivation category) is associated with the growth parameters (i.e., initial status, linear growth, quadratic growth, and cubic growth).
- W_j is an explanatory variable included to analyse the predictor's effect on inter-individual variation on outcome variable
- r_{ij} refers to the random effects (i.e., amount of variance) that are unexplained by the predictor.

Throughout the modelling process, maximum likelihood (ML) and mixed model method were used to examine fixed and random effects of the predictors. Selection of the best model was based on the values of -2 log likelihood, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). AIC and BIC are the indices of relative goodness-of-fit that compares the different set of models (Littell et al., 2000). The advantages of using these indices are ‘speed and generality’, which provide an easy and simple basis for selecting the best-fit model (Burnham and Anderson, 2003; p.288). The downside of this approach is that it can be used with a single chain of nested models only (ibid). In my research, this disadvantage does not apply because the models used in the analyses are nested in a single chain: individual level model M_i is nested under group model M_{ij} (ibid).

The intra-class correlation coefficient (ICC) was used to explore the variance in the health outcome measures as a result of the inter-individual differences. This was computed using Equation 10, below. ICC was also used to measure the level of autocorrelation of the outcome measures between the survey waves. ICC is a commonly used tool to quantify the reliability and consistency of the model (as measured by the proportion of variance by a grouping factor) to measure the within-class difference of the outcome variable (Heinrich and Lynn, 2001, Weir, 2005). Like most correlation coefficients, the value of ICC can range between 0 and 1. While the values close to 0 indicate that the observations are not similar within the group, the values closer to 1 indicate that the observations are *highly* similar within the group. As a rule of thumb, ICC of 0.25 and above or 25 percent of intra-class variation requires further exploration of the relationship, possibly by using growth curve modelling (Heinrich and Lynn, 2001, Shek and Ma, 2011).

$$ICC = \frac{Estimate\ of\ Intercept}{(Estimate\ of\ Residual + Estimate\ of\ Intercept)} \qquad 10$$

The benefit of using growth curve modelling is the possibility of testing the different variance and covariance structures, this improves the predictive power of the models. In this research, I tested the relevance of unstructured, compound symmetric and first-order autoregressive covariance structures for the three health outcome measures. Models 6, 7 and 8 test the relevance of these covariance structures. Unstructured covariance (UN) is the most commonly found structure model and can handle the structural errors with no assumptions (Shek and Ma, 2011). Compound symmetric (CS) structure examines if the covariance and variance of an individual survey participant remain constant over the study period (Littell et al., 2000). On the other hand, first-order autoregressive covariance indicates a heterogeneous variance and that the covariance decreases with increasing Time (survey waves) (Littell et al., 2000, Shek and Ma, 2011). In the following section, I present the model selection process and the final fitted trajectories for each health outcome measure included in the study.

Trajectories of health outcomes

EQ5D-VAS

Using Equation 10, ICC was computed from the estimates for Model 1, which is presented in Table 5.7 (see below). The ICC was 260.66 / (155.23+260.66) = 0.626, which suggests that almost 63 percent of total variation in EQ5D-VAS scores was due to inter-individual differences. The high proportion of variance thus indicates the relevance of applying growth modelling to EQ5D-VAS. While comparing the intra-individual variation of EQ5D-VAS scores between Model 1 and Model 2, the residual variance decreased by 10.63 (from 155.23 to 144.6), see Table 5.7, below. This means almost seven percent (10.63/155.23*100) of intra-individual variation in EQ5D-VAS scores was a result of linear rate of change.

Table 5.7: Estimates of covariance parameters from different models for EQ5D-VAS

Models	Parameter		Estimate	Std. Error	95% CI Lower Bound	95% CI Upper Bound
Model 1	Residual		155.23	6.21	143.51	167.90
	Intercept (Variance)		260.66	18.16	227.39	298.80
Model 2	Residual		144.60	7.05	131.42	159.10
	Intercept + Time	UN (1,1)	298.91	22.61	257.73	346.68
		UN (2,1)	-44.28	13.36	-70.46	-18.09
		UN (2,2)	16.26	11.39	4.12	64.18
Model 3	Residual		132.09	9.30	115.06	151.64
	Intercept + Time + Time^2	UN (1,1)	322.82	25.27	276.91	376.34
		UN (2,1)	-12.57	3.97	-20.34	-4.79
		UN (2,2)	2.23	1.03	0.91	5.51
		UN (3,1)	0.42	0.20	0.03	0.80
		UN (3,2)	-0.08	0.05	-0.19	0.02
		UN (3,3)	0.00	0.00	0.00	0.02
Model 5 (with predictors)	Residual		132.13	9.30	115.09	151.68
	Intercept + Time + Time^2	UN (1,1)	287.25	23.54	244.63	337.29
		UN (2,1)	-11.97	3.82	-19.46	-4.47
		UN (2,2)	2.20	1.02	0.88	5.48
		UN (3,1)	0.39	0.19	0.02	0.76
		UN (3,2)	-0.08	0.05	-0.18	0.02
		UN (3,3)	0.00	0.00	0.00	0.02

Model 2 was then fitted to examine the individuals’ trajectories and to assess if time had any effect on it. Table 5.8 (see below) presents the estimates of the fixed effects from model 2. The findings suggest that the average EQ5D-VAS score was 71 and it increased significantly over time (β=3.75, p<0.01). The significant residual and intercept suggest the presence of intra-individual differences and this can be explained by individual-level predictors.

Table 5.8: Estimates of fixed effects from different models for EQ5D-VAS

Models	Parameter	Estimate	Std. Error	95% CI Lower Bound	95% CI Upper Bound
Model 2	Intercept	71.09	0.75	69.61	72.57
	Time	3.75	0.54	2.69	4.80
Model 3	Intercept	70.25	0.78	68.71	71.79
	Time	0.97	0.15	0.68	1.27
	Time Sq.	-0.04	0.01	-0.05	-0.02

Model 3 was then fitted to assess if EQ5D-VAS scores changed at a quadratic rate (by adding *time*time* into the previous model), i.e. if the rate accelerated or decelerated over the survey period. There was a positive linear trend with EQ5D-VAS score initially (β=0.97, p<0.01) but with a deceleration afterwards (β= -0.04, p<0.01) (See Table 5.8, above). While comparing the intra-individual variation of EQ5D-VAS scores between Model 1 and Model 3, the residual variance decreased by 23.1 (from 155.23 to 132.09), see Table 5.7, above. This means almost 15 percent (23.1/155.23) of intra-individual variation in EQ5D-VAS scores was a result of the linear and quadratic rate of change. Furthermore, as the quadratic model improved model fit, the parameters from the linear and quadratic models were taken forward to the next step of modelling (see Table 5.9, below).

Table 5.9: Test of model fit between different models for EQ5D-VAS

Information Criteria	Model 1	Model 2	Model 3	Model 5
-2 Log Likelihood	16989.48	16929.24	16893.60	16813.31
Akaike's Information Criterion (AIC)	16995.48	16941.24	16913.60	16851.31
Schwarz's Bayesian Criterion (BIC)	17012.29	16974.86	16969.63	16957.78

I tested if EQ5D-VAS scores followed a cubic rate of change but the model of fit did not improve and the model could not explain the growth better than the quadratic model (Model 3). See Appendix C-9 (page: 298) for the results obtained from the testing of the cubic model. Model 4 was then skipped and as part of model 5, the predictors were introduced into the model.

Table 5.10: Estimates of fixed effects of the final model for EQ5D-VAS with the predictors

			95% CI	
Parameter	Estimate	Std. Error	Lower Bound	Upper Bound
Intercept	69.70	0.77	68.19	71.21
Time	1.00	0.15	0.70	1.30
Time Sq.	-0.04	0.01	-0.06	-0.02
Deprivation	5.67	0.76	4.18	7.16
Sex	0.00	0.77	-1.51	1.52
Age	-0.15	0.04	-0.24	-0.07
Time * Deprivation	-0.06	0.15	-0.36	0.24
Time Sq. * Deprivation	0.001	0.01	-0.01	0.02
Time * Sex	-0.02	0.15	-0.32	0.28
Time Sq. * Sex	0.00	0.01	-0.01	0.02
Time * Age	0.00	0.01	-0.01	0.02
Time Sq. * Age	0.00	0.00	0.00	0.00

Deprivation, age and gender were then added into the quadratic model to test their predictor effects. Table 5.10 (above) presents the estimates of fixed effects for the final model with the predictors. Deprivation was statistically significant on its own but was not a significant predictor of linear or quadratic changes in EQ5D-VAS scores. However, deprivation accounted for about nine percent [(144.6– 132.13) / 144.6 = 0.086] of the intra-individual variation in EQ5D-VAS scores (see Table 5.7, above).

As the EQ5D-VAS scores followed a quadratic rate of change, Equation 7 was used to fit the trajectories. Based on the values from Table 5.10, trajectories were fitted for the least and the most deprived areas of Stockton-on-Tees and Equation 7 was modified to Equation 11. The trajectories for the least and the most deprived areas are presented in Figure 5.2.

$$Y_{ij} = 69.7 + 1(\text{Time}) - 0.04(\text{Time}^2) + 5.67(\text{Deprivation}) - 0.06(\text{Deprivation} * \text{Time}) + 0.001(\text{Deprivation} * \text{Time}^2) + r_{ij} \quad 11$$

Replacing the values assigned to the most deprived areas (-1) and the least deprived areas (1) to the above equation yielded the individual trajectories for each group as Equation 12 and Equation 13:

For least deprived areas (1)

$$Y_{ij} = 69.70 + 1(\text{Time}) - 0.04(\text{Time}^2) + 5.67(1) - 0.06(1 * \text{Time}) + 0.001(1 * \text{Time}^2) + r_{ij}$$

$$Y_{ij} = 75.37 + 0.94(\text{Time}) - 0.039(\text{Time}^2) + r_{ij} \quad 12$$

For most deprived areas (-1)

$$Y_{ij} = 69.70 + 1(\text{Time}) - 0.04(\text{Time}^2) + 5.67(-1) - 0.05(-1 * \text{Time}) + 0.001(-1 * \text{Time}^2) + r_{ij}$$

$$Y_{ij} = 64.03 + 1.05(\text{Time}) - 0.041(\text{Time}^2) + r_{ij} \quad 13$$

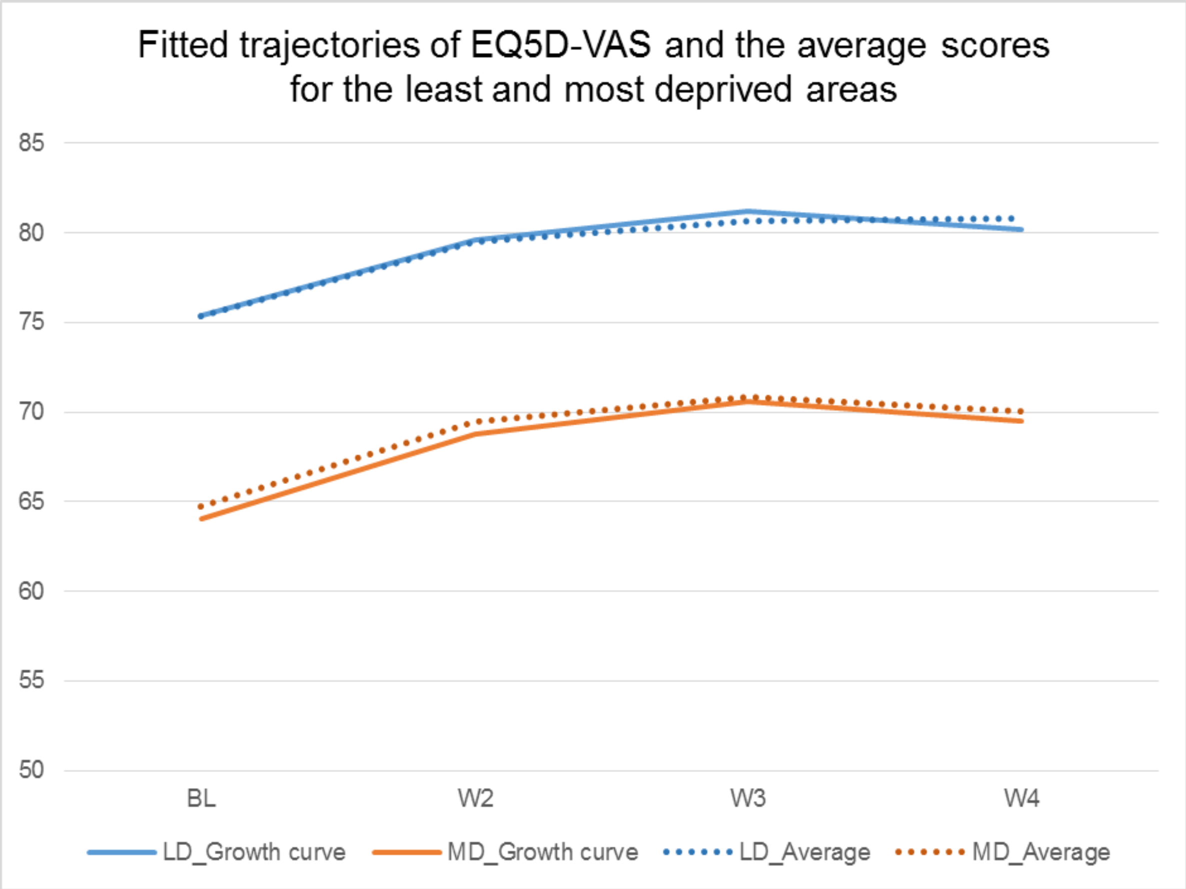

Figure 5.2: Fitted trajectories of EQ5D-VAS for the least and most deprived areas compared to the average scores from the survey

I also tested the three covariance structures to make sure the right model selection process was adopted. Table 5.11 (below) summarises the results of the three covariance structures (unstructured, computed symmetry and first-order autoregressive) that were tested with the dataset. The values for two log-likelihood (-2LL), AIC and BIC were compared between the three covariance structures. From the results, unstructured covariance structure was found to be the best model as its values for -2LL, AIC and BIC were the lowest. This indicates that UN models can improve model prediction compared to the rest of the covariance structure models. All the models and results discussed earlier were based on the unstructured (UN) covariance structure model, which is now justified by this testing.

Table 5.11: Comparison of the information for the three covariance structure models used to test goodness-of-fit

Covariance structure	-2LL	AIC	BIC
Unstructured	16806.19	16850.19	16973.47
Computed symmetry	16841.45	16869.45	16977.89
First order autoregressive (AR1)	16952.19	16980.19	17058.64

EQ5D Scores

The ICC from Model 1 was 0.026/ (0.04+0.026) = 0.3936, which indicates that more than 39 percent of total variation in EQ5D scores was due to the inter-individual variation (see Table 5.12, below). Model 2 was then fitted to explore the linear effect of Time on EQ5D scores. While comparing the intra-individual variation of EQ5D scores between Model 1 and Model 2, the residual variance decreased by 0.005 (from 0.04 to 0.035). This means 14 percent (0.005/0.04) of intra-individual variation in EQ5D-VAS scores was a result of the linear rate of change. The estimate of $\beta = -0.012$ (*SE = 0.001, p*<0.05) indicates that the survey participants with high EQ5D scores had a slower rate of decrease compared to those having lower EQ5D scores.

Table 5.12: Estimates of covariance parameters from different models for EQ5D scores

Models	Parameter		Est.	Std. Error	95% CI Lower Bound	95% CI Upper Bound
Model 1	Residual		0.040	0.002	0.037	0.044
	Intercept (Variance)		0.026	0.002	0.022	0.031
Model 2	Residual		0.035	0.001	0.032	0.037
	Intercept + Time	UN (1,1)	0.032	0.002	0.027	0.037
		UN (2,1)	-0.012	0.001	-0.014	-0.009
		UN (2,2)	0.004	0.000	-	-

The mean estimated initial status of EQ5D score was 0.82 and its rate of linear growth was -0.0001, which indicates an almost flat curve (see Table 5.13, below). Furthermore, the effect of Time was not significant. The model building process for EQ5D was thus stopped.

Table 5.13: Estimates of fixed effects from Model 2 for EQ5D scores

			95% CI	
Parameter	Estimate	Std. Error	Lower Bound	Upper Bound
Intercept	0.822	0.010	0.803	0.841
Time	-0.0001	0.001	-0.002	0.001

SF8PCS scores

Compared to the previous two health outcome measures, the ICC for SF8PCS was higher. More than 70 percent 83.63 / (35.13 + 83.63) of the total variation in SF8PCS scores was due to the inter-individual differences (see Table 5.14, below).

Table 5.14: Estimates of covariance parameters from different models for SF8PCS scores

					95% CI	
Models	Parameter		Est.	Std. Error	Lower Bound	Upper Bound
Model 1	Residual		35.13	1.39	32.50	37.97
	Intercept (Variance)		83.63	5.34	73.80	94.77
Model 2	Residual		33.10	1.62	30.07	36.45
	Intercept + Time	UN (1,1)	86.14	6.07	75.03	98.89
		UN (2,1)	-0.29	0.27	0.82	1.25
		UN (2,2)	0.04	0.02	0.01	0.10
Model 5 (with predictors)	Residual		32.97	1.61	29.96	36.29
	Intercept + Time	UN (1,1)	73.11	5.38	63.29	84.44
		UN (2,1)	-0.31	0.25	-0.81	0.19
		UN (2,2)	0.03	0.02	0.01	0.10

The mean estimated initial status of SF8PCS score was 48.05 and its rate of linear growth was -0.001, which indicates an almost flat curve (see Table 5.15, below).

Though the effect of time was not significant, the random error terms associated with the intercept and time were significant. This indicates the role of individual predictors in predicting this inter-individual variation.

Table 5.15: Estimates of fixed effects Model 2 for SF8PCS scores

			95% CI	
Parameter	Est.	Std. Error	Lower Bound	Upper Bound
Intercept	48.05	0.39	47.28	48.82
Time	-0.001	0.02	-0.04	0.04

I tested if SF8PCS scores followed a quadratic rate of change but the model of fit did not improve and the model could not explain the growth better than the linear model (Model 2). See Appendix C-10 (page 300) for the results obtained from the testing of quadratic model. Model 3 and 4 were then skipped and as part of model 5, the predictors were introduced into the linear model. The goodness-of-fit showed an improved model fit for linear growth modelling, both with and without predictors (see Table 5.16, below).

Table 5.16: Test of model fit between different models for SF8PCS

Information Criteria	Model 1	Model 2	Model 5
-2 Log Likelihood	14222.4	14218.5	14107.1
Akaike's Information Criterion (AIC)	14238.4	14230.5	14121.1
Schwarz 's Bayesian Criterion (BIC)	14245.2	14244.1	14198.3

Deprivation, gender and age were then added to the linear model to test their predictor effects. Table 5.17 (below) presents the estimates of fixed effects for the final model with the predictors. Deprivation was statistically significant on its own but was not a significant predictor of linear changes in SF8PCS scores. However, deprivation accounted for more than six percent [(35.13 – 32.97) / 35.13 = 0.0615] of the intra-individual variation in SF8PCS scores.

Table 5.17: Estimates of fixed effects of the final model for SF8PCS scores with the predictors

			95% CI	
Parameter	Est.	Std. Error	Lower Bound	Upper Bound
Intercept	47.64	0.38	46.90	48.38
Time	0.005	0.02	-0.04	0.05
Deprivation	2.53	0.37	1.80	3.26
Sex	-0.47	0.38	-1.22	0.27
Age	-0.17	0.02	-0.21	-0.13
Time * Deprivation	0.04	0.02	-0.01	0.08
Time * Sex	-0.02	0.02	-0.07	0.02
Time * Age	0.002	0.00	0.00	0.00

As the SF8PCS scores followed a linear rate of change, Equation 7 was used to fit the trajectories. Based on the values from Table 5.17 (above), trajectories were fitted for the least and the most deprived areas of Stockton-on-Tees and Equation 7 was modified to Equation 14. The trajectories for the least and deprived areas are presented in Figure 5.3 (below). While the SF8PCS scores had a tendency to increase with time in the least deprived areas, it was just the opposite in the most deprived areas, where there was a decline in time.

$$Y_{ij} = 47.64 + 0.005(\mathrm{Time}) + 2.53(\mathrm{Deprivation}) + 0.4(\mathrm{Deprivation} * \mathrm{Time}) + r_{ij} \qquad 14$$

Replacing the values assigned to the most deprived areas (-1) and the least deprived areas (1), Equation 14 yielded the individual trajectories for each group as Equation 15 and Equation 16:

For least deprived areas (1)

$$Y_{ij} = 47.64 + 0.005(\text{Time}) + 2.53(1) + 0.4(1 * \text{Time}) + r_{ij}$$

$$Y_{ij} = 50.17 + 0.405(\text{Time}) + r_{ij} \quad (15)$$

For most deprived areas (-1)

$$Y_{ij} = 47.64 + 0.005(\text{Time}) + 2.53(-1) + 0.4(-1 * \text{Time}) + r_{ij}$$

$$Y_{ij} = 45.11 - 0.395(\text{Time}) + r_{ij} \quad (16)$$

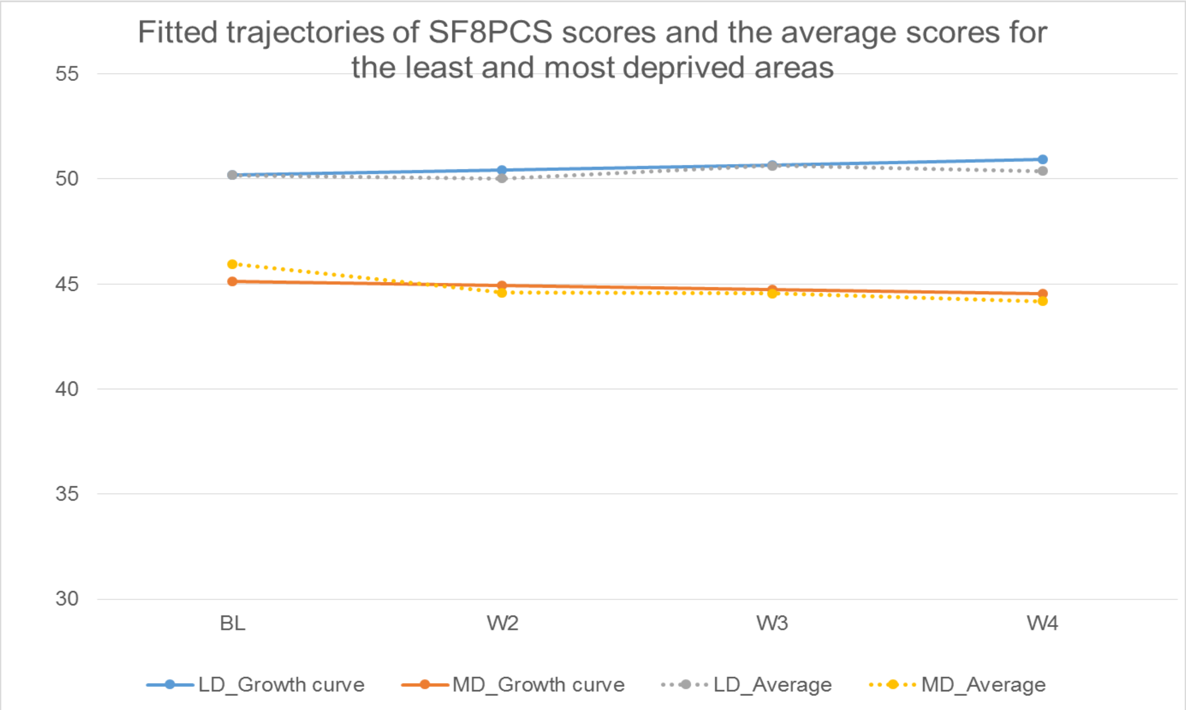

Figure 5.3: Fitted trajectories of SF8PCS scores for the least and most deprived areas compared to the average scores from the survey

Synthesis of the findings

It is not the aim of this chapter to provide an outline of competing methodological approaches and ontological justifications for studying the impacts of austerity on health inequalities. The objective of this chapter was to identify not only the difference in health outcome measures during the survey period but whether the trends are statistically significant and the extent to which they vary between the most and the least deprived neighbourhoods of Stockton-on-Tees. This chapter, however, presents the trend of health outcome measures to build a case that suggests that the gap in general health remained constant and that the physical health gap slightly worsened over the study's time period. The results confirmed the role of time in shaping the health divide in Stockton-on-Tees. Based on the assumptions and the findings, it can be argued that there is a strong relationship between public spending cuts. Welfare reform cuts and the health inequalities in Stockton-on-Tees. The findings from this chapter show that the type of austerity pursued since 2010 is damaging to health outcomes and has resulted in policy-induced health inequalities. In line with the argument by Botta (2014), the findings from this chapter also make the case that the austerity programme may turn out to be self-defeating and the source of inequalities, rather than being the remedy for the financial crisis. The findings also highlight that the health impacts of austerity can be observed in a time frame as short as two years, with the most deprived areas being more affected than the least deprived areas.

Limitations of the analytical approaches

Though the multiple imputation technique produced a final estimate by combining the parameter estimates from the imputed dataset, it may not be consistent. This is the because the results could slightly vary during each procedure, even with the same dataset (Newman, 2003). For the multiple imputation process, the dataset from the baseline survey included the 733 cases with complete information. This the same dataset used in the analysis of composition-context analysis presented in Chapter 4. This was done as the MCMC technique used for MI imputes a value based on the previous observation. This resulted in the 103 cases that were not included in the baseline analysis being excluded from multiple imputation as well.

The growth modelling that I adopted despite its strengths, still has limitations. The number of time points is one of many factors that determine the predictability of any growth modelling. In this research, there were only four survey points, so the testing of higher order polynomial trends was not feasible (Curran et al., 2010). In addition, the power of the models used could have been increased if there had been more survey waves (Shek and Ma, 2011). As the follow-up surveys were conducted at six months intervals, an assumption was made that the participants' health situation would remain constant during the "window period", which may not be the case in reality. Another limitation of this approach is its inability to show 'true' causal relationships (Tu et al., 2013). This is the case as the predictors can change with time and in my models, only 'time-invariant' predictors were selected. Selection of an appropriate growth model is not always straightforward, especially when the data is limited. Inappropriate model selection thus can result in an unstable estimate and highly collinear random coefficient (Grimm et al., 2011). Acknowledging all these limitations, the interpretation of the findings from a growth model still require the consideration of the underlying theories (Curran and Willoughby, 2003)

Summary

In the first part of the chapter, I presented the findings of the missing data analysis using two approaches: survival analysis and multiple imputation. The survival analysis explored the probability of remaining in the following wave and compared its results between the most and the least deprived areas of Stockton-on-Tees. The findings suggest a higher probability of drop-out amongst participants from the most deprived areas compared to their counterparts, which is a common issue (Oliver et al., 2005). Multiple imputation was carried out to test the impact of missing data on the analysis of the gap in the general and physical health measures. The findings from the multiple imputation suggest a borderline impact of missing data on the results of general health outcome measures (EQ5D-VAS and EQ5D scores). There was, however, a minimal impact on the results of SF8PCS measures because of the missing data.

The second part of the chapter was focused on growth models to track the within-individual and between-individual differences in health outcome measures over time. To do this, growth curve modelling technique was used. The findings of the analyses suggest that the EQ5D-VAS scores followed a quadratic rate of change whereas SF8PCS followed a linear rate of change. The trend analysis showed a constant gap in average EQ5D-VAS scores between the most and the least deprived areas. However, the gap was widening for SF8PCS scores, with declining scores in the most deprived areas. This indicates the significance of 'time' and the welfare reform initiatives implemented as part of the austerity programme. This analysis could not be carried out with the EQ5D scores as a significant relationship with could not be established and goodness-of-fit did not improve when building the models. This chapter has complemented the findings of **Chapter 4** in showing that there is a significant health inequalities gap in Stockton-on-Tees and that the gap is increasing for SF8PCS scores. These findings are discussed further in the following chapter (**Chapter 6**).

Chapter 6: Discussion

Introduction

This thesis has investigated the gap in general and physical health between people living in the most and the least deprived neighbourhoods of the Borough of Stockton-on-Tees in the North East of England. The primary aim of this research was to gain a greater understanding and insight into health inequalities in an age of austerity within this geographical context—by examining the relationship between place and health inequalities. The aims of this chapter are:

1) To summarise and discuss the principal findings of the analysis of geographical health inequalities in Stockton on Tees.
2) To show that the research questions presented in **Chapter 3** have been adequately addressed.
3) To revisit the theories of health inequalities that were outlined in **Chapter 2** in light of my findings.
4) To discuss the strengths and limitations of the thesis.

In the first part of the chapter, I present the principal findings of the statistical analyses and relate them to existing literature. In the following section, I discuss the significance of this research and critically discuss the limitations of the study. I believe this research has made a significant contribution to the health geography literature and the policy discourse around health inequalities. In the final section, I discuss potential further research arising from this study.

Principal findings

This section explores the findings which relate to geographical inequalities in physical and general health in Stockton-on-Tees and compares them to other studies in the field.

Three validated health outcome measures—two measuring general and one measuring physical health were used: the EQ5D-VAS, the EQ5D and the SF8PCS.

EQ5D-VAS represents the perceived health status of the participant, which is measured in a scale of 0-100, 0 being the worst and 100 the best health state they can imagine (Warren et al., 2014).

The EQ5D scores range between – 0.594 and 1.00, the latter being better health and considers individual's mobility, self-care, ability to carry out usual activities, pain and discomfort and level of anxiety and depression.

Using eight questions that focus on the health status of the participants during the last four weeks, SF8PCS measures the physical health status in a scale of 0-100: the higher the score, better is the physical health state (Garthwaite et al., 2014).

The first part of this section discusses the findings from the longitudinal analyses, which focused on the trend and patterns of health inequalities.

This thesis has explored the notions of composition and context and analysed the relative contribution of different risk factors. For example the contribution of material, behavioural, psychosocial and neighbourhood factors. The second part of this section will make specific reference to the literature related to the different determinants of health and wellbeing and discuss the relationship between individual social determinants and their interaction with the local environment to produce inequalities in general and physical health.

Overall trend and patterns of health inequalities

Using data from the longitudinal survey, descriptive and analytical statistics were used to explore if there were gaps in general and physical health between the most deprived and least deprived areas of Stockton-on-Tees and whether these gaps changed over time. The findings were viewed from a spatiotemporal perspective—looking at how the health divide evolved over time for different places. The findings presented in this section attempt to answer the two research questions, presented in ***Chapter 3*** *(page: 75)*:

> What is the extent of health inequalities in physical and general health in Stockton-on-Tees? (Research question a.)
>
> How have health inequalities in Stockton-on-Tees changed during austerity? (Research question c.)

In ***Chapter 4*** and ***Chapter 5,*** I showed the inequalities in general and physical health between the people living in the most and the least deprived areas of Stockton-on-Tees using data from the longitudinal survey. For all three health outcome measures and throughout the study period, there was a significant gap in physical and general health. People living in the least deprived areas had higher chances of having better general and physical health compared to those living in the most deprived areas. This supports the ongoing argument regarding the damaging effects of deprivation on people's health and wellbeing (Bambra and Garthwaite, 2015, Rahman et al., 2016, Stuckler et al., 2017).

Adjusting for age and gender, multilevel models were applied to analyse the gap in general and physical health. On average, people from the most deprived areas could expect to have a 10 point lower score for the EQ5D-VAS measure compared to those living in the least deprived areas, this was the case for each survey wave. There was a significant gap in EQ5D scores, however, fluctuating during wave 3: the gaps were 0.12, 0.13, 0.07 and 0.14 during baseline and the subsequent waves respectively. The fluctuation during wave 3 could be attributed to the missing data. As highlighted in chapter 5, for EQ5D scores, almost 40 percent of the relative loss of efficiency while estimating the parameter for deprivation during wave 3 was due to the missing data. Also, 60 percent of the increase in variance was linked to missing data for the same wave. No particular trend was observed with the two general health measures, but a steady increase in the gap between the two areas was observed with the physical health measure (SF8PCS). The estimated gap in SF8PCS increased from 4.76 (95% CI: 2.8, 6.73) during the baseline to 6.53 (95% CI: 4.42, 8.64) during the final wave, a 37 percent increase.

I presented the trajectories along with the rate of change of the health outcome measures in ***Chapter 5,*** which is a novel approach and has not previously been used. In line with the findings in ***Chapter 4***, EQ5D-VAS increased '*quadratically'* during the survey period: the rate of change was higher between baseline and wave 2, which was followed by a slower rate of increase between wave 2 and wave 3 and a decline when reaching the final wave. Maheswaran et al. (2015) argue that self-reported general health measures can reflect the immediate impacts of policy changes on current health, which, I believe could explain the constant gap in general health between the areas.

SF8PCS scores, on the other hand, showed a linear rate of change, however, the gap was widening: with increasing scores for the least deprived areas and a declining trend for the most deprived areas. This lends support to the argument of Beatty et al. (2017) that in the post-financial crisis period, the health of the most deprived groups is not increasing as it is amongst the least deprived groups.

In general, there was a constant gap between the two groups in general health throughout the study period while the gap widened for the specific physical health measure SF8PCS. Wunsch et al. (2010) argue the need to understand causal relations in order to forecast these social phenomena and devise necessary actions. My assumption while looking at the trajectories was that time is equivalent to austerity because the austerity measures were phased in gradually over time. My findings support the argument that during a time of austerity, inequalities in health get wider (Abebe et al., 2016, Barr et al., 2017, Stuckler et al., 2017) and that austerity can be understood as the cause of this gap. A study by Abebe et al. (2016) has found that there was a significant increase in poor self-reported health during the recession and after the widespread introduction of public spending cuts in the UK Bambra and Garthwaite (2015) have suggested that during times of austerity, spatial health inequalities will increase and this will disproportionately affect the older industrial areas such as Stockton-on-Tees. More recently, compared to the post-financial crisis period, the general health of UK has slowly improved, but unequally with the most disadvantaged groups lagging behind (Beatty et al., 2017, Pearce, 2013). For example, a report by Royal College of Paediatrics and Child Health (2017) has shown that although overall health outcomes of children are improving, the children from the deprived backgrounds have far worse health outcomes than those growing up with the least deprived backgrounds. Barr et al. (2016) have found an increase in adverse mental health outcomes in the most deprived areas of the UK.

The compositional and contextual explanations of health inequalities

The multilevel analysis also explored the determinants which contribute to the health gap, in terms of compositional and contextual factors. The findings presented in this section attempt to answer the remaining two research questions, which were presented in ***Chapter 3***:

> How do compositional and contextual factors explain the gap? (Research question b.)
>
> How does the role of compositional and contextual factors change in Stockton-on-Tees during the period of austerity? (Research question d.)

The key compositional determinants included: material factors such as income, recipient of benefits, employment and unhealthy housing conditions (dampness, lack of central heating); psycho-social factors such as happiness, lacking companionship, being isolated and feeling left out; and behavioural factors such as frequency of physical exercise and alcohol use. Likewise, the key contextual factors included: neighbourhood noise; pollution and environmental problems in the neighbourhood; neighbourhood crime; feeling safe in the neighbourhood and the feeling of belongingness to the neighbourhood. In addition to the contribution of the individual-compositional and area-level contextual factors, there was a significant clustering effect between these two different categories. My research also found that there was a certain proportion of the health gap, which was unexplained by the compositional and contextual factors. A simple representation of the relationship of compositional, contextual, and interaction between the two categories and the unexplained state with health inequalities is presented in Figure 6.1 (below).

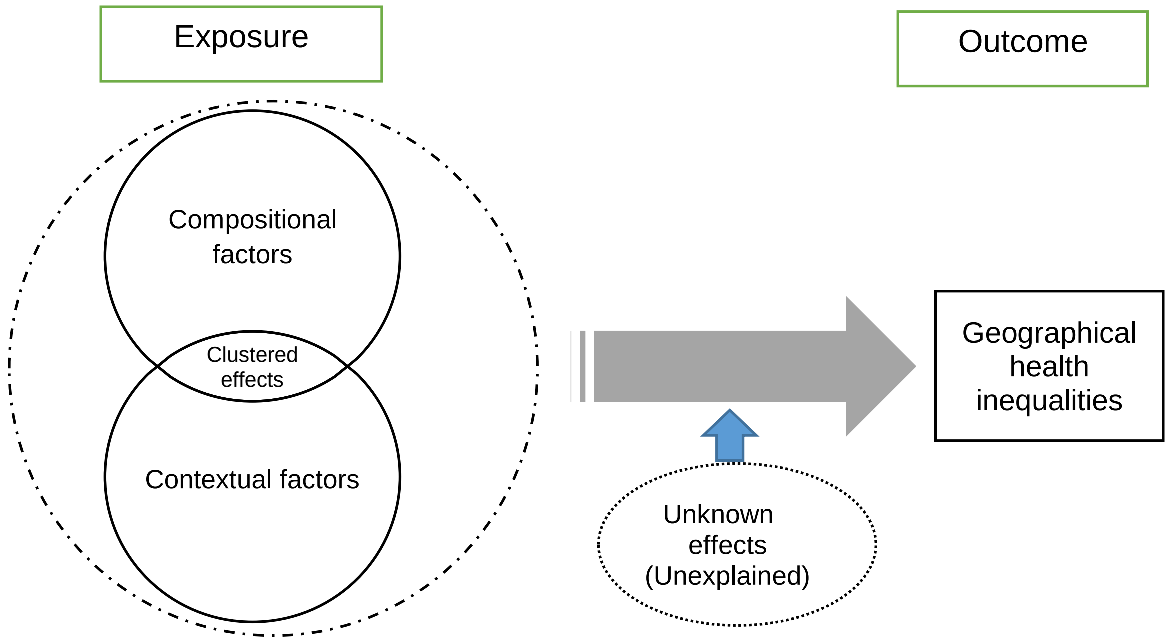

Figure 6.1: Understanding geographical inequalities in health

The relationship between health inequalities and the social determinants of health has been well established. This study adds to the substantial evidence on the role of individual/compositional (Marmot and Allen, 2014) and area level/contextual factors (Barnett et al., 2016, Cummins et al., 2005, Pearce, 2015) in creating the health gap. This was done by exploring the relative contributions of these determinants and further looking at how this changed over time. Association between individual-level factors and health inequalities have been found which is consistent with previous research. For example, Skalicka et al. (2009) found a strong association between material factors (such as employment status and financial difficulties) and mortality amongst men. This study found that about 52 percent of the risk of mortality was explained by material factors. Arber et al. (2014) found associations of income and other socio-economic factors with self-assessed health and Skalicka et al. (2009) have shown the strong role of behavioural factors (such as the type and frequency of physical activity, smoking and consumption of alcohol) in health inequalities, with these factors explaining the risk of mortality by education by about 37 percent. The findings show that these compositional and the contextual factors make a direct as well as indirect (clustered) contribution to the health gap. The contribution of individual-level compositional factors was more pronounced than the neighbourhood level contextual factors in explaining health inequalities. For all three health measures and for each wave, all compositional factors combined had significant direct contributions, which were higher than the contribution of the contextual factors (such as neighbourhood noise, pollution and crime). Among the compositional factors and in most of the cases, material factors related to income and the household economy (such as household income, paid job, worklessness within the household, dampness in the house and lack of central heating) were the most important predictors of the health gap. This matches with the qualitative findings from other research from the UK (Egan et al., 2015, Moffatt et al., 2016). A longitudinal analysis of the British Household Panel Survey (BHPS) carried out by Pevalin et al. (2017) explored the long-term health consequences of housing problems (tenure type) and 'equivalent household income'[5]. In this study, Pevalin et al. (2017) have found that persistent exposure to housing problems resulted in poorer health conditions and the exposure in the past could have health consequences in the present. Likewise, a study from Norway by Skalicka et al. (2009)

[5] Pevalin et al. (2017) have equivalized monthly income using the McClements Equivalence Scales (Mcclements, L. D. 1977. Equivalence scales for children. *J. Public Econ.,* 8**,** 191-210.). The equivalent income shows how income scales are related to commodity scales, and indicates the component parts of changes in commodity demand stemming from changes in family circumstances.

attributed material factors as the most important compositional factors in explaining the inequalities in mortality.

The important contribution of household income to health inequalities is also demonstrated by Arber et al. (2014). Arber et al. (2014) argue that socio-economic deprivation (material deprivation and financial strain) can result in health inequalities through psychosocial pathways such as reduced social participation, increased likelihood of social exclusion, which are followed by stress, anxiety and helplessness. With my research findings, I also found a two-way relationship between worklessness and poor health. Research conducted in England by Pemberton et al. (2016) found that the current labour market does not appropriately cater for the needs of the people with existing health conditions which excludes them from labour market. Using data from population surveys for England, a study by Moller et al. (2013) attributed higher prevalence of morbidity (mental health problems and limiting long-term illness) and mortality with rising unemployment. Following the financial crisis, the gap in unemployment between the most and the least deprived groups increased in the UK (Moller et al., 2013). I agree with the argument of Moller et al. (2013) that this difference has disproportionately impacted vulnerable families and communities. Worklessness within households impacts individuals and their families (Bambra, 2011, Warren et al., 2013). Bambra (2011) argues that in capitalist societies, work is the main source of income to sustain families and to meet family needs. Thus, worklessness within a household will lower the socio-economic position of the family as a whole and as O'Connor and Kirtley (2017) argue the 'sense of poverty' (self-perception of the family members belonging to a lower social class) is one of the mechanisms that expand the impacts of individual-level worklessness to families. Edwards (2012) in his report highlighted a sharp rise and a high concentration of benefits claimants in the most deprived areas of Stockton-on-Tees, after the welfare reforms of 2012. The same report highlighted the diminishing resources were available to support the voluntary and community sector service that are crucial in dealing with the issues arising from changes to social security, such as an increased demand for advice relating to welfare rights and housing. The Welfare reforms mostly affected vulnerable families with low incomes, families with members on out of work benefits, the long-term sick and disabled (Edwards et al., 2013). With more households from the deprived areas of Stockton-on-Tees facing economic hardships and the limited availability of collective resources and welfare support, health of the people from these households may suffer more, a concept known as '*deprivation amplification*': area level deprivation can amplify the health impacts of individual-level socio-economic status (Bambra, 2016, Macintyre, 2007). The changing socio-economic conditions of the households and that of the borough of Stockton-on-Tees as part of the welfare reforms when viewed in conjunction with the findings from my research could be correlated and used as an explanation of prevailing and/or widening health inequalities.

When compared to material and contextual factors, psychosocial and behavioural factors made less contribution to the health gap. The relative contribution of psychosocial factors (such as happiness scores, feeling isolated) towards general health gap (EQ5D-VAS and EQ5D) gradually increased with time. For example, from a one percent contribution to the gap in EQ5D-VAS scores during baseline to almost 29 percent during the final wave. Noticeably, people who had higher happiness scores (scale of 0-10) were more likely to have higher scores for all three health outcomes, for example, an increase of one in the happiness scale was associated with a 2.24 points increase in EQ5D-VAS scores during baseline and a 3.06 points increase during wave 2. These findings lend support to the argument of Friedli (2009) that happiness is a key element of general wellbeing. I agree with Veenhoven (2008) that happiness, as a compositional factor, is not just a predictor of better physical and mental wellbeing, it has a strong correlation with contextual factors such as the healthy living environment. Veenhoven (2008) further argues that happiness of an individual also depends on the wider socio-political context of the country—material wealth, political democracy, freedom and governance. Welfare reform and austerity were linked with a decrease in happiness score in Greece and Portugal (Blanchflower and Oswald, 2011) and as Veenhoven (2008) argues there is the probability of causality of the political context on the happiness of an individual. Having this in the background, and considering the findings that the average happiness scores decreased among the most deprived areas during the study period, I argue that the welfare cuts have had negative impacts on people's psychosocial aspects. Loneliness, which was assessed as feeling left out and/or isolated was present in one or both forms in the health inequalities models and had significant negative contributions during each wave. These psychosocial factors often impact health from a behavioural pathway, for example, Lauder et al. (2006) found that lonely people had higher odds of adopting sedentary lifestyles and smoking. This could be the case among my survey participants as well because relatively more people from the most deprived areas reported of feeling lonely and left out compared to those from the least deprived areas (12% vs. 3%). Likewise, smoking (37% vs. 10%) and who never did physical exercise (32% vs. 25%) were also more prevalent in the most deprived areas. In addition, the frequency of physical exercise was significantly associated with all health outcome measures and during each survey wave.

The contributions of behavioural factors fluctuated between the waves for all health outcome measures. For example, the behavioural factors explained six percent of the health gap for EQ5D-VAS scores during baseline, 2.4 percent during wave 3 and over 28 percent during wave 4. Throughout the study period, it was found that the participants who did less physical exercise had higher chances of having poorer general and physical health, which is consistent with studies conducted in Spain, Switzerland and England (Chatton and Kayser, 2013, Galan et al., 2013, Maheswaran et al., 2013). As argued by Warburton et al. (2006), there is a two-way relationship between health outcomes and physical exercise: poor health outcome could be the cause or the consequence of less physical exercise. My research involved older population and their health conditions could have an impact on the frequency of physical exercise. However, my research was not designed to explore the frequency of physical exercise as an outcome measure.

Consumption of alcohol was however positively associated with better health outcomes (participants consuming alcohol could expect to have better general and physical health), which is similar to the finding by Powers and Young (2008) and . In a linked study, Mattheys et al. (2016) found a similar relationship for inequalities in mental health outcomes. Mattheys et al. (2016) have found that people who had better mental health outcomes and who consumed alcohol did so while socialising with family and friends. I agree with this finding and the psycho-social aspect of alcohol consumption could have provided protective roles in the overall health and wellbeing of the participants. This finding, however, contradicts with the existing evidence on the detrimental effects of alcohol consumption (Rehm, 2011, Scarborough et al., 2011). The damaging health effects of alcohol could be pronounced if it is problematic drinking. These behavioural factors were significantly associated with the health gap but their contributions were mostly smaller than that of material and contextual factors.

In general, the relative contributions of behavioural factors towards the health gap was increasing over time (for example, for EQ5D-VAS, it increased from 6 percent during baseline to 28 percent in the final wave). This could indicate that during the times of austerity, a focus should also be made to promote healthy behaviours to safeguard the health of the people and to reduce health inequalities. This, however, does not mean that all the focus has to be in health behaviours.

My research is one of the few studies looking at the relative contribution of contextual factors to the health divide. Ross and Mirowsky (2008) have argued that to correctly infer the contextual effects, multilevel modelling with adjustment of comprehensive individual characteristics should be adopted in the study. In my analyses, I adjusted the results for age, gender and the deprivation status of the place to determine the contribution of contextual factors. People living in neighbourhoods where they felt unsafe walking alone after dark had higher chances of having significantly lower scores for all three health outcome measures included in our study. For example, people living in those neighbourhoods could expect to have two-points lower EQ5D-VAS scores (as seen in the baseline, wave 2 and wave 3), one or more points gap in SF8PCS scores. Furthermore, a constant negative association of crime in neighbourhoods was found with general health (people living in areas with crimes could expect to have scores lower by 0.02, 0.4 and 0.01 during baseline, wave 2 and wave 4 respectively). A longitudinal study conducted in Australia by Foster et al. (2016) has associated long-standing physical and mental health problems with a lower level of neighbourhood safety. The same study found a significant increase in recreational walking time with an increased perception of neighbourhood safety. I agree with Ruijsbroek et al. (2015) that behavioural factors such as physical activities are often determined by contextual factors such as neighbourhood crime and feeling unsafe.

Neighbourhood safety perception is a key feature of the contextual accounts of geographical health inequalities (Baum et al., 2009, Foster et al., 2016, Smith et al., 2015, Tamayo et al., 2016), with unsafe neighbourhoods particularly detrimental to people's general and physical health; in my research people from most deprived areas were more likely to live in unsafe neighbourhoods (for example, more than 12 percent described that they would not feel safe walking alone in their neighbourhood after dark in the most deprived areas compared to less than two percent in the least deprived areas) (Foster et al., 2016).

In my research, a higher proportion of survey participants from the most deprived areas reported problems with pollution in their neighbourhood (12.6% vs. 3.4%) and neighbourhood noise (23.9% vs. 11.1%). This suggests that the people living in areas with higher levels of neighbourhood noise and environmental problems can expect to have poorer physical and mental health outcomes. For example, people living in areas with noise pollution could expect to have as much as four-points lower EQ5D-VAS (wave 4) and as much as 2.59 scores lower for the SF8PCS measure (wave 3). This is in keeping with a substantial body of literature which suggests an association between health inequalities and levels of outdoor air pollution (Cesaroni et al., 2012, Marshall et al., 2009), with deprived areas being disproportionately and adversely affected.

Marshall et al. (2009) have argued that neighbourhood pollution and environmental problems can have direct health impacts (cardiopulmonary morbidities, such as higher blood pressure and chronic obstructive pulmonary diseases-COPD) and indirect impacts through behavioural pathways (for example by limiting physical exercise). The disproportionate distribution of pollution and environmental problems between the most and the least deprived areas of Stockton-on-Tees could be linked the health gap.

When looking at the composition-context distinction, this study has found that in most of the cases, the relative contributions of the compositional factors is more than that of contextual factors (for example 68.9% vs. 15.3% during wave 4 for EQ5D-VAS scores), which is the case for all three health measures. This is in keeping with other research but it does suggest a stronger role for context than previous estimates (Macintyre, 1997). Most notably, though, this research shows the importance of the interaction of compositional and contextual variables (Cummins et al., 2007). There were substantial indirect (clustered) effects for all three health outcomes and for all waves, which is an indication of the interaction of the factors representing the different groups of explanatory variables. The clustered effects were as high as 45.8 percent for EQ5D scores (baseline), 44.6 percent for EQ5D-VAS (baseline and wave 3) and 27.5 percent for SF8PCS scores (wave 4). For all three outcome measures, the combined analysis explains the highest amount of the health gap, which demonstrates the important interaction between the individual-level material and contextual-environmental factors in causing the health gap. A study by De Clercq et al. (2012) among Flemish communities has revealed a complex interaction between individual material factors and the neighbourhood context to produce health inequalities. These findings lend support to the idea of the ‘mutually reinforcing’ nature of compositional and contextual factors(Cummins et al., 2007).

In this research, the secondary data sources used to measure context were based on fixed administrative boundaries (such as lower super output areas-LSOAs or wards) and they were found to have little influence on the health gap. However, the contextual factors from the survey measured at an individual level made a significant contribution to the health gap. This may be because individuals have relatively dynamic and fluid area definitions and most often, Euclidian distance (the ‘ordinary’ straight-line distance between two points in Euclidean space) used in research misses to the realities of how the place is experienced (Cummins et al., 2007). The neighbourhoods that the survey participants referred to were not confined to the geographical boundaries of the LSOAs but to where they felt they belonged to and therefore there was variation by individuals (Bernard et al., 2007, Horlings, 2016). This level of data is not usually available at a national or regional scale. It also indicates that looking at the role of place in the context of social space rather than in a geographical (with a fixed physical boundary) sense produces a clearer picture of the problem (Gatrell et al., 2004). Looking at place as a social space will then help us understand the ‘qualities of relatedness and connectedness’ of the compositional and contextual factors in creating the health gap (Williams, 2003, p. 142).

The role of public spending cuts

This survey started after the start of the austerity programme in the UK and as discussed in ***Chapter 2***, the rollout of some welfare reforms (such as the Universal Credit) are also still underway. This study is unable to show direct links between these programmes and the health gap. My research questions were concerned with inequalities in general and physical health over time. I also wanted to explore if there was any link between austerity and the health gap. The longitudinal survey has highlighted the existence of a significant and almost constant gap in general health over time. Also, the inequalities gap in physical health was expanding, with the most deprived areas having declining average scores. In ***Chapter 4,*** I demonstrated that individual-level material and area level contextual factors are the most important contributors to the gap. There was a noticeable gap between the two areas (the least deprived areas had better status than the most deprived areas) for material and contextual factors: levels of unemployment, the amount of people not in paid jobs, individuals in receipt of benefits, households with no working adult, housing tenure, the level of household annual income, levels of neighbourhood noise, levels of neighbourhood pollution, fear of crime and whether people felt safe walking in their local area after dark. There was no change in these gaps throughout the survey period. These findings add to the existing literature on how global financial crisis of 2008 and the austerity that followed has caused, helped sustain or widen the local inequalities in general and physical health (Barr et al., 2017, Basu et al., 2017, Nunn, 2016, Ruckert and Labonte, 2017). The linked studies have found damaging effects of austerity and welfare cuts for the mental health wellbeing for people from the most deprived areas of Stockton-on-Tees (Mattheys et al., 2016, Mattheys et al., 2017).

The UK government had a comprehensive programme in place between 1997 and 2010, which aimed at reducing health inequalities in England (Mackenbach, 2010). One of the key objectives of this large-scale strategy (the English Health Inequalities Strategy[6]) was to reduce the geographical inequalities in health, as measured by life expectancy (Barr et al., 2017). National level research has shown that there was a high level of geographical health inequalities before the strategy which declined when the strategy was implemented but increased once the strategy came to an end in 2010

[6] The key targets of the strategy were to reduce the relative gap in life expectancy at birth (LE) between the most deprived local authorities (called Spearhead) and the English average by 10% by 2010 and to cut relative inequalities in infant mortality rates (IMR) between manual socio-economic groups and the English average by 10% from 13% to 12%
The strategy focused on four themes to achieve the targets: supporting families; community engagement; improving health care; and addressing the wider social determinants of health.

(Barr et al., 2017). Regarding the post-2010 period, Barr et al. (2017) have further argued that the increasing trend of inequalities is due to the 2008 financial crisis and the resulting politics of austerity. As part of austerity, several health-related initiatives were reversed (for example the abolition of Strategic Health Authorities and the Primary Care Trusts) (Vizard and Obolenskaya, 2015). Due to austerity, welfare spending has been subjected to major budget cuts in the UK, a 1.3 percent fall between 2014 and 2019 is predicted (British Medical Association, 2016). Barr and Taylor-Robinson (2014) have highlighted that the use of a deprivation indicator in the resource allocation formula in NHS England for Clinical Commissioning Groups (CCGs) has resulted in a £8 (in real terms) cut per head in the poor areas.

Stuckler et al. (2017) argue that austerity impacts health either through ‘social risk effects’ or through ‘healthcare effects’. The social risk effect mechanism deals with the socio-economic issues such as rising unemployment, poverty, food insecurity and homelessness. As a report by Wilson and Foster (2017) found there were significant negative socio-economic impacts in the deprived communities of UK after the welfare reforms were introduced in 2010 and after the implementation of further measures 2015. Whereas the healthcare effect mechanism explains how health inequalities can be the results of budget cuts to the healthcare and social sectors (Stuckler et al., 2017). Existing evidence suggests that the impacts of welfare reform are more damaging to the poorest parts of society (Pearce, 2013), could be the explanation for the widening gap in physical health in Stockton-on-Tees.

A study by Hills et al. (2015) that examined the effects of the financial crisis and austerity found that households in the poorest deciles suffered at least a 10 percent of the reduction in their weekly earnings compared to less than five percent among the richest. In my research, the differential status of socio-economic factors or household resources between the two areas provides an indication that welfare reform's impact varies in those areas, with the most deprived areas most badly affected. Furthermore, some of these socio-economic factors (such as household income, a workless adult member in the house and having a paid job) were significantly associated with the health gap. This coincides with the evidence base (Heggebø and Elstad, 2017). Furthermore, Nunn (2016) has argued that the inequalities in household resources can induce even greater inequalities in the future. This is because these inequalities, are inherited and 'accumulated' by future generations. I agree with Nunn (2016) that prevailing socio-economic inequalities may be linked to the current welfare cuts and thus resulting health divides are political in nature.

Strengths and limitations of the study

As discussed briefly in ***Chapter 2,*** prevailing understanding of general and physical health is mostly dominated by biomedical models. One of the major findings of this research project is that there is a need to look into general and physical health from social and geographical perspectives. The findings have highlighted the significant role of the individual-compositional as well broader contextual factors in determining health and health inequalities. This research contributes to the literature in health inequalities research by showing a link between social inequality and the gap in general and physical health outcomes. The findings support the social determinants of health explanation, exploring how the compositional and contextual factors induce health inequalities directly or indirectly through interactions.

This study comprehensively reviewed the health inequalities literature, drawing from several fields of inquiry (for example, geography, sociology, epidemiology and economics) to demonstrate the relationship of the compositional and contextual factors with health inequalities. One of the main strengths of this research is that it examined health inequalities at a small and fine-scale in a borough which has the highest geographical health gap (as measured by life expectancy) in England. Secondly, I performed quantitative analyses of the longitudinal survey dataset, which provides a more accurate basis to make inferences and derive conclusions on the relationship of place, health inequalities and austerity. The analysis has also helped to identify the potential future research avenues, which are discussed later in this chapter.

This study is one of the first to examine localised geographical inequalities in health in a detailed way using multiple health indicators in a time of austerity. The context of austerity is important when thinking about how local-contextual factors and compositional-individual factors influence health and the health gap because macro-level politics trickles down and shapes the local context (Bambra, 2016). It is increasingly argued in the health inequalities literature that the influence of context/place should not just be considered as a purely local or neighbourhood level but at a more macro or societal level: a *vectoral* approach (Bambra, 2016, Cummins et al., 2007). When the survey was conducted between 2014 and 2016, it was done so in the context of significant reductions to Social Security benefits and local government services in Stockton on Tees.

The findings suggest a link between health and the material conditions of households. Furthermore, the clear health gap between those living in most and least deprived areas indicates the negative impact of welfare reform on material conditions. This supports previous research into the effects of austerity and welfare reform on health conducted at the national level (Barnes et al., 2016, Barr et al., 2015, Loopstra et al., 2015, Niedzwiedz et al., 2016).

I would argue that these findings around the contributions of compositional and contextual factors in creating health gap can be generalised to other areas. However, it should be noted that Stockton-on-Tees in itself is an extreme and a unique case because, within the borough, places of high and low affluence are located side by side. In addition, it is situated in the region with relatively higher degrees of social inequality (Dorling, 2015). This research is significant because it evaluates austerity's influence in shaping the social landscape in Stockton-on-Tees, and shows that there are more pronounced impacts in the most deprived areas. Among the compositional factors, material conditions (including the socio-economic factors) are important aspects of overall health and wellbeing, and a continuous and targeted event of cuts directly worsen the socio-economic position of people already in poverty. This is more likely to increase the gap in health inequalities.

Although this study is based on a longitudinal survey based on a stratified random sample, it is subject to a number of important limitations. A detailed discussion of the strengths and limitations of the methodological approaches is presented in **Chapter 3** (see page 107). There are issues relating to response and attrition in the follow-up surveys, as discussed in chapter 3, which could affect the generalisability of the study findings. Also, self-reported outcome measures were used, and it is possible that such measures could have limited precision and reliability (Mathews and May, 2007).

However, it should be noted that, validated measures that are widely used in population surveys

Whilst this is not necessarily a limitation, this study relates only to one place—Stockton-on-Tees and for a period of two years. The research adopted a health gap approach and explored the health gap between the neighbourhoods in two extreme ends of deprivation and not the whole of Stockton-on-Tees. The data sources and subsequent analysis were able to show associations of different compositional and contextual factors with health outcome measures. Despite using a random sampling technique, the sample ended up being older and had more female participants than would be expected based on census estimates of the general population. However, this limitation was addressed by adjusting for both age and gender in my statistical models—to minimise the effect upon the generalisability of the main findings.

Another limitation was around the hierarchical nature of the data and the multilevel analysis of it. This approach could introduce ‘dependence of the observations at the lower levels’, whereby factors at lower levels seem to make more contribution than the level nesting it (Hox, 2010). Finally, when presenting the contribution of the contextual factors towards the health gap, the duration of exposure to these factors is not known as this longitudinal survey was carried out over a fairly short time period.

Contributions to health geography and public health research

The results and discussions presented here complement and extend recent studies that have focused on how health inequalities could be understood and provide clues on how we could address the situation. There are several key implications of this project on the academic as well as the political sphere, and the following section discusses those key contributions.

As discussed in ***Chapter 1*** and ***Chapter 2***, as well as being few in number, the studies in the UK conducted to date which explore the extent of geographical health inequalities during austerity have also been conducted on a national scale and utilised national level datasets. National level statistics (such as the Census, Health Survey of England) are often criticised for failing to represent and explain the proximal area level situations or even the inequalities that persist between/in regional and local levels (Bambra, 2013a, Cummins et al., 2005, Shouls et al., 1996). Those studies exploring different localities have also focused on local authority level data rather than looking at a finer geographical scale such as at a neighbourhood or ward level, for example, see Barr et al. (2016). The indicators used have often been mortality rather than morbidity. This identifies a clear need for more localised studies that apply geographical theories to better understand the extent and causes of geographical inequalities in health in this time of austerity. Furthermore, focusing at a local scale provides us with a unique opportunity to get detailed primary information on health and the social determinants at a small geographical scale, which is not the case with secondary data (such as the census or Health Survey for England).

This research is one of the first to address this gap in the literature by estimating the magnitude of local inequalities in physical and general health during a time of austerity via a case study of Stockton on Tees - the local authority in England with the biggest health divide. Furthermore, this is one of the first studies to examine geographical health inequalities during the time of austerity at a finer scale—LSOA.

For the health geography literature, this study contributes in methodologically by using a different statistical approach to the examination of the relative contribution of context, composition and their interaction (Copeland et al., 2015, Skalicka et al., 2009). It also contests the scales of contextual data that can explain the local health gap. Something which Pickett and Pearl (2001) have explicitly highlighted as needed in terms of enhancing our understanding of geographical health inequalities. This study adds to the significance of ‘mutually reinforcing’ nature of compositional and contextual factors. In addition, the study also shows the importance of the interaction of compositional and contextual factors (Cummins et al., 2007).

This thesis offers an insight into the relationship of austerity, place and health inequalities. The findings of this research make the case that austerity is shaping the health divide in Stockton-on-Tees. This complements the argument that ‘health is politically determined’, influenced by the wider socio-political and macroeconomic context, for example, economic recession and austerity (Bambra et al., 2005). This research is significant because it evaluates austerity’s influence in the social landscape in Stockton-on-Tees, and shows that there are more pronounced impacts in the most deprived areas. As the findings from this research were not definitive in terms of showing the causal effects of austerity on health inequalities, it calls for a more critical conceptualisation of the political economy of health (Schrecker and Bambra, 2015).

Implications for future research

While looking into the effects of place in creating health inequalities, there are a number of further research possibilities. The results presented in this thesis add to the knowledge of how compositional and contextual factors influence health inequalities. The findings have also indicated that there is a complex relationship between these factors and their relationship health inequalities. This section explores the areas that warrant further research.

It is not possible, with the available longitudinal data, to explore all the mechanisms that might be involved in causing the health gap. The existence of direct and indirect contributions of different factors, and at different levels highlights a complex system in play to create health gap. This research has found significant interactions between the compositional and contextual factors, which calls for the use of ‘relational approach’ in understanding the contribution of individual and area-level factors in future research. The relational approach accounts for the horizontal and vertical interaction between these factors – in addition to their individual contributions (Cummins et al., 2007). Furthermore, this complexity means that qualitative research may also be more helpful in revealing the roles that they play. This approach is likely to yield more in-depth knowledge on the role of the compositional and contextual factors in explaining the health gap.

One of the key impressions I had was how variables defined by fluid boundaries (such as neighbourhood noise, crime and feeling unsafe walking in the neighbourhoods after dark) made significant contributions to the health gap compared to those with a fixed area boundary as defined by LSOA (such as area-level employment rate). This calls for a substantive exploration to assess if this connection is valid. This will have a significant implication to further use of fixed geographical/administrative boundaries in the exploration of place effects on health. Due to the limitations of the data sources, the role of physical environment was not explicitly analysed. More in-depth exploration of the role of contextual factors is more likely to fulfil this gap.

Material deprivation or material factors and neighbourhood factors were among the most important contributors to the health gap. These factors are mostly determined by the existing policies at a higher level (Marmot et al., 2010). By acknowledging the fact that the causes of health inequalities lie ‘upstream’—the socio-political context (Smith et al., 2016), effective implementation of welfare policies are key solutions to them. If, as Lundberg (2010) argues, specific policies are more effective in addressing health inequalities, compared to overall social welfare, research should be directed towards analysing these approaches from a ‘policy evaluation’ point of view (p. 634). Policy evaluation, in this case, would be able to explore the effects and consequences of the specific policy on the health and wellbeing of the people. Even in that case, the judgement of those policies should be based on the standard of health the most deprived areas have (Bambra, 2013b, Fritzell and Lundberg, 2005). Exploration of the differential impacts of the specific welfare policies on the most and least deprived areas is thus a prime area of research, which can feed into the policies by suggesting *meaningful* (as Bambra (2013b) identifies) ways of addressing health inequalities.

Summary

This chapter has summarised the principal findings of the research and compared them with the existing evidence. Starting with the main findings, I have discussed the overall trend and pattern of health inequalities in Stockton-on-Tees. I also explored the compositional and contextual circumstances of the health gap and their relative contributions towards the gap. I then discussed the possible links between welfare cuts and health gap. I then explored the significance and limitations of the research project as a whole. Limitations were discussed mostly from a methodological point of view and special focus was put on the data sources and the analytical approach. I also discussed the potential contributions of this thesis to academia. Finally, being based on the research experience, the chapter has presented the areas of further research. The next chapter will present my concluding remarks and policy implications of the research findings.

Chapter 7:   Conclusions

This thesis has examined the magnitude, determinants and the trends in the gaps between physical and general health outcome measures in the most and the least deprived neighbourhoods of the borough of Stockton-on-Tees. It has employed geographical perspectives to investigate the contribution of individual-level compositional as well as area-level contextual factors with the health outcome measures. The study set out to address some of the gaps in the research by estimating the magnitude of health inequalities during a time of austerity via a case study of Stockton on Tees - the local authority in England with the biggest health divide in terms of life expectancy at birth.

As a response to the global financial crisis of 2008, the coalition government of 2010 initiated a wide ranging austerity programme in the UK, which has been continued by the Conservative governments since 2015. As part of the five-year project funded by the Leverhulme Trust, this thesis has explored the human cost of austerity at a local scale—Stockton-on-Tees. Using geographical perspectives, this research has come to bridge the knowledge gap because most of the previous studies were conducted from an economic perspective (Karanikolos et al., 2013a, Karanikolos et al., 2013b, Kentikelenis et al., 2014, McKee et al., 2012). This has helped establish the linkage of physical systems and human-societal dynamics. The strengths of this research are the dataset (from the longitudinal survey that represented a finer geographical scale—LSOA) and the time during which the research was undertaken. The data for the survey was collected between 2013 and 2015, which has provided a window of opportunities to explore the disproportionate impacts of austerity on the general and physical health of the people living in the most and the least deprived areas. This research used data from a survey, which collected information about individuals, households and neighbourhoods. My central argument is that the breadth and depth of the dataset have provided a more accurate basis to make inferences and derive conclusions on the relationship of place, health inequalities and austerity. This is one of the first pieces of research that has explored the geographical health divide. Furthermore, this project also tackled the challenge faced by other health geography research: such as a lack of appropriate data to represent a finer scale of geography (Bambra, 2013a, Cummins et al., 2005, Shouls et al., 1996).

This thesis makes an important contribution to the ongoing debate about context and composition in the aetiology of geographical inequalities in health. Using a detailed survey of individuals, it found a constant and a significant health gap across a variety of validated measures during the survey period.

My research also used a different statistical approach to the examination of the relative contribution of compositional and contextual factors and their interactions in explaining these gaps - within the macroeconomic context of austerity. This thesis has highlighted the significant direct as well as indirect contributions of individual-compositional and area-level contextual factors in determining this gap, with individual-level compositional factors accounting for the majority. This thesis has further established that ‘place’ and its attributes matter for health inequalities, these contextual factors either contribute directly or interact with the compositional factors in the creation of the health gap. The research findings have significant potential to feed into policy making to devise initiatives aimed at addressing place-based inequalities in health, these are discussed in the following section.

Implications for policy

Health inequalities are the results of complex phenomena and their fundamental causes *'lie upstream, in the social, economic and political environment in which we live and work*' (Smith et al., 2016; p. 12). Addressing health inequalities requires policies that tackle inequalities in income and the socio-environmental contexts within which people live. This research further reinforces the recommendations made by Marmot et al. (2010) in the *Strategic review of health inequalities in England,* commissioned by the government of UK The findings are in keeping with the areas highlighted in the review, this project makes the following recommendations:

Recommendation 1: Address material deprivation by improving employment and work environments

One of the key findings of this research was that there were a high proportion of workless households (at least one member out of work) in Stockton-on-Tees, this was higher in the most deprived areas and it gradually increased at each wave. Unemployment is an important life event, which not only induces stress, it is a primary determinant of health inequalities (Marmot et al., 2010, Marmot and Allen, 2014). The unequal distribution of this burden and the resulting material deprivation was strongly associated with health gap in Stockton-on-Tees. The economic hardship faced by households in lower income bands and mostly in the deprived neighbourhoods has negative impacts on health and wellbeing. Welfare reform (Blanchard and Leigh, 2013) has disproportionately increased hardship to the most vulnerable groups and poverty has increased as a result of decreased family income and the removal of social safety nets (Bini Smaghi, 2013). As argued by Bambra et al. (2016), there are inadequate social safety nets in the UK to protect vulnerable people from the harsh socio-economic impacts of financial crisis and welfare cuts. It is thus a recommendation of this thesis that policies should be developed with special priorities to ensure a 'guaranteed' minimum income level. The average age of survey participants was slightly older, which could indicate that they may not be able to work due to old age or long term illness. The safety net of guaranteed minimum income could put people above the poverty line and can make significant improvements in the standards of living (Davis et al., 2014).

Recommendation 2: Shift focus from health promotion to overall social determinants of health

Amongst the explanations regarding the failure of the government to address health inequalities, lack of data and evidence on the level and extent of inequalities is often cited (Lynch, 2017). Health inequalities should remain to be a key political issue as the macro-level structure are considered to be the 'causes of the causes' of health inequalities (Marmot, 2005; p. 1102). Most of the policies aimed at reducing health inequalities, tend to focus on the biomedical perspectives of health and not on the overall health and wellbeing. These policies usually target individuals and their behavioural attributes and put less or no focus on the overall social determinants (Alvaro et al., 2011, Clark, 2014). If, as Bambra et al. (2010) suggest, it is the lack of accessible evidence on wider social determinants to the policy makers that results in the divergence of the policies, then the answer is to shift the research focus. As argued by Alvaro et al. (2011), bringing a change to the contemporary policy structures calls for, at least in part, a shift in the target of the government policies. To have substantive policy changes, an active role and commitment of the government is crucial and this should be continuously fed by research.

In keeping with the arguments made by Baum and Fisher (2014), my research has found a relatively weaker role for behavioural factors in explaining the health gap. In contrast, health promotion policies aimed at reducing health inequalities tend to put more focus on health-related behaviours and not the social and environmental structures that favour or bring about those behaviours at first place (Lynch, 2017). Baum and Fisher (2014) further argue that these behavioural and lifestyle factors are easier to identify and requires less resources to treat which makes them more appealing to the policy makers. Though the set of behavioural factors are also making significant contributions to the health gap, this study has found that material factors, related to income and deprivation are among the key determinants of poor general and physical health. This provides an indication that policy initiatives should be directed more towards addressing material deprivation in order to tackle health inequalities.

My research is one part of this endeavour and has explored the link between an individual, place and health inequalities. Keeping this in the background, it now presents a case that to have an effective public health policy, which can eventually address the health gap, we should shift the focus to the macro-level and act on the distal causes of health inequalities rather than just focusing on the micro-level proximate causes (for example the behavioural factors such as tobacco and alcohol use). My research, therefore, provides an empirical justification to the policy makers to shift their focus to the socio-environmental aspects along with other health promotion actions.

Recommendation 3: Create and develop healthy neighbourhoods

This study has further established that ‘place’ and its attributes matter for health inequalities, these contextual factors either contribute directly or interact with the compositional factors in causing to the health gaps. More people from the most deprived areas of Stockton-on-Tees reported having problematic physical and social environments in their neighbourhoods compared to those from the least deprived areas. These environmental factors were found to have a strong relationship with the health outcome measures.

The findings suggest that the areas with a higher degree of environmental pollution and noise could expect to have poorer health and wellbeing, which, as Galster (2010) argues, complies with the 'environmental mechanism' of health gap. The level of difference and the resulting health gap also indicates the significance of 'environmental (in)justices and health' (Pearce, 2015). In addition, through the 'social-interactive mechanisms', the socio-environmental factors such as perceived neighbourhood safety, the prevalence of neighbourhood crime, the extent to which people felt that they belonged and the degree to which they were attached to the place also contributed to the health gap. It is thus a recommendation of this thesis that policy should focus on creating healthy neighbourhoods, which not only focus on the physical but the social environment as well. To mitigate the socio-environmental gaps, as highlighted by Marmot et al. (2010), evidence-based community regeneration programmes could be effective. Community and social capital is an important predictor of better health and wellbeing (Stafford et al., 2008). Social capital is determined by the level of community engagement and the sense of belongingness. For social capital to be sustainable, it has to be built locally based on the experiences, with community participation and ownership by the neighbourhoods. The existing evidence shows the existence of poor or inadequate social capital in the most deprived neighbourhoods (Marmot et al., 2010, Stafford et al., 2008). Thus to regenerate communities that are healthy and resilient, community-based regeneration programmes should aim to improve the social capital, with special focus in the most deprived areas. However, these regeneration programmes can only be successful if they receive sufficient financial and material resources to operate and sustain. The effectiveness of these regeneration programmes is also dependent on the inclusiveness and the extent of equal opportunities for all in the target communities. These programmes can not only remove barriers to community participation and cohesion but can give neighbourhoods the control of local interventions and services by having their voice. The problems of pollution and noise could partly be addressed by improving good quality open and green spaces to the close proximities of the neighbourhoods, with a special focus on the deprived areas. Green spaces not only minimise the problem of pollution but also act as ‘therapeutic landscapes’ and exposure to them has been linked with better health and wellbeing of the people (Cairns-Nagi and Bambra, 2013, Curtis, 2010). As such, it is recommended that more resources be allocated to maintain and/or establish these green spaces.

Concluding comments

The work presented in this PhD thesis contributes towards understanding the geographical health divide during the time of austerity. Exploiting the power of longitudinal data, this thesis has revealed the causal relationships between different compositional and contextual factors with the geographical health divide in Stockton-on-Tees. This research has shown the extent to which ‘place’ and its attributes matter for health inequalities, these contextual factors either contribute directly or interact with compositional factors in the creation of the health gap between the most and the least deprived neighbourhoods. The results presented in this thesis reinforces the need to understand composition and context of health inequalities from a relational perspective. The study has also found damaging effects of austerity on health outcomes. The health divide in Stockton-on-Tees can thus be understood as the policy-induced *geographical health divide*. Against the current backdrop of austerity and changes in welfare programmes, it is crucial to consider their adverse consequences on health and wellbeing.

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Appendices

Appendix A: Outputs from the PhD

Appendix A-1: Peer-reviewed publications arising from the thesis

Bhandari, R., Kasim, A., Warren, J., Akhter, N. & Bambra, C. 2017. Geographical inequalities in health in a time of austerity: Baseline findings from the Stockton-on-Tees cohort study. *Health & Place,* 48**,** 111-122.

Appendix A-2: Conference proceedings and presentations

Bhandari, R., Bambra, C., Warren, J., Kasim, A., Akhter, N. (2017) *"Context or composition: what can explain geographical health inequalities?"* 17th International Medical Geography Symposium (IMGS), Angers, France, 4th July

Bhandari, R. (2017) *"Context or composition: what can explain geographical health inequalities?";* Annual 3rd year conference, Department of Geography, Durham University, Durham, 16th March

Bhandari, R., Bambra, C., Warren, J., Kasim, A. (2016) "*Geographies of Health Inequalities in a Time of Austerity: a case study of Stockton-on-Tees*". RGS-IBG Annual International Conference, London, 30th August- 2nd September

Bhandari, R. (2016) "*Geographies of Health Inequalities in a Time of Austerity: a case study of Stockton-on-Tees*". ENRGHI 2016, Organised by RGS Geographies of Health and Wellbeing Research Group (GHWRG); University of Glasgow, 16th June

Bhandari, R. (2016) *Geographies of Health Inequalities in a Time of Austerity: a case study of Stockton-on-Tees.* WRIHW Early Stage Research Conference, Queen's Campus, Durham University, 8th June

Appendix B: Methodology

Appendix B-1: Grid for selecting individuals

Assigned Number of Address	Total Number of Eligible Persons					
	1	**2**	**3**	**4**	**5**	**6 or more**
1 or 2	1	1	2	2	3	3
3	1	2	3	3	3	5
4 or 5	1	2	3	4	5	6
6	1	1	1	1	2	2
7 or 8	1	1	1	1	1	1
9	1	2	3	4	5	5
10 or 11	1	2	2	3	4	4
12	1	1	1	2	2	2

Source: Hoinville et al., 1977:82

Appendix B-2: Consent form

It is important that only people who want to do so participate in this study. You should also be aware that you do not need to answer any particular question and that you may withdraw from the research at anytime you wish.

Please tick the box to indicate you agree with the following statements:

The study has been explained to me.	☐
I understand that my participation is voluntary and that I am free to withdraw from the research at any time.	☐
I understand that the answers I give will be recorded.	☐
The information I give will be used in the final report and any subsequent academic publications arising from the study.	☐
I understand that only the researchers and research secretary will have access to the information I give and that the information will be anonymised and stored securely.	☐

I understand the above information and agree to participate in this study

Participant signature Date

Researcher signature Date

Appendix B-3: Information sheet: Survey

Study of Health and Health Inequalities in Stockton-on –Tees

We are researchers from Durham University who are undertaking a survey of the health. The research wants to find out what the impact of government policy, especially spending and welfare cuts are having on living standards of households and the health of individuals. In order to do this we are collecting information from 750 households in the borough of Stockton –on- Tees.

This will involve talking to a researcher on a one to one basis who will visit you in your home. They will ask some questions about your household and everyone who lives there. They will then select one of the adults in the household to ask about their personal situation, any health issues they many have and ask them to complete some further health assessment questions. This will take no longer than 60 minutes.

We will contact the same individual to ask the health questions again after 6 months, one year, two years and three years in order to see whether their health has improved, stayed the same or got worse over the time period. We will do this over the telephone and it will take no longer than 30 minutes. Anyone can of course refuse to answer any question that they wish to, or opt out of the research altogether at any point. All information given will remain completely confidential. We will be recording your answers. However, you will not be identified by name and none of the information you give will be passed to anyone outside of the research team.

All participating households will receive a £10 high street shopping voucher to thank them for their time and help.

If you would like any further information, please get in touch with Jon Warren on jonathan.warren@durham.ac.uk or 0191 334082

Appendix C: Results

Appendix C-1: Key socio-demographic indicators from the survey, compared with the 2011 census findings for Stockton-on-Tees, North East region of England and the whole of England.

Indicators	Measure	England	North East	Stockton-on-Tees (total)	Stockton-on-Tees (from ONS)		Average from the Stockton-on-Tees survey	
					Least Deprived	Most Deprived	Least Deprived	Most Deprived
2011 Population: All Usual Residents (Persons, Mar11)	Count	53,012,456	2,596,886	191,610				
2011 Population: Males (Persons, Mar11)	%	49.18	48.89	49.10	49.1	48.6	43.0	41.0
2011 Population: Females (Persons, Mar11)	%	50.82	51.11	50.90	50.9	51.3	57.0	59.0
White Ethnic group	%	85.42	95.33	94.62				
People aged 65 and above	%	16.34	17.31	15.63	15.4	15.3	32.4	26.3
Retired among usual 16-74 years population	%	13.68	15.97	14.76	14.8	13.0	37.5	31.4
All households who owned their accommodation outright (Households, Mar11)	%	30.6	28.6	29.4	34.1	20.0	51.2	17.1
All households who owned their accommodation with a mortgage or loan (Households, Mar11)	%	32.8	33.2	39.1	51.0	29.0	36.6	10.4
Economically Active; Employee; Full-Time (Persons, Mar11)	%	38.6	36.8	37.6	44.4	30.9		
Economically Active; Employee; Part-Time (Persons, Mar11)	%	13.7	14.2	15.7	15.7	15.8		
People aged 16 and over with 5 or more GCSEs grade A-C, or equivalent (Persons, Mar11)	%	15.2	15.7	16.9	25.6	12.8	26.5	4.8
People aged 16 and over with no formal qualifications (Persons, Mar11	%	22.5	26.5	23.8	13.6	33.4	22.3	45.5
No Cars or Vans in Household (Households)	%	25.8	31.5	25.9	9.4	42.4	6.4	57.0

Appendix C-2: Data cleaning process for EQ5D-VAS, EQ5D and SF8PCS analysis

Variable	Baseline	Wave 2	Wave 3	Wave 4	Action Taken
Damp	1 missing	1 missing	18 missing	-	Deleted Case
Warm	1 missing	-	17 missing	-	Deleted Case
Household Income	71 missing	35 missing	32 missing	25 missing	Deleted Cases
Workless house	-	-	-	8 missing	Deleted cases
Job Skill level	536 missing	343 missing	314 missing	274 missing	Deleted variable from analysis
Individual Income	57 missing	24 missing	30 missing	166 missing	Deleted variable from analysis
Education	1 missing	1 missing	-	-	Deleted Case
Job security	535 missing	343 missing	314 missing	274 missing	Deleted variable
Job stress	535 missing	343 missing	314 missing	274 missing	Deleted variable
Job satisfaction	535 missing	343 missing	314 missing	274 missing	Deleted variable
Neighbourhood Safety perception	19 missing	-	-	-	Deleted cases
Neighbourhood pollution	-	-	17 missing	-	Deleted cases
Satisfied with the neighbourhood	-	-	10 missing	4 missing	Deleted cases
Crime and violence in neighbourhood	-	-	17 missing	-	Deleted cases
Feeling isolated	1 missing	-	-	-	Deleted case
Happiness scale	1 missing	-	-	-	Deleted case
Alcohol units	3 missing	-	-	-	Deleted cases
Fruit and veg intake	6 missing	-	3 missing	4 missing	Deleted cases
Weekly Exercise in mins	11 missing	59 missing	44 missing	90 missing	Deleted variable
SF8 scores	3 missing	-	-	-	Deleted cases
EQ5D-VAS Scores	6 missing	-	1 missing	-	Deleted cases

Appendix C-3: Initial analysis for EQ5D-VAS and individual variables

		EQ5D-VAS (P-value)			
Explanatory Variable	**Test**	**BL**	**W2**	**W3**	**W4**
Material Explanations					
Is the individual in employment	T Test	0.001	<0.001	0.002	0.275
Housing Tenure	ANOVA	0.01	0.680		
Is this a workless household	T Test	<0.001	0.001	0.350	0.609
Is the household in receipt of benefits	T Test	0.002	0.001	0.003	0.435
Is the household in receipt of housing benefit	T Test	0.002	0.668	0.019	0.082
Own (a) vehicle(s)	T Test	0.085	0.074	0.113	0.019
Are there problems with damp in the home	T Test	0.010	0.206	0.314	0.972
Is the household warm enough?	T Test	0.013	0.596	0.655	0.151
Household is too dark	T Test	0.068	0.609	0.024	0.008
Education Level	ANOVA	0.091	0.481	0.428	0.771
Household Income	LR	<0.001	<0.001	0.001	0.177
Psychosocial Explanations					
Happiness Scale	LR	<0.001	<0.001	<0.001	<0.001
Levels of feeling isolated from others	ANOVA	0.001	<0.001	<0.001	<0.001
How often feel left out	ANOVA	<0.001	<0.001	<0.001	<0.001
How often lack companionship	ANOVA	<0.001	<0.001	<0.001	<0.001
How often the individual meets socially with friends, family or work colleagues	ANOVA	0.207	0.038	0.007	0.006
Living with someone else in the house	T Test	0.078	0.033	0.435	0.085
Behavioural Explanations					
Do you drink alcohol	T Test	0.085	0.046	0.078	0.056
Total weekly alcohol units	LR	0.001	0.001	0.088	0.001
Number of daily portions of fruit and veg	LR	0.074	<0.001	0.651	0.014
Do you smoke	T Test	0.115	0.640	0.961	0.650
Frequency of physical exercise	ANOVA	0.002	0.729	0.087	0.505
Contextual explanations		<0.001	<0.001	<0.001	0.643
How safe feel walking alone after dark	ANOVA	<0.001	<0.001	0.001	
Crime violence and vandalism in the neighbourhood	T Test	<0.001	<0.001	0.001	
Noise from neighbours/street	T Test	0.024	0.167	0.868	0.246
Pollution in neighbourhood	T Test	0.014	0.025	0.673	0.014
Satisfied with the neighbourhood	T Test	0.004	0.453	0.966	0.525
Belongingness to the place	T Test			0.313	

*LR= Linear Regression

Appendix C-4: Initial analysis for EQ5D scores and individual variables

		EQ5D Scores (P-value)		
Explanatory Variable	**Test**	**BL**	**W2**	**W4**
Material Explanations				
Is the individual in employment	T Test	0.002	<0.001	0.011
Is this a workless household	T Test	<0.001	0.040	0.025
Is the household in receipt of benefits	T Test	0.052	0.002	0.121
Is the household in receipt of housing benefit	T Test	<0.001	0.027	0.002
Own (a) vehicle(s)	T Test		0.099	0.253
Are there problems with damp in the home	T Test	<0.001	0.032	0.340
Is the household warm enough?	T Test	<0.001	0.638	0.454
Household is too dark	T Test	0.819	0.532	0.073
Education Level	ANOVA	0.106	0.887	0.776
Household Income	LR	<0.001	0.001	0.006
Psychosocial Explanations				
Happiness Scale	LR	<0.001	<0.001	<0.001
Levels of feeling isolated from others	ANOVA	<0.001	<0.001	<0.001
How often feel left out	ANOVA	<0.001	<0.001	<0.001
How often lack companionship	ANOVA	<0.001	<0.001	<0.001
How often the individual meets socially with friends, family or work colleagues	ANOVA	0.049	0.623	0.320
Living with someone else in the house	T Test		0.033	0.435
Behavioural Explanations				
Do you drink alcohol	T Test	0.001	<0.001	0.011
Total weekly alcohol units	LR	0.001	<0.001	0.200
Number of daily portions of fruit and veg	LR	0.095	0.598	0.566
Do you smoke	T Test	0.016	0.828	0.220
Frequency of physical exercise	ANOVA	<0.001	<0.001	0.032
Contextual explanations			<0.001	
How safe feel walking alone after dark	ANOVA	<0.001	<0.001	0.007
Crime violence and vandalism in the neighbourhood	T Test	0.007	0.014	0.387
Noise from neighbours/street	T Test	0.035	0.305	0.001
Pollution in neighbourhood	T Test	0.003	0.600	0.968
Satisfied with the neighbourhood	T Test			0.154
Belongingness to the place	T Test			0.084
Access to GP	LR		0.290	
Alcohol outlet density in the neighbourhood	LR		0.050	
Fast-food outlet density in the neighbourhood	LR		0.031	

*LR= Linear Regression

Appendix C-5: Initial analysis for SF8PCS Scores and individual variables

		SF8PCS scores (P-value)			
Explanatory Variable	**Test**	**BL**	**W2**	**W3**	**W4**
Material Explanations					
Is the individual in employment	T Test	<0.001	<0.001	0.014	0.031
Is this a workless household	T Test	<0.001	0.026	0.252	0.567
Is the household in receipt of benefits	T Test	0.027	0.003	0.018	0.042
Is the household in receipt of housing benefit	T Test	0.001	0.010	0.004	0.003
Own (a) vehicle(s)	T Test	0.265	0.159	0.245	0.083
Are there problems with damp in the home	T Test	0.001	0.040	0.075	0.631
Is the household warm enough?	T Test	0.007	0.358	0.769	0.728
Household is too dark	T Test	0.198	0.326	0.005	0.296
Education Level	ANOVA	0.305	0.638	0.992	0.728
Household Income	LR	<0.001	0.002	0.007	0.005
Psychosocial Explanations					
Happiness Scale	LR	<0.001	<0.001	<0.001	<0.001
Levels of feeling isolated from others	ANOVA	<0.001	<0.001	<0.001	0.002
How often feel left out	ANOVA	<0.001	<0.001	0.004	0.206
How often lack companionship	ANOVA	<0.001	<0.001	0.011	0.030
How often the individual meets socially with friends, family or work colleagues	ANOVA	0.230	0.196	0.686	0.498
Living with someone else in the house	T Test	0.003	0.460	0.082	0.146
Behavioural Explanations					
Do you drink alcohol	T Test	0.008	<0.001	0.001	<0.001
Total weekly alcohol units	LR	0.005	<0.001	0.002	<0.001
Number of daily portions of fruit and veg	LR	0.172	0.978	0.890	0.784
Do you smoke	T Test	0.113	0.780	0.105	0.067
Frequency of physical exercise	ANOVA	<0.001	<0.001	<0.001	0.004
Contextual explanations					
Safety perception	ANOVA	<0.001	<0.001	<0.001	0.009
Crime violence and vandalism in the neighbourhood	T Test	0.048	<0.001	0.096	0.579
Noise from neighbours/street	T Test	0.073	<0.001	0.015	0.028
Pollution in neighbourhood	T Test	0.302	<0.001	0.414	0.284
Satisfied with the neighbourhood	T Test			0.417	0.257
Belongingness to the place	T Test			0.202	0.351
Access to GP	LR		0.060	0.063	0.233
Social Fragmentation Index	LR		0.034	0.055	0.186
IMD OD scores	LR		0.110	0.490	0.478
Alcohol outlet density in the neighbourhood	LR		0.084	0.167	
Fast-food outlet density in the neighbourhood	LR		0.054	0.472	

*LR= Linear Regression

Appendix C-6: Estimates of fixed effects for the final models for EQ5D-VAS

Baseline

Parameter	Estimate	Std. Error	df	t	Sig.	95% CI Lower Bound	95% CI Upper Bound
Intercept	.942	.073	722.532	12.829	.000	.797	1.086
Deprivation	.012	.022	58.879	.549	.585	-.032	.057
Sex	.000	.018	730.522	.019	.985	-.034	.035
Age	-.003	.001	689.215	-6.135	.000	-.004	-.002
Workless HH	-.057	.019	728.832	-2.947	.003	-.096	-.019
Household warm	.048	.025	732.941	1.898	.058	-.002	.098
Household damp	-.048	.026	730.878	-1.836	.067	-.099	.003
Alcohol	.053	.019	730.662	2.858	.004	.017	.090
Isolated	-.068	.022	731.145	-3.063	.002	-.112	-.025
Exercise	-.017	.004	646.760	-4.123	.000	-.025	-.009
Left out	-.048	.022	731.289	-2.194	.029	-.091	-.005
Lack of companionship	.039	.018	732.076	2.106	.036	.003	.075
Happy scale	.029	.005	730.530	5.389	.000	.018	.039
Pollution	-.038	.032	696.363	-1.160	.247	-.101	.026
Crime	-.020	.024	730.258	-.833	.405	-.066	.027
Safety perception	-.032	.011	724.517	-3.020	.003	-.053	-.011

a. Dependent Variable: EQ5D Final Value.

b. This parameter is set to zero because it is redundant.

Wave 2

Parameter	Estimate	Std. Error	df	t	Sig.	95% CI Lower Bound	95% CI Upper Bound
Intercept	74.996	6.037	477	12.422	0.000	63.133	86.859
Deprivation	4.374	1.668	477	2.623	0.009	1.098	7.651
Age	-0.110	0.052	477	-2.111	0.035	-0.212	-0.008
Sex	-2.103	1.557	477	-1.351	0.177	-5.161	0.956
Workless HH	-4.502	1.771	477	-2.542	0.011	-7.983	-1.022
Alcohol	4.269	1.568	477	2.722	0.007	1.187	7.350
Neighbourhood noise	-1.788	2.008	477	-0.891	0.374	-5.733	2.157
Safety perception	-2.424	0.869	477	-2.789	0.005	-4.131	-0.716
Happy scale	3.057	0.483	477	6.331	0.000	2.108	4.006
Left out	-5.546	1.436	477	-3.863	0.000	-8.367	-2.725
Exercise	-2.480	0.469	477	-5.288	0.000	-3.401	-1.558

a. Dependent Variable: Wave2: Q75. Health Thermometer Score.

b. This parameter is set to zero because it is redundant.

Wave 3

Parameter	Estimate	Std. Error	df	t	Sig.	95% CI Lower Bound	95% CI Upper Bound
Intercept	100.490	5.489	442	18.306	.000	89.701	111.278
Deprivation	5.160	1.801	442	2.866	0.004	1.621	8.699
Age	-0.045	0.060	442	-0.754	0.451	-0.162	0.072
Sex	-3.233	1.721	442	-1.878	0.061	-6.615	0.150
Employment	4.165	2.091	442	1.991	0.047	0.054	8.275
Household benefits	-3.814	2.107	442	-1.810	0.071	-7.955	0.326
Isolated	-5.708	1.747	442	-3.267	0.001	-9.143	-2.274
Lack of companionship	-2.988	1.438	442	-2.078	0.038	-5.814	-0.161
Exercise	-2.535	0.530	442	-4.782	0.000	-3.577	-1.493
Safety perception	-2.033	0.936	442	-2.171	0.030	-3.873	-0.193
Belongingness	-0.249	1.114	442	-0.224	0.823	-2.439	1.941

a. Dependent Variable: Wave3: Q75. Health Thermometer Score.

b. This parameter is set to zero because it is redundant.

Wave 4

Parameter	Estimate	Std. Error	df	t	Sig.	95% CI Lower Bound	95% CI Upper Bound
Intercept	80.551	6.298	369	12.790	0.000	68.167	92.936
Deprivation	7.201	1.848	369	3.897	0.000	3.567	10.834
Age	-0.106	0.055	369	-1.952	0.052	-0.214	0.001
Sex	-4.288	1.756	369	-2.441	0.015	-7.742	-0.834
Double glazing	9.562	5.241	369	1.825	0.069	-0.744	19.868
Alcohol	5.251	1.795	369	2.925	0.004	1.721	8.780
Isolated	-5.953	1.951	369	-3.051	0.002	-9.790	-2.116
Lack of companionship	-3.914	1.885	369	-2.076	0.039	-7.622	-0.207
Neighbourhood noise	-4.258	2.805	369	-1.518	0.130	-9.774	1.259
Pollution	-1.330	3.903	369	-0.341	0.734	-9.004	6.345
Belongingness	0.313	1.101	369	0.284	0.776	-1.851	2.478
Neighbourhood crime	-0.295	2.678	369	-0.110	0.912	-5.562	4.972

a. Dependent Variable: Wave4: Q75. Health Thermometer Score.

b. This parameter is set to zero because it is redundant.

Appendix C-7: Estimates of fixed effects for the final models for EQ5D Scores

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% CI Lower Bound	95% CI Upper Bound
Intercept	.942	.073	722.532	12.829	.000	.797	1.086
Deprivation	.012	.022	58.879	.549	.585	-.032	.057
Sex	.000	.018	730.522	.019	.985	-.034	.035
Age	-.003	.001	689.215	-6.135	.000	-.004	-.002
Workless HH	-.057	.019	728.832	-2.947	.003	-.096	-.019
Household warm	.048	.025	732.941	1.898	.058	-.002	.098
Household damp	-.048	.026	730.878	-1.836	.067	-.099	.003
Alcohol	.053	.019	730.662	2.858	.004	.017	.090
Isolated	-.068	.022	731.145	-3.063	.002	-.112	-.025
Exercise	-.017	.004	646.760	-4.123	.000	-.025	-.009
Left out	-.048	.022	731.289	-2.194	.029	-.091	-.005
Lack of companionship	.039	.018	732.076	2.106	.036	.003	.075
Happy scale	.029	.005	730.530	5.389	.000	.018	.039
Pollution	-.038	.032	696.363	-1.160	.247	-.101	.026
Crime	-.020	.024	730.258	-.833	.405	-.066	.027
Safety perception	-.032	.011	724.517	-3.020	.003	-.053	-.011

a. Dependent Variable: Baseline: EQ 5D Score.

b. This parameter is set to zero because it is redundant.

Wave 2

Parameter	Estimate	Std. Error	df	t	Sig.	95% CI Lower Bound	95% CI Upper Bound
Intercept	.925	.086	475.863	10.812	.000	.757	1.093
Deprivation	.027	.025	39.712	1.068	.292	-.024	.079
Age	-.001	.001	440.555	-1.402	.162	-.002	.000
Sex	-.031	.021	476.938	-1.514	.131	-.072	.009
Employment	.070	.024	476.341	2.906	.004	.023	.117
Happy scale	.023	.006	464.666	3.536	.000	.010	.035
Isolated	-.073	.019	473.874	-3.895	.000	-.110	-.036
Alcohol units	.003	.001	472.925	3.507	.000	.001	.005
Exercise	-.047	.006	473.329	-7.474	.000	-.059	-.035
Safety perception	-.034	.012	473.066	-2.956	.003	-.057	-.012
Neighbourhood crime	-.044	.027	476.207	-1.609	.108	-.097	.010

a. Dependent Variable: Wave2: EQ 5D Score.

b. This parameter is set to zero because it is redundant.

Wave 4

Parameter	Estimate	Std. Error	df	t	Sig.	95% CI Lower Bound	95% CI Upper Bound
Intercept	.747	.101	369	7.417	.000	.549	.945
Deprivation	.053	.030	369	1.765	.078	-.006	.111
Sex	.010	.025	369	.398	.691	-.040	.060
Age	-.002	.001	369	-2.024	.044	-.003	.000
HH housing benefit	-.093	.036	369	-2.565	.011	-.164	-.022
Happy scale	.035	.009	369	3.921	.000	.017	.053
Isolated	-.052	.024	369	-2.183	.030	-.099	-.005
Exercise	-.011	.006	369	-1.727	.085	-.024	.002
Neighbourhood noise	-.093	.039	369	-2.347	.019	-.170	-.015
Neighbourhood crime	-.014	.038	369	-.362	.718	-.088	.060
Safety perception	-.014	.013	369	-1.126	.261	-.039	.011

a. Dependent Variable: Wave4: EQ 5D Score.

b. This parameter is set to zero because it is redundant.

Appendix C-8: Estimates of fixed effects for the final models for SF8PCS Scores

Baseline

Parameter	Estimate	Std. Error	df	t	Sig.	95% CI Lower Bound	95% CI Upper Bound
Intercept	51.265	2.434	682.694	21.062	0.000	46.486	56.044
Deprivation	0.221	0.988	40.895	0.224	0.824	-1.773	2.216
Sex	-0.069	0.772	729.741	-0.089	0.929	-1.585	1.447
Age	-0.123	0.023	637.239	-5.356	0.000	-0.169	-0.078
Workless HH	-3.931	0.834	708.667	-4.714	0.000	-5.569	-2.294
Household damp	-2.316	1.112	732.925	-2.083	0.038	-4.498	-0.133
Alcohol units	0.059	0.026	732.609	2.242	0.025	0.007	0.110
Exercise	-0.807	0.177	541.016	-4.562	0.000	-1.154	-0.459
Happy scale	1.091	0.200	730.148	5.448	0.000	0.698	1.484
Safety perception	-1.014	0.453	726.080	-2.239	0.025	-1.904	-0.125
IMD outdoor subdomain scores	-2.857	1.244	61.087	-2.297	0.025	-5.343	-0.370
Neighbourhood noise	-0.595	1.010	730.904	-0.589	0.556	-2.577	1.388
Pollution	-0.020	1.396	539.919	-0.014	0.989	-2.763	2.723

a. Dependent Variable: SF8 Physical Health Final Value.
b. This parameter is set to zero because it is redundant.

Wave 2

Parameter	Estimate	Std. Error	df	t	Sig.	95% CI Lower Bound	95% CI Upper Bound
Intercept	55.873	3.509	474.717	15.921	0.000	48.977	62.769
Deprivation	0.568	1.635	52.981	0.348	0.730	-2.712	3.849
Age	-0.068	0.029	408.083	-2.372	0.018	-0.124	-0.012
Sex	-1.305	0.864	474.655	-1.510	0.132	-3.002	0.393
Employment	3.834	1.006	476.991	3.812	0.000	1.858	5.810
Happy scale	0.552	0.265	469.832	2.079	0.038	0.030	1.073
Left out	-2.649	0.800	465.742	-3.313	0.001	-4.221	-1.078
Alcohol units	0.110	0.040	475.971	2.768	0.006	0.032	0.188
Exercise	-1.637	0.258	451.876	-6.350	0.000	-2.143	-1.130
Safety perception	-1.858	0.478	449.810	-3.889	0.000	-2.797	-0.919
IMD Crime scores	-0.944	0.790	65.043	-1.194	0.237	-2.523	0.635
Neighbourhood noise	-0.329	1.101	475.592	-0.299	0.765	-2.492	1.834

a. Dependent Variable: Wave2: SF8 Physical Health Score.

b. This parameter is set to zero because it is redundant.

Wave 3

Parameter	Estimate	Std. Error	df	t	Sig.	95% CI Lower Bound	Upper Bound
Intercept	63.699	2.500	443	25.482	0.000	58.786	68.612
Age	-0.127	0.028	443	-4.461	0.000	-0.183	-0.071
Sex	-0.365	0.972	443	-0.376	0.707	-2.276	1.545
Deprivation	2.310	1.148	443	2.013	0.045	0.055	4.565
HH receiving housing benefit	-3.655	1.257	443	-2.908	0.004	-6.125	-1.185
Alcohol units above safety limit	3.440	1.163	443	2.957	0.003	1.153	5.726
Neighbourhood noise	-2.592	1.305	443	-1.986	0.048	-5.157	-0.027
Pollution	-0.548	1.698	443	-0.323	0.747	-3.884	2.789
Isolated	-2.581	0.819	443	-3.150	0.002	-4.191	-0.970
Exercise	-1.268	0.301	443	-4.219	0.000	-1.859	-0.678
Safety perception	-1.529	0.535	443	-2.857	0.004	-2.580	-0.477

a. Dependent Variable: Wave3: SF8 Physical Health Score.

b. This parameter is set to zero because it is redundant.

Wave 4

Parameter	Estimate	Std. Error	df	t	Sig.	95% CI Lower Bound	Upper Bound
Intercept	42.506	4.726	369	8.995	0.000	33.213	51.798
Deprivation	2.736	1.238	369	2.210	0.028	0.301	5.171
Sex	-0.673	1.074	369	-0.627	0.531	-2.786	1.439
Age	-0.104	0.034	369	-3.022	0.003	-0.172	-0.036
Household income	0.225	0.109	369	2.058	0.040	0.010	0.440
Alcohol	4.445	1.062	369	4.187	0.000	2.357	6.532
Happy scale	0.999	0.378	369	2.643	0.009	0.256	1.742
Isolated	-2.843	1.228	369	-2.314	0.021	-5.258	-0.427
Left out	3.484	1.312	369	2.655	0.008	0.903	6.065
Exercise	-0.629	0.267	369	-2.354	0.019	-1.154	-0.103
Neighbourhood noise	-2.496	1.619	369	-1.542	0.124	-5.679	0.687
Safety perception	-0.972	0.519	369	-1.871	0.062	-1.99	0.049

a. Dependent Variable: Wave4: SF8 Physical Health Score.

b. This parameter is set to zero because it is redundant.

Appendix C-9: The details of the variables included in the multiple imputation procedure

Variables in the final analytical model	Auxiliary variables**
Socio-demographic variables - Age - Sex - Deprivation status **Health outcome measures**** - EQ5D-VAS - EQ5D scores - SF8PCS scores	**Material variables** - Employment status - Workless household - Household income - HH receiving benefits - Housing benefits - Damp in HH - HH with heating problem - Dark households **Psychosocial variables** - Left out - Happiness scale - Lack of companionship - Frequency of social meeting - Frequency of social contact **Behavioural variables** - Smoking - Alcohol - Weekly alcohol units

	- Frequency of exercise - Daily portions of fruit and vegetables **Contextual variables** - Safety perception - Neighbourhood noise - Pollution and grim - Crime and vandalism - Belongingness with the place - Satisfied with the place

** Data from all waves were used to perform MI

Appendix C-10: Results obtained from the testing of cubic model for EQ5D-VAS

Model Dimension [a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables
Fixed Effects	Intercept	1		1	
	TIME2	1		1	
	TIME2_SQ	1		1	
	TIME2_CU	1		1	
Random Effects	Intercept + TIME2 + TIME2_SQ + TIME2_CU[b]	4	Unstructured	10	SURVEYID
Residual				1	
Total		8		15	

a. Dependent Variable: Health Thermometer Score.

Information Criteria [a]	
-2 Log Likelihood	17602.341
Akaike's Information Criterion (AIC)	17632.341
Hurvich and Tsai's Criterion (AICC)	17632.582
Bozdogan's Criterion (CAIC)	17731.392
Schwarz's Bayesian Criterion (BIC)	17716.392

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Health Thermometer Score.

Estimates of Fixed Effects [a]

						95% CI	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	70.188	0.769	860.726	91.222	0.000	68.678	71.698
TIME2	1.245	0.319	3342.368	3.900	0.000	0.619	1.870
TIME2_SQ	-0.083	0.045	2518.005	-1.817	0.069	-0.172	0.007
TIME2_CU	0.002	0.002	2006.628	0.998	0.319	-0.002	0.005

a. Dependent Variable: Baseline: Health Thermometer Score.

Estimates of Covariance Parameters [a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% CI Lower Bound	95% CI Upper Bound
Residual		5.020	3.064	1.638	0.101	1.518	16.603
Intercept + TIME2 + TIME2_SQ + TIME2_CU [subject = SURVEYID]	UN (1,1)	428.925	20.903	20.520	0.000	389.852	471.913
	UN (2,1)	-55.403	4.560	-12.151	0.000	-64.340	-46.466
	UN (2,2)	47.086	0.323	145.638	0.000	46.457	47.724
	UN (3,1)	5.041	0.601	8.394	0.000	3.864	6.218
	UN (4,1)	-0.140	0.021	-6.690	0.000	-0.181	-0.099

a. Dependent Variable: Baseline: Health Thermometer Score.

Appendix C-11: Results obtained from the testing of quadratic model for SF8PCS

Model Dimension [a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables
Fixed Effects	Intercept	1		1	
	TIME2	1		1	
	TIME2_SQ	1		1	
Random Effects	Intercept + TIME2 + TIME2_SQ[b]	3	Unstructured	6	SURVEYID
Residual				1	
Total		6		10	

a. Dependent Variable:: SF8 Physical Health Final Value.

Information Criteria[a]

-2 Log Likelihood	14214.423
Akaike's Information Criterion (AIC)	14234.423
Hurvich and Tsai's Criterion (AICC)	14234.533
Bozdogan's Criterion (CAIC)	14300.462
Schwarz's Bayesian Criterion (BIC)	14290.462

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: SF8 Physical Health Final Value.

Estimates of Fixed Effects [a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% CI Lower Bound	95% CI Upper Bound
Intercept	48.105	0.404	740.171	119.013	0.000	47.312	48.899
TIME2	-0.046	0.071	494.943	-0.648	0.518	-0.186	0.094
TIME2_SQ	0.003	0.004	444.255	0.696	0.487	-0.005	0.010

a. Dependent Variable: Baseline: SF8PCS Score.

Estimates of Covariance Parameters [a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% CI Lower Bound	95% CI Upper Bound
Residual		32.400	2.222	14.581	0.000	28.325	37.062
Intercept + TIME2 + TIME2_SQ + TIME2_CU [subject = SURVEYID]	UN (1,1)	88.324	6.584	13.416	0.000	76.318	102.218
	UN (2,1)	-1.356	0.920	-1.474	0.141	-3.159	0.447
	UN (2,2)	0.223	0.227	0.980	0.327	0.030	1.646
	UN (3,1)	0.060	0.047	1.289	0.197	-0.031	0.152
	UN (3,2)	-0.008	0.012	-0.646	0.518	-0.031	0.015
	UN (3,2)	0.000	0.001	0.404	0.686	0.000	0.033

a. Dependent Variable: Baseline: SF8PCS Score.