The stress pathway: a biosocial investigation of neighbourhood deprivation and health relationships

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Abstract

This thesis explores the stress pathway between places and health, investigating a biosocial process by which deprivation can later manifest in the health outcomes of individuals and contribute to health inequalities. This thesis brings together conceptual and methodological innovations in health geography, lifecourse epidemiology and the emerging biosocial paradigm to address two vital gaps in current understandings of health and place relations. The first is the need for longitudinal research which advances knowledge on how health changes over the lifecourse and its long-term relationships with personal and neighbourhood circumstances. The second gap relates to research which attends to the mechanisms for the biological embodiment of context and exposure histories. The British Household Panel Survey and Understanding Society are used to quantitatively investigate through multilevel modelling the shape of trajectories in mental and general health over time and how these relate to neighbourhood and individual-level deprivation exposure. Additionally, this thesis integrates biodata from Understanding Society to explicitly test the stress pathway by investigating: whether relationships of neighbourhood deprivation with physical and mental health are mediated by allostatic load – as a marker of cumulative biological weathering in response to chronic stress; and how different exposure histories of deprivation and social capital are related to later allostatic load. Overall, this thesis offers support for the stress pathway, with neighbourhood deprivation exposure consistently associated with inequalities in allostatic load, different health dimensions and health through allostatic load. However, the story is also one of heterogeneity: in the development of mental and general health over time and in the varying strength of health relationships with deprivation when considered proximally or distally, both in scale and temporally.

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Author’s Declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's *Regulations and Code of Practice for Research Degree Programmes* and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

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Chapter 1. Introduction

I Thesis overview

This thesis investigates the stress pathway between places and health, which posits that deprived neighbourhoods and disadvantaged circumstances represent stressful environments, and that exposure to chronic stress in this manner can negatively impact health through a cumulative weathering process (Daniel et al., 2008; Geronimus, 1992; Hajat et al., 2015). The stress pathway provides a biosocial mechanism that can link contexts and health outcomes, offering a process to explain health inequalities. The literature review and synthesis chapter that follows overviews and brings together developments in health geography (Kearns and Moon, 2002; Murdoch, 2006; Rosenberg, 1998, 2016b), lifecourse epidemiology and biosocial studies (Guthman and Mansfield, 2012; Krieger, 1994, 1999; McEwen and Seeman, 1999) with the exposome concept (Wild, 2012). A biosocial health geography is proposed as a way of progressing understandings of health and place relationships, helping to address two vital research gaps identified from the literature. These are: the need for research which advances knowledge on how health changes over time and its dynamic, long-term relationships with multiple exposures; and research which attends to the biosocial mechanisms for the biological embodiment of context over time. The investigation of the stress pathway in this thesis attends to these research gaps and fits within the proposed biosocial health geography framework put forward in the following chapter.

Together, this thesis contributes to understandings of health inequalities and health and place relationships. The use of a novel, non-parametric modelling approach reveals how the general health of younger cohorts is improved relative to their generationally older peers. Thus, revealing a potentially positive health outlook for these younger generations as they continue through life. However, the story remains one of persistent social gradients in health, with neighbourhood and individual-level disadvantage related to worse health through time – in line with the stress pathway theorisation. Variability in how deprivation relates to individual health is also shown, including interactions with age. Therefore, this thesis reveals the relative importance of neighbourhood conditions at different points in the lifecourse, giving insight

into the development of health inequalities. This thesis further contributes to the literature on health inequalities by testing the biological mechanism of the stress pathway, providing a novel examination of allostatic load as a mediator in a neighbourhood framework. The corroboration of the stress pathway hypothesis offered is then extended when it is demonstrated that different histories of exposure to neighbourhood deprivation relate to later allostatic load, when controlling for the influence of more proximal circumstances. Support is given for the biological embedding of disadvantage over time as an explanation for health inequalities.

To explore the stress pathway and the relationships of health and exposures over time, this thesis addresses four major research questions:

(1) What is the shape of age and cohort health trajectories over time?
(2) Is heightened exposure to deprivation over time associated with worse general health and how does neighbourhood deprivation interact with social capital and individual-level disadvantage?
(3) Are relationships of deprivation and health mediated by allostatic load as a measure of cumulative biological weathering in response to stress?
(4) How are different exposure profiles of deprivation and social capital related to later allostatic load?

The first research question, answered in Chapter 3, is motivated by the need for clearer understandings of how health changes over the lifecourse. Chapter 3 ('Illness and the lifecourse: does the relationship vary by cohort?') demonstrates the baseline patterning of self-rated and mental health for ageing and cohort effects. It provides insight into these temporal dynamics, and additionally exposes health inequalities by exploring interaction effects between age and cohort trends. The self-rated health of the youngest cohorts – born in the 1990s – is shown to be better relative to earlier cohorts when they were assessed at a similar age. Chapter 3 advocates for the use of an exploratory multilevel modelling methodology to investigate changes in health over time, without having to impose a parametric structure on the data. Doing so enables us to reveal the 'true' underlying shape of age and cohort trajectories in health. Addressing this first research question is a crucial initial

step in investigating relationships of exposures and health over time; it highlights the health patterns that need to be explained through examination of stress pathway exposures.

Chapter 4 ('How does deprivation relate to health over time?') directly builds on the first empirical analysis. Here the purpose is to investigate the role neighbourhood deprivation has in terms of influencing health trajectories and relationships. In doing so, Chapter 4 addresses the second major research question, and deals with the premise underlying the stress pathway hypothesis: that living in deprived areas relates to worse health. This second empirical analysis uses rich longitudinal data (see the section 'Thesis data' below for more information on the datasets used) and employs multilevel cross-classified growth curve models (Goldstein, 1994; Steele, 2008). Overall, heterogeneity in exposure-health relationships is demonstrated, revealing how the impact of neighbourhood deprivation varies with individual-level status. It is additionally shown that the importance of neighbourhoods and the impact of neighbourhood deprivation on self-rated health varies with age.

Having demonstrated that characteristics of neighbourhood disadvantage relate to health outcomes and trajectories, Chapter 5 ('An investigation of whether allostatic load mediates associations between neighbourhood deprivation and health') extends the investigation of the stress-pathway. This is achieved by directly testing an underlying biosocial mechanism, namely that exposure to deprived environments incites a stress response, which through chronic activation can negatively impact on health. The analysis in Chapter 5 employs the concept of allostatic load to characterise the cumulative burden of chronic stress on the body (McEwen and Seeman, 1999; McEwen and Stellar, 1993), using biomarker information from Understanding Society to directly operationalise an allostatic load index (University of Essex, 2014). In this chapter, I find that the association between neighbourhood deprivation and measures of physical and mental health is mediated by allostatic load, in answer to the third main research question of the thesis. Ultimately, this investigation provides a novel contribution to a biosocial health geography of health and place relationships.

The final empirical chapter (Chapter 6 – 'Allostatic load and exposure histories of disadvantage') addresses the need to understand the dynamics of exposure over time and to integrate the biosocial into health studies. It extends the investigation of the stress pathway

under a biosocial lens from the preceding mediation study by exploring how different histories of exposure to neighbourhood deprivation and social capital are related to allostatic load as a distal outcome (thesis research question four). Latent class growth analysis is employed to distinguish trajectories of deprivation and social capital, capturing heterogeneity of exposure for distinct sub-groups of the population (Jung and Wickrama, 2008). Following from the previous analytical chapters, the final analysis displays support for the stress pathway hypothesis by demonstrating that histories of higher deprivation exposure over a 20-year period were related to worse allostatic load. Therefore, offering support for a biological embedding of disadvantage over time through chronic stress exposure.

II Thesis papers

The empirical chapters and literature review were designed as paper contributions and written with publication in mind. Two chapters of this thesis have already been published with two more submitted to journals as detailed below.

- Chapter 2 was published online in *Progress in Human Geography* on 7th May 2018, under the citation: Prior L., Manley D. and Sabel C.E., 2018. Biosocial health geography: new 'exposomic' geographies of health and place. *Progress in Human Geography*, https://doi.org/10.1177/0309132518772644.

- Chapter 5 was published in *Health & Place*, under the citation: Prior L., Manley D. and Jones K., 2018. Stressed out? An investigation of whether allostatic load mediates associations between neighbourhood deprivation and health. *Health & Place*, 52, 25-33.

- Chapter 3 was submitted to *PLOS One* on 7th February 2019.

- Chapter 6 was submitted to *Social Science & Medicine* on 25th April 2019.

The work presented in Chapter 2 represents the published article with very minor alterations to enable consistency with the thesis. Additionally, a short paragraph in the relational geography section was added which serves to further highlight the potential of relational approaches to inform new conceptualisations of the body and the emergence of disease. Lucy Prior was the lead author, conducting the literature synthesis, writing and all re-writing following peer review. Authors David Manley and Clive E. Sabel provided guidance and review comments. Chapter 5 in this thesis presents the article originally published in *Health & Place* with very minor alterations for thesis consistency. Additions have also been made to the background section, including a lifecourse study of material and social adversity, and another exemplifying the need to consider other national contexts in the study of allostatic load. Supplementary results are also presented at the end of the chapter, which are in addition to that which was published. Lucy Prior was the lead author and completed the research design, data preparation, analysis and write-up, with authors David Manley and Kelvyn Jones providing review and guidance. The content of Chapter 3 is similar to that in the submitted manuscript, with minor changes to enhance clarity in reference to the thesis work and expansion of the introductory and discussion sections. Lucy Prior was the lead author, devising and conducting the data preparation, analysis, and write-up. The co-authors, in listed order, were Kelvyn Jones and David Manley, who provided review comments and guidance in completing the analysis. Chapter 6 is an extended version of the manuscript submitted to *Social Science & Medicine*. Extra detail was included on studies in the background section and the methods section offers a fuller accounting of the methodology employed for the thesis. Additional analysis of descriptive deprivation trajectories was also included in the thesis chapter as well as a figure showing the shape of the exposure histories (this was incorporated with the supplementary information for the journal submission). Lucy Prior was the sole and lead author.

III Thesis data

Throughout this thesis two major sources of data are used: the British Household Panel Survey (BHPS) and the subsequent Understanding Society, The UK Household Longitudinal Study

(UKHLS) (University of Essex et al., 2018b). Both are panel surveys, tracking and repeatedly interviewing adult members of households over time. Their aim was to improve understanding of social and economic change in the UK (Fumagalli et al., 2017; Knies, 2018; Taylor et al., 2010). Therefore, the studies provide a rich, longitudinal data source for a range of social and health variables[1].

British Household Panel Survey

The BHPS was an annual survey interviewing adult (16 plus years of age) members of a nationally representative sample of households from Great Britain, which ran for 18 waves between 1991 and 2009. The BHPS was designed to access more than 5,000 households, providing approximately 10,000 individual interviews. The Original Sample Members (OSMs) comprise the core longitudinal sample of the dataset and these include all enumerated individuals from the initial selection of 8,167 households in Wave 1. Private household addresses were selected using a two-stage stratified, clustered probability design using systematic sampling. 250 postcode sectors were initially selected as the Primary Sampling Units (PSUs) followed by sampling of delivery points (equivalent to addresses) within each PSU (Taylor et al., 2010).

Subsequent waves annually re-sampled adults from households containing at least one member who was resident in a household which was interviewed at Wave 1. This thesis makes use of the original sample recruited in 1991 and, additionally, includes the Scottish and Welsh extension samples which were added at Wave 9. As in all longitudinal studies, attrition is an issue, but due to the re-sampling structure and following rules, the BHPS was able to maintain a broadly representative sample from Britain throughout the timespan of the study. Figure 1.1 shows the number of full interviews achieved at each wave; further details on response statuses through time can be found in the BHPS user guide (see Taylor et al., 2018).

[1] Detailed information about the surveys is available through the survey websites: https://www.understandingsociety.ac.uk and https://www.iser.essex.ac.uk/bhps.

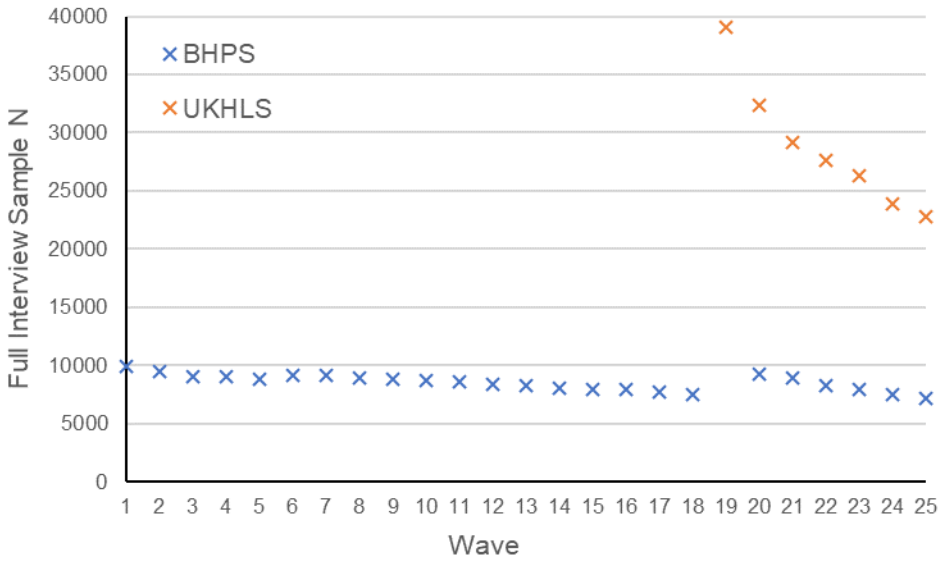

Figure 1. 1 Full interview attrition in the BHPS and UKHLS. Waves 1 to 18 are the BHPS, Waves 19 to 25 represent the UKHLS.

Understanding Society, The UK Household Longitudinal Study

Understanding Society, or the UKHLS, is the successor to the BHPS. It follows in the tradition of the BHPS, continuing the objective of improving understanding of social and economic change (Knies, 2018). This thesis makes use of the first 7 waves of data (collected between 2009 and 2017), as the eighth wave was only released in November 2018, after completion of the empirical analyses.

The UKHLS is larger in scope than the BHPS, with a significantly expanded sample size. This thesis uses the General Population Sample from Great Britain, which is the result of a stratified two-stage sampling design similar to the BHPS. The first stage of the sampling process was a systematic random sample of 2,640 postcode sectors, selected with a probability proportional to the number of residential addresses in the sector. The second stage of the sampling design involved a systematic random sample of 18 addresses within each of the selected sectors. This generated an initial sample of 47,520 addresses from England, Scotland and Wales (Knies, 2018). Additionally, consenting members of the BHPS who were still active at the final wave, became part of the UKHLS at Wave 2. This provides the opportunity to extend analysis of the BHPS sample through from 1991 to 2017. The UKHLS

dataset is available with harmonised BHPS data from the UK Data Service (Fumagalli et al., 2017; University of Essex et al., 2018b). The full interview response rates for the UKHLS general population sample for Great Britain and the continuing BHPS sample members are shown in Figure 1.1.

Furthermore, at Waves 2 and 3 of Understanding Society nurse health assessments were carried out, taking direct objective health measures and collecting blood samples from which a range of biomarkers were derived (University of Essex and Institute for Social and Economic Research, 2014b). An eligible subset of the General Population Sample of Great Britain from the UKHLS was sampled at the Wave 2: 15,591 adults participated in the nurse health assessment, of these 10,175 persons consented to have a blood sample taken. At Wave 3 a subset of the former BHPS sample from Great Britain was assessed in the health survey. This resulted in a sample of 5,053 adults, of which 3,342 provided a blood sample (McFall et al., 2014).

The nurse collected data provides a range of anthropometric and biometric measures which may act as clinical precursors to major health conditions. Combining this detailed health information with the rich social data from the main survey facilitates investigation of biological pathways between environmental exposures and health. The focus of this thesis is on the stress pathway of places and health. Stress will be operationalised through the concept of allostatic load, as a cumulative biological weathering related to repeated stress exposure (McEwen and Seeman, 1999). Therefore, the Understanding Society biomarker data will be used to construct indices of allostatic load, comprising markers from across major bodily systems. Documentation of the nurse assessment and the biomarker data is available in McFall et al. (2014) and Benzeval et al. (2014).

Introduction to Chapter 2

There is a long tradition in geography of studying health and how health outcomes relate to the social and physical world (Brown et al., 2010, 2017; Diez Roux and Mair, 2010; Gatrell and Elliott, 2009; Jones and Moon, 1992; Kawachi and Berkman, 2003; Philo, 2016; Rosenberg, 2014, 2016a, 2016b). This chapter overviews and brings together developments in various geographical health literatures, lifecourse epidemiology and in the emerging biosocial paradigm. It seeks to position a new biosocial health geography, demonstrating how the exploration of biosocial mechanisms is aligned with the concepts of relational geography and lifecourse perspectives, and can further understanding of health inequalities in revealing mechanisms for the embodiment of exposure. In the final section, the concept of the exposome is drawn upon, as a framework in which to situate and extend a biosocial geography. It brings together ideas of dynamic exposure and the lifecourse with a toolkit of methodological developments which suit the investigation of the biological embedding of disadvantage, such as mediation analysis.

This thesis sits within the idea of a biosocial health geography as put forward in this chapter and aims to address two vital gaps in current understandings of health relationships which were identified in review of the literature, namely questions of *how* and *when*. In other words, the need for more knowledge on health over time and the relationships it has with varying exposures, and the need for further understanding of the biological embodiment of context and experience. By assessing long-term trajectories of health and their relationships to neighbourhood and individual-level exposures (this is the main aim of empirical Chapters 3 and 4 – investigating age and cohort trends in health and their relationship to deprivation respectively) this thesis seeks to integrate ideas of dynamic exposure and temporality as identified from the exposome concept and lifecourse epidemiology.

Additionally, the identified gaps in the literature – concerning understanding the lifecourse dynamics of health and investigating the mechanisms of health and place relations – are addressed through exploration of the stress pathway; the action of the stress response system in reaction to lifecourse and quotidian exposures is a vital physiological link

between contexts and health. Two of the following analytical chapters (Chapters 5 and 6) investigate the stress pathway through drawing explicitly on the biosocial process of allostatic load. Allostatic load is brought forward in this review chapter as a concept by which to access and investigate a biological record of social exposure to aid in the exploration of health inequalities. This review chapter also highlights the continuing need for longitudinal studies with a long time frame (of decades or more) in studies of health and place, particularly in the assessment of biosocial pathways.

Chapter 2. Biosocial health geography: new 'exposomic' geographies of health and place

I Introduction

A theme of exposure and exposures underlies work aiming to reveal the complexities of geographies of health. There is a substantial literature investigating relationships between health and place (Brown et al., 2010, 2017; Gatrell and Elliott, 2009) and a variety of place-based exposures have been linked with a range of health outcomes, including, for example, cardiovascular disease incidence, risky health behaviours and depression (Diez Roux et al., 2016; Diez Roux and Mair, 2010; Malambo et al., 2016; Richardson et al., 2015). Research is often focused on specific – in temporal and spatial senses – risk factors, toxins or social features, the emphasis being on *this* or *that* place, green space, community networks or distribution of services. We argue in this chapter that a perspective of continual accumulating exposure, foregrounded by a Hägerstrandian time geography of lifepaths, can be achieved through a biosocial geography. By interrogating the imprint of entangled biological and social exposures new insight may be uncovered into the fluid nature of health and place relations, helping to address key lacunae in our current knowledge.

Gaps currently exist in our understanding of the means through which places transmit to individuals and the action of these processes over time. The increasing use of longitudinal data as well as developments in lifecourse modelling provide a means to address this problem (Lekkas et al., 2017; Mishra et al., 2009; Ruijsbroek et al., 2016; Sabel et al., 2009). However, much of the work through which we comprehend health and place remains based upon cross-sectional analyses or short-run temporal windows. For example, over 70% of the US-based studies reviewed by Arcaya et al. (2016) were cross-sectional. The implied assumption of simultaneity of effect not only lacks plausibility in many cases, but also hinders insight into the long-term, accumulated imprints of exposure.

The biological mechanisms for the embodiment of place represent a second void in the health and place literature. There is an established epidemiological literature that has taken up the

'bio' in the form of biomarker assessments, recognising the usefulness of bio-processes such as epigenetics and feedbacks of the stress system to accessing the temporality of health relationships (Ben-Shlomo and Kuh, 2002; Gustafsson et al., 2010; Ploubidis et al., 2014; Tehranifar et al., 2017). However, to date there have been relatively few attempts to integrate biosocial ideas with insights from the health and place literature, meaning geographers have important insights to add. More specifically, although biosocial ideas speak to the plasticity of biological development and the permeability of bodies, an integration with developments in the theorisation of place – notably work on relational geographies – is lacking.

The chapter that follows briefly explores the current linkages proposed in the health and place literature and highlights the current state of the art work. We revisit the developments in the theorisation of place, the influence of local context, and health relationships that have emerged in the geographic and epidemiological literatures over the past 30 or so years, highlighting the potential of relational geographies and biosocial theory in combination as an avenue for fruitful inquiry. This integration is exploited to think about extensions to exposomic geographies and the use of the exposome as a holistic framework through which the complex *how* and *when* of health and place relationships may be addressed.

II Geographies of health and place

Geography, the context in which people live and become, has long been understood as important to health (Jones and Moon, 1992). A concern with place has dominated geographies of heath in recent times. Health and place studies theorise and debate the role of local context in influencing health and wellbeing, privileging more-than-individual perspectives that appreciate the multi-scalar and social construction of life (Jones and Moon, 1993).

Place experienced a notable resurgence of interest in health studies starting from the early 1990s. This debate was stimulated by a need for a 'new' geography of health that would offer more socially informed discussions of health (Kearns, 1993). This 'health geography' was formulated as a progression from medical geographies utilising biomedical models focused

on curative medicine and proximate causal interests (see also Philo, 2016). Medical geography was critiqued for its detached perspective, where context tended to be reduced to a spatial sense of location and uncritically employed as 'container' (Jones and Moon, 1993; Kearns, 1993). Furthermore, health geography brought an increasing connection to critical geographies through knowledge of the social production of health inequalities (Kearns and Moon, 2002). An increased awareness of place and the structural systems in which place is embedded reflected an enhanced sensitivity to difference (Hayes, 1999; Jones and Moon, 1993; Kearns, 1995; Kearns and Moon, 2002). Therefore, a concern with place was a central unifying theme to a reformed health geography that reflected growing socio-ecological models, the active role of local context and the importance of lived experience (Kearns, 1993; Kearns and Moon, 2002; Rosenberg, 1998).

Driven by these debates, there was a marked increase in health and place studies. From a quantitative research standpoint, there was an explosion of investigations that sought to demonstrate contextual effects on individual life chances (Kawachi and Berkman, 2003; Van Ham et al., 2012). The context versus composition debate was a recurring theme in these studies; the contention being whether found associations were the result of 'true' contextual effects or whether they were a function of the characteristics of the individuals residing in that place. The concurrent propagation of multilevel techniques helped to inform this discussion by providing a means to simultaneously model at multiple scales of analysis.

From the plethora of multilevel studies feeding into the debate, analyses identified significant associations of areal or neighbourhood socioeconomic disadvantage with worse health outcomes. Contextual relationships were demonstrated for a broad spectrum of health measures and behaviours, for example: mortality (Bosma et al., 2001), self-rated health (Cummins et al., 2005), physical health (Voigtländer et al., 2010), limiting and long-term illness (Gould and Jones, 1996; Malmstrom et al., 2001), cardiovascular diseases and risk factors (Sundquist et al., 2004), mental health (Mair et al., 2008; Skapinakis et al., 2005), as well as smoking and alcohol use (Duncan et al., 1999; Matheson et al., 2012). Review studies reveal the consistency in associations of disadvantage with poor health over time and across study designs and contexts (Arcaya et al., 2016; Diez Roux and Mair, 2010; Pickett and Pearl, 2001;

Riva et al., 2007; Schüle and Bolte, 2015). Whilst many of these studies take up the use of 'neighbourhood' as terminology to refer to local context, the relationships identified are active across a range of scales and are not restricted to the urban setting 'neighbourhood' traditionally connotates.

Whilst the existence of an association between areal disadvantage and poorer health is widely acknowledged, inconsistencies exist with some studies not identifying statistically significant contextual variations, whilst the size and nature of effects can vary considerably by the health outcome measured and the contextual measures utilised (Riva et al., 2007; Schüle and Bolte, 2015). Additionally, selection effects and the historical sorting of 'healthy' and 'unhealthy' populations remains largely unaccounted for due to a lack of longitudinal studies, a point repeatedly highlighted in commentaries on the neighbourhood literature (see Diez Roux and Mair, 2010; Hedman and Van Ham, 2012). There remains ongoing uncertainty in the search for a definitive answer to the context versus composition debate and the substantive importance of place.

The context versus composition debate is one avenue through which researchers have tried to explain identified contextual associations. However, the dualistic divide imposed by the context versus composition dichotomy has been criticised for hindering knowledge of the dynamic entanglements of people and places (Cummins et al., 2007; Macintyre et al., 2002). The debate in part encouraged a predilection for identifying direct and independent areal associations (Riva et al., 2007). In response, researchers were urged to embrace the heterogeneity and multiscalar nature of health relations (Cummins et al., 2007; Small and Feldman, 2012). Rather than searching for elusive, overall effects ad infinitum, research addressing how different social and physical environments across the lifecourse may variously impact the health of populations was called for (Macintyre and Ellaway, 2003). In other words, research was in part refocused on the question of process, with theorising and testing plausible pathways linking places and health a central aim (Riva et al., 2007; Van Ham and Manley, 2012).

The call to investigate the mechanisms of place has produced an extensive literature, both quantitative and qualitative, revealing various features of health and place relations.

Important factors have emerged along major topical themes which we will touch on here. Access to services, particularly of health services are of long-standing interest to health geographers, covering a range of facilities from primary health care, screening and prevention, as well as services related to specific conditions such as mental health (Bissonnette et al., 2012; Ngamini Ngui et al., 2012; Rosenberg, 2014). The role of green space and features of the physical environment is a prominent theme. There has been extensive research emerging under a nexus between food, activity and the built environment (Rosenberg, 2016a, 2016b), where studies have examined the phenomenon of food deserts, access to recreational facilities and green spaces, physical activity and walkability (Bridle-Fitzpatrick, 2015; Ivory et al., 2015; Kurka et al., 2015; Schüle et al., 2017; Weimann et al., 2015). The concept of therapeutic landscapes is important in revealing the wellbeing that can be drawn from places, emphasising the role of lived experience and the embodied nature of landscape relationships (Bell et al., 2017; Finlay et al., 2015; Gesler, 1992; Hordyk et al., 2015). Social mechanisms have received attention from health geographers, with research evidencing the benefit of social capital (Bourdieu, 1986; Putnam, 2000) across a range of health outcomes (Aminzadeh et al., 2013; Kim et al., 2008; Murayama et al., 2015). Others have highlighted the complex dynamic operating between place, social capital and disorder, individual experience and health over time (Cattell, 2001; Hooper et al., 2015; Kuipers et al., 2012; Ross and Mirowsky, 2001; Steenbeek and Hipp, 2011).

This diversity of studies has provided insight into potential mechanisms of place and health relationships; deprivation and disadvantage in the form of poorer quality and access to resources, disordered environments, low social capital and discrimination are routinely identified as associated with poor health. However, there are still avenues to further our knowledge and unpack the black-box of place and health. Key criticisms of place-focused health geography are the continuing lack of attention to the theoretical frameworks underpinning research, particularly regarding: the processes by which individuals become exposed to networks of disadvantage; the varying spatial-temporal shape of relations; and the mechanisms that operate at the porous interchange of people and places (Diez Roux and Mair, 2010; Rosenberg, 2016b; Singh et al., 2016). We argue that to address these concerns

and progress the discipline, health geographers should engage with biosocial theories and new understandings of bio-processes. The next section exposes how accessing the processes of biological embodiment can align health geography with theoretical developments in understandings of place and can further existing models of health and health inequalities.

III Process and plasticity

Relational geography and biosocial theory

To progress the health geography literature, we look towards an engagement with theoretical developments from across the social sciences. This is particularly relevant to quantitative health geographers, who have tended to rely on static notions of exposure, and uncritical assumptions of the causal power of space (Guthman and Mansfield, 2012; Kwan, 2013; Rosenberg, 2016b). Relational geographies are a pertinent thoroughfare to advancing health geography as they align with a focus on exposure and embodiment, on place and health.

A 'relational turn' has gained traction across geography disciplines since the early 2000s. The movement reflects a desire to move away from structuralist understandings, towards more mobile, open-ended and networked conceptualisations of space and place (Amin, 2004; Boggs and Rantisi, 2003; Jones, 2009; Murdoch, 2006). Relational thinking provides a processual understanding of space and place. It takes up post-structuralist thought on the interpretation of meaning and action in the interactions between heterogeneous actors, human and non-human (Jones, 2009; Murdoch, 2006). Under a relational lens, space and place are no longer formulated as containers of process, existing absolute, rather, as Massey (1994) advocated, space is formed of social relations. Within this relational understanding, place becomes understood, not as a bounded, static entity with a fixed identity defined by what is within, but rather as a moment's constellation of social relations (Massey, 1994; Murdoch, 2006).

A health geography inspired by relational thinking necessitates bringing forward the temporal dimension through longitudinal research. The dominant format of cross-sectional analysis implicitly relies upon assumptions of the power of static space and its bounded features to

determine outcomes. In contrast, relational theorisations treat space and time as inextricably entangled; social relations are played out across and themselves construct space-time. The spatial cannot be understood when divorced from the temporal. The inherent dynamism implicated in such a theorisation is important for articulating an open-ended plasticity to space and place. As Harvey (1996) described, the creation of spaces is in the temporary stabilisation of relations, of 'permanances' that are not permanent but rather open to change and 'perpetual perishing'. Places viewed through the lens of relational thought necessarily become porous to 'outside' influences; the 'global' is always entwined with the production of the 'local' (Massey, 1994). Employing this formulation of space and place, therefore, also helps to shift health and place researchers from dualistic perspectives of individual health determined by factors within place, reinforcing the interconnectedness of relations across interfolding scales over time. For instance, relational work on poverty has expanded inquiry of the production of disadvantage beyond the boundaries of specific nations, territories or spaces (Elwood et al., 2017).

By comprehending the plasticity and open-ended becoming of people and places relational geography aids the study of health inequalities. Social relations are imbued with meaning and power, and through repetitive processes of interactions networks are continually remade which can strengthen or weaken the capabilities of people within those networks (Massey, 1991). By tracing relations of place over time, geographers can help to distil circuits of power that serve to marginalise certain populations (Murdoch, 2006). For example, feminist geographers have used relational approaches to gender to understand its construction in embodied social relations and stratifications that serve to reproduce oppressive relations (Connell, 2012; Massey, 1994).

Health inequalities are a major motivation for health researchers. Health (the ability to achieve a state of physical, mental and social wellbeing) is recognised as a fundamental human right (Braveman and Gruskin, 2003; Marmot, 2007). Health inequalities which reflect social hierarchies and societal structures, as revealed by the World Health Organisation's Commission on the Social Determinants of Health (World Health Organisation, 2008), are viewed as avoidable and unjust. The Dahlgren and Whitehead (1991) model of the social

determinants of health is an influential framework for those aiming to assess health inequalities, across academic and policy spheres (Bambra et al., 2010; Department of Health, 2008; Whitehead and Popay, 2010). The model conceptualises a layered picture of the factors important to health, expanding from constitutional factors such as age and sex, to individual lifestyle factors, social and community networks, living and working conditions and the general socioeconomic, cultural and environmental climate. This multiscale model emphasises the interdependence between the social determinants as they act in process, with the separate layers viewed as levels for policy interventions (Dahlgren and Whitehead, 1991). The viewpoint advocated by the social determinants of health, therefore, aligns with a relational viewpoint on the interconnections of social and health processes from the global to the local.

Under the social determinants model the most proximate factors of age, sex and genetic makeup are viewed as given and are not considered as contributors to *social* inequities in health. They are, therefore, placed outside the control of policy. To a degree this may be true. However, it is important to retain an appreciation for the entanglements of these factors with the broader social determinants. This is particularly clear in relation to sex and gender. Sex is not purely a biological mechanism but always intermingled with gendered social relations (Springer et al., 2012). This melange of biological and social processes serves to place this constitutional factor under the purview of health policy and the potential for change. It is such 'biosocial' conceptualisations which are missing from Dahlgren and Whitehead's (1991) model, reflected in a wider lack of attention to the biological in the place and health literatures.

Equally relational and biosocial approaches to health geography can inform new conceptualisations of the body and the human. For instance, scientific work around the microbiome has informed understandings of bodies as changeable configurations of a multitude of microbial and animal life (Lorimer, 2017). In doing so, relational perspectives inform on the specific human, non-human and socio-ecology assemblages through which to evaluate the emergence of disease (Andrews, 2018; Lorimer, 2017).

Calls for theoretical models which reflect the entanglement of social and biological phenomena have been made in other health literatures. From social epidemiology, work by Nancy Krieger has made the case for an 'ecosocial' theory of health (Krieger, 1994, 1999). Krieger (1994) critically evaluated the long-standing and widely accepted web of causation model, revealing the biomedical individualisation and the consequent focus on the proximate causes of ill health promulgated in epidemiological studies. The argument was for the integration of social perspectives into epidemiological work. The social offers an understanding of population health as more than the sum of individual health and is an integral way of understanding health inequalities. The benefit of an ecosocial or biosocial framework is in bringing forward the conceptualisation of health differentials as socially produced through and within dynamic biological processes; the biological is not rejected but understood in process with social relations (Krieger, 1999).

Engaging with biosocial theory is essential to understanding the embodiment of place, how social relations become incorporated in the changing health of bodies. It provides a framework which reflects bodies as porous and mutable, open to processes beyond the individual. Our understanding of health inequalities, marginalisation and resilience can be progressed by using a biosocial framework to track the imprint of disadvantage. Evidently, geographic thought and relational understandings of space and place are a useful accompaniment to biosocial theory. They direct thought to the emergent nature of geographical relations and thus to the nature of exposures and being 'exposed'. For instance, Hall and Wilton (2017) highlighted the potential of relational theories to expose the production of dis/abled bodies in the interplay of social structures, objects and spaces with the physical, biological realities of impairment. In the following section, we unpack how new and developing understandings of bio-processes are invigorating discussion for biosocial, relational frameworks of health geographies.

Biosocial processes

Biosocial research has been expanding in recent years, through increasingly rich data resources, innovations in data methodologies, and discoveries linking biological data to health and social lives. Importantly, increasing knowledge of the development of later life health

states and the ongoing interactions between exposures and biological responses is offering novel insights into the marginalisation of some populations and the growth of health inequalities.

Research on lifecourse epidemiology and the developmental origins of health and disease has highlighted that exposures in early life, particularly during gestation, can have long-standing impacts in the later life outcomes of individuals. The foetal origins hypothesis (or Barker hypothesis), based on an identified link between being small at birth and adult cardiovascular disease and Type II diabetes, was instrumental in the development of these research fields (Barker, 1995; Barker et al., 1989, 1993). The hypothesis posits that foetal undernutrition is associated with adaptive responses that impart a biological 'memory' of undernutrition, which in combination with exposures through life can increase an individual's chances of poor health outcomes (Barker, 1995; Barker et al., 1993, 2002; Hales and Barker, 2001).

Studies of the developmental origins of disease have also indicated the operation of the stress response system can be differentially programmed by experiences over the gestational period, early life and childhood, implicating tobacco exposure, maternal affect, and social interactions and trauma (Brooker et al., 2016; Clark et al., 2016; Del Giudice et al., 2011; Flinn et al., 2011). The stress system plays a vital role in regulating responses to environmental stressors, including playing a role in behavioural responses. The importance of early life environments is further emphasised by studies which link macroeconomic and social conditions with birth outcomes. Work by Margerison-Zilko et al. (2017) related increases in the unemployment rate of US states to heightened risk of pre-term births, making adjustment for selection into live birth. Additionally, they were able to demonstrate the extra burden on pre-term birth risk associated with the Great Recession (2007-2009). The plasticity of development can thus reveal histories of patterned marginalisation and vulnerability that contribute to health inequalities.

Epigenetics – that is processes which alter gene expression without altering the underlying genetic sequence – are posited to play a role in the embodiment of the environment signposted by developmental studies (Guthman and Mansfield, 2012; Thayer and Kuzawa, 2011). The emerging field of epigenetics highlights the plasticity of phenotypic development,

and in doing so proffers a suite of challenges to traditional notions that continue to underlie many approaches to health studies. For example, the nature-nurture divide is blurred: epigenetic processes highlight that genes do not entirely determine phenotype. Rather, genes provide a range of possible outcomes that the biological system can manifest in interaction with the environment (Guthman and Mansfield, 2012; Kuzawa and Sweet, 2009). This revelation of epigenetics furthers the need to integrate biosocial theory with the social determinants of health to reveal new sites of policy relevance.

The complex temporality of epigenetic processes also highlights the inadequacies of contemporaneous spatial measures of exposure (Guthman and Mansfield, 2012). Responses to epigenetic triggers can have long lag times, for instance research from animal studies on mice suggests altered maternal nutrition during pregnancy can stimulate epigenetic changes in the offspring resulting in different phenotypes in adulthood (Jirtle and Skinner, 2007). Research has also revealed some epigenetic processes can be heritable leading to intergenerational effects (Guthman and Mansfield, 2012; Thayer and Kuzawa, 2011). For example, the impact of psychosocial stress on parents can be transmitted across generations through DNA methylation modifications affecting germ line cells (Franklin et al., 2010). Studies of epigenetic processes invite a relational perspective where the dynamics of time are privileged, and more so, epigenetic studies necessitate a lifecourse approach that pays attention to timing as well as social and historical context (Ben-Shlomo and Kuh, 2002; Elder, 1998). Kuzawa and Sweet (2009) reviewed evidence for lifecourse and developmental pathways of cardiovascular disease, highlighting how social environments and epigenetic bio-processes in combination offer more apt explanations for persistent racial disparities in cardiovascular disease outcomes.

Explaining health inequalities requires not only understanding of the early life origins of health states, but also an understanding of the accumulative, interactive processes acting between bodies and environments. Measures of biological age, such as DNA methylation age – a measure of the cumulative effects of epigenetic processes (Horvath, 2013) – can be used to explore accelerated ageing which may reflect increased exposure to negative experiences. Here, the concept of allostatic load provides an avenue for accessing the imprints of

heterogeneous exposure over the lifecourse. Allostatic load refers to a weathering or 'wear and tear' on the body induced through chronic exposure to various stressors, whether they be from the familial, workplace, neighbourhood or wider environment (McEwen and Seeman, 1999; McEwen and Stellar, 1993). Exposure to stressors incites the protective 'fight or flight' response in the body, however repeated cycles of this response over time result in a cascade of dysregulations across systems of the body (Juster et al., 2010). It is this multisystem biological response to chronic stress which is characterised by allostatic load and which increases the chances of poor health (Juster et al., 2010; McEwen, 2008; McEwen and Seeman, 1999). Allostatic load, therefore, represents a biosocial process to understand the consequences of cumulative and long-term exposure to stressful circumstances that those who are part of vulnerable, exposed and marginalised populations are more likely to experience.

Identifying common processes linking a multitude of exposures to differentially healthy bodies demonstrates the aptness of biosocial thinking to studies of health. Epigenetic and allostatic mechanisms highlight the porosity of the body to its environment, challenging those geographies of health which have placed bodies as passive subjects. By bringing forward the mutability of biological function, knowledge of bioprocesses helps position the environment as an active component in health systems. Echoing the view championed by relational geography, place also becomes more than mere container for human action when biologically plausible pathways are considered (Guthman and Mansfield, 2012). Therefore, biosocial processes provide access to the signature of socially patterned histories of experience, offering insight into mechanisms by which vulnerable populations may be constrained to lifecourses of ill health.

The expanding biodata resource across social surveys, as in, for instance, the UK with the Understanding Society study (University of Essex and Institute for Social and Economic Research, 2017), the Avon Longitudinal Study of Parents and Children (University of Bristol, 2017) and the UK Biobank (Biobank UK, 2016), is facilitating the assessment of biosocial pathways over the lifecourse. Biomarkers improve our knowledge of health processes by serving as indicators of the state of physiological systems (Crimmins et al., 2010). For example,

returning to allostatic load, it is possible to utilise objectively measured biomarkers to construct indices of load for use in quantitative analyses. The theoretical background of the allostatic load concept as both a predictor of physical and mental health outcomes (Hwang et al., 2014; Juster et al., 2010; Kobrosly et al., 2014) and as a biological response to stressful experiences, such as poverty and psychological distress (Kakinami et al., 2013; Szanton et al., 2005; Winning et al., 2015), has been corroborated in this way.

However, biomarker studies have tended towards individual-level perspectives of social exposure, with more limited consideration of geographies of disadvantage. In other words, place has been neglected in comparison to the bio. This is particularly evident among longitudinal or lifecourse studies. Research which has introduced considerations of place in relation to biodata has generally utilised single-point-in-time measures of contemporaneous contextual exposure (Barrington et al., 2014; Bellatorre et al., 2011; Stein Merkin et al., 2009; Theall et al., 2012). Where biodata has been integrated with a lifecourse framework, studies have aimed to model relationships of individual-level socioeconomic gradients. For example, a burgeoning literature relating to allostatic load and the stress response has evidenced cumulative impacts of individual disadvantage across life stages (Gruenewald et al., 2012; Kakinami et al., 2013; Ploubidis et al., 2014). There remains a need to explore pathways for the embodied expression of socially structured geographies of inequality. The next section will highlight the concept of the exposome as a potential framework in which to situate a biosocial health geography.

IV Exposomic health geography

The convergence of relational geographies and biosocial theory produces a nexus ripe for progressing bio-geographies of health. This section exposes technological and methodological developments in health and place research, exploring how a health geography reflecting the plasticity of people and places can be applied through the lens of the exposome. To a large extent the 'tool-box' for this undertaking already exists, the challenge is to bring a diverse range of techniques together under the framework of the exposome to implement the research of a lifecourse biosocial geography.

Following the completion of the Human Genome Project, Wild (2005) proposed the exposome as a complement to the genome, recognising the fundamental importance of the environment to the development of health but the deficiencies in capturing environmental exposure. The exposome is devised to encompass every exposure which an individual experiences, from conception to death (Wild, 2005, 2012). To facilitate implementation of the exposome, it categorises exposure into: internal exposures (processes and factors within the body); specific external exposures (including chemical toxins and pollutants, diet, lifestyle and infectious agents); and general external exposures (the broader causes of health, such as social and economic forces) (Jacquez et al., 2015; Wild, 2012). However, the exposome is concerned with pathways of exposure, placing the overlap and dynamic interaction between these domains as of vital importance.

The exposome as originally conceived, covering the totality of life, can appear non-operational. It may invite an overly simplistic and deterministic viewpoint whereby health outcomes are considered explained through representing all that can be easily measured and quantified. However, rather than attempting to 'sequence' the exposome it its entirety, health geographers can benefit from reconsidering the exposome through a framework for biosocial geographies of health. As this final section explicates, the exposome can be conceptualised within a Hägerstrandian space-time geography and a heterogeneous, multiscalar, mobile characterisation of exposure which aligns the concept with developments in geographical thought and methods.

The exposome is allied with a drive to understand the plasticity of people and places, where health is appreciated as the sum of interactive and heterogeneous processes across the lifecourse (Wild, 2012). It takes a broad conceptualisation of the environment, reminding researchers of how individuals and places are situated and constituted within a wide range of environmental scales. In this way, applying studies of health through the lens of the exposome helps avoid strictly dualistic thinking where place is set up in apparent opposition to individual-level explanations (Diez Roux, 2001; Macintyre et al., 2002; Riva et al., 2007). The holistic nature of the exposome is particularly beneficial to the integration of biosocial ideas into geographic health enquiry; processes and exposures in the body are explicitly understood

alongside external environmental factors. Three large scale initiatives in the European Union – EXPOsOMICS (Vineis et al., 2017), Human Early-Life Exposome (HELIX) (Vrijheid et al., 2014) and the Health and Environment-wide Associations based on Large population Surveys (HEALS, 2017) – are foregrounding projects in the practical assessment of the exposome and demonstrate the interconnected biosocial viewpoint advocated by the concept. The projects are concerned with gathering, collating and analysing environmental exposure data, social survey data and biological data deriving from '-omic' technologies, in order to understand the interactions of environment and health through biological process.

Employing a biosocial health geography through the lens of the exposome will improve the purview of the exposome concept, particularly in regard to the social dimension. So far, exposome research has targeted more proximal causes of health, aiming to elucidate the minutiae of specific chemical or biological factors. Studies have focused on, for example: processes of DNA damage (Nakamura et al., 2014); carcinogenesis and cancer stage latencies (Jacquez et al., 2015); air pollution (Steinle et al., 2015); and chemical toxins (Rager et al., 2016). These studies do not present the wider complexities of the processes linking people and their environment. Assessment of the broader social forces important to health is at this point underappreciated. For instance, the Genetic GIScience framework for exposome research provided by Jacquez et al. (2015) gives cursory acknowledgement to social exposures. The lack of the social is damaging to exposomic studies; environmental exposures and their biological correlates cannot be separated from the broader social, economic, political and cultural relations in which they are embedded. Recognising the interdisciplinary potential of the exposome, particularly through integration of geographic and epidemiologic ideas, will be important in enabling the exposome to achieve its proposed potential (Stingone et al., 2017).

The multi-environment conceptualisation of the exposome, alongside relational perspectives, highlights the inadequacies of the static, bounded contextual definitions often employed in quantitative health studies, particularly those employing multilevel modelling. The readily available administrative or political definitions applied are unlikely to correspond to real-world arenas of exposure for highly mobile persons (Perchoux et al., 2013). Indeed, Montello

(2001) highlighted the discordance between analysis scale – the scale at which administrative units are defined – and phenomenon scale, the scale where phenomena exist in social structure(s). Technical developments have helped to address some of the inadequacies of 'off-the-shelf' measures (Owen et al., 2016). Boundary issues can be overcome by creating eco-centric bespoke areas for each individual participant (Hedman et al., 2013). Modelling spatial dependencies and spillovers in multilevel analysis gives an element of porosity to areal units and can help to better understand the phenomenon scale (Chaix et al., 2005; Owen et al., 2016). Additionally, a wider range of contexts beyond the residential environment can be examined in studies through the use of cross-classified multilevel models. For example, Aminzadeh et al. (2013) employed a model of individuals nested within both neighbourhoods and schools for their evaluation of social capital and adolescent wellbeing.

In aiming to more adequately capture contexts and exposures, the exposome draws upon the logic of Hägerstrand's time geography, understanding individual movements and immobilities as continuous trajectories through space-time (Schærström, 2014). This perspective privileges movement and relational thinking and echoes arguments made in the geographic and health literatures for the use of 'people-based' exposure measures (Kwan, 2009). These have been driven by understandings of the personal nature of place definitions (Milton et al., 2015) and the undeniable role of movement in shaping the 'dosage' of particular environments (Galster, 2012). Space-time geographic approaches alongside growing technologies for capturing movement have helped to inform new operationalisations of context.

Activity-based approaches to defining context are a growing method for revealing the varied environments of quotidian experience. Neighbourhood effects research in particular has been criticised for privileging the residential environment (Perchoux et al., 2013). Tools such as the interactive mapping application presented by Chaix et al. (2012) can be employed to collect spatial information based on regularity of destinations, establishing habitual patterns of locations by which to construct activity-space contextual definitions (Kwan, 2012; Perchoux et al., 2013).

Global Positioning Systems (GPS) are an increasingly popular tool to access spatio-temporal activity patterns. For example, Yoo et al. (2015) utilised GPS measures to characterise individual time-activity patterns, using the frequency and density of timepoints to define habitual mobility. GPS technology provides data-rich information on continuous space-time trajectories, and in combination with other sensing technologies such as portable and personal sensors, momentary and self-report assessments and methods like social network analysis, it is possible to create detailed exposure datasets (Kwan, 2012; Turner et al., 2017). For example, in a pilot study by Steinle et al. (2015), contextual and time-activity information was gathered with diaries and used in conjunction with GPS linked personal air quality data to assign activity patterns to particular microenvironments of importance, such as home, work and transport. These technical developments in measurement enable researchers to more closely align their data with the theoretical background of continual, shifting exposure. There is also the potential to reveal momentary pathways of exposure to both subjective and biological responses. For instance, Shoval et al. (2018) demonstrate the use of traditional survey methods alongside sensors of electrodermal activity to characterise emotional responses of tourists in Jerusalem.

The exposome presents the lifecourse and temporality as of central importance for comprehending multiplicitous exposures, lending the exposome to assessments of biosocial models. Geographers have long understood it is highly informative to track the contexts in which people live throughout their lifecourse. For instance, Glass and Bilal (2016) showed that the environment at birth has a high degree of 'stickiness': people tend to persist within the same type of socioeconomic contexts as those they are born into. Long-standing and emerging knowledge on biological processes also continues to highlight how exposures in early life and periods of developmental change can carry influence throughout the lifecourse. Tracking the migration patterns of people between areas (or not) over the lifecourse also helps researches to access the role of selection effects (Hedman and Van Ham, 2012; Jokela, 2014, 2015), and the opportunity structures within which individuals are embedded. For example, Coulter et al. (2016) proposed a conceptual framework for investigations of residential mobility using a lifecourse approach alongside insights from the 'new mobilities'

literature. They positioned residential mobility and immobility as relational, active practices, linking lives through time and space, and connecting people to structural conditions that may be enabling or constraining (Coulter et al., 2016). By framing residential mobility as a relational practice acting over the lifecourse, such an approach showcases the benefit of lifecourse geographies to understanding the development and maintenance of inequalities.

Clearly, it is not feasible to evaluate individuals for every moment of their lives, indeed it may not be desirable; researchers must use assessments at different timepoints, covering critical events of developmental change, as well as important life stages (Wild, 2012). It remains a particularly difficult task to capture local area and social characteristics over the lifecourse. In a lot of cases this is due to the data constraints of particular studies and research contexts. However, the growth of longitudinal cohort and panel datasets across and within national contexts, as well as rich population register data from countries such as Denmark, Sweden and the Netherlands, is providing an expanding longitudinal data resource. For example, Gustafsson et al. (2014) capitalised on Swedish cohort data linked to residence information, demonstrating a cumulative impact of neighbourhood disadvantage on allostatic load in midlife for men, but not for women. Residential histories have been used to implicate an environmental risk factor for Amyotrophic Lateral Sclerosis, helping to reveal the interplay of genetic and environmental factors in the aetiology of the disease (Sabel et al., 2009). Removing the privilege usually given to current environments and accepting the possibility for space-time lags between exposure and response (Schærström, 1996) was an important theoretical underpinning to this work.

Increasing efforts at geographic linkage and methodological innovations in lifecourse place research are also opening new avenues for longitudinal geographic health research. The collaborative geographic linkage project being undertaken by Cohort and Longitudinal Studies Enhancement Resources (CLOSER, 2016) is aiming to provide geographic information for a range of longitudinal studies. The developing arena of historical geographic information systems is also expanding opportunities for analysing people and places over time (Pearce, 2015). For example, Pearce et al. (2016) demonstrate the construction of an urban green space measure covering a 100-year period for the Edinburgh region in Scotland, drawing upon

historical and contemporary resources such as maps, aerial photographs and land-use data. Developments in lifecourse and longitudinal research will help to expand the temporal restrictions placed on our comprehension of health and place processes by cross-sectional and short-run analyses. Moreover, alongside geographic linkage and GIS developments which are improving the quantitative assessment of health and place over time, qualitative methods such as oral histories (Bornat et al., 2000) offer a complementary resource for accessing the accumulation of different exposures over time.

Qualitative methods help to reveal the messy complexities of people and places over time, and through personal accounts of experience can provide insight into factors and potential pathways important in shaping the trajectories of individual lifecourses (O'Campo et al., 2009; Temelová and Slezáková, 2014). Interviews and participatory methods may get closer to the grain of the interplay of lived experience, the accumulation of experience across varied personal landscapes, and states of health and wellbeing. By recognising the non-quantifiable, insights from qualitative methods would also help prevent deterministic employments of the exposome.

However, qualitative methods are not able to capture the interplay of the biological and the social over time which biosocial theory and the exposome concept demonstrate are vitally important for comprehending health inequalities. Indeed, part of the value of exploring bio-processes such as epigenetics and allostatic load is their ability to offer a record of social exposure by which to trace the reproduction of disadvantage over time. Additionally, providing quantitative evidence for exposomic health and place relations, in relation to specific, measurable health outcomes, helps to strengthen the evidence base to bring forward to policy makers. It is important to use larger cohort and panel studies to expose biosocial geographies of disadvantaged groups who are constrained to particular exposure environments across their lifecourse.

The exposome reminds researchers of the inextricability of the body and the external world by proposing a genome-plus view of the environment, where exposures and processes within and outside the body are intertwined. One mode to implement assessments of the biosocial, to get closer to accessing the permeability of the body to social relations, is to use mediation

analysis. Mediation is conceived as a causal phenomenon, whereby the relationship between two variables is accounted for by an intervening variable – a mediator (Baron and Kenny, 1986; Hayes and Preacher, 2014). It is a method for exploring potential mechanisms linking factors of interest (Mackinnon et al., 2007). Therefore, mediation analysis, which incorporates techniques such as path analysis and structural equation modelling, offers a methodological framework for accessing the processes by which contexts manifest in health states (Hayes and Preacher, 2010; Pardo and Román, 2013). Conceptually mediators are used to explain how external events become expressed in the physiological and psychological state of bodies (Baron and Kenny, 1986).

The explicit investigation of intervening pathways using mediation analysis techniques is also relatively uncommon in health geography, particularly in the assessment of biologically plausible pathways in health and place studies. For example, the concept of allostatic load presents a means through which the bodily response to stress exposures can be accessed. However, the two studies which have investigated whether allostatic load mediated individual-level socioeconomic gradients in health status have not provided in-depth assessment of the mediating pathways and their action. They rely instead on the attenuation of a previous relationship which may also occur if a variable is a confounder (Hu et al., 2007; Sabbah et al., 2008). The primary difference of a mediator to a confounder being that a mediator is positioned in a causal chain between the independent and dependent variable; for a confounder there is not the same directionality of the relationship. There is a mismatch between the aim of understanding the pathways through which the environment may manifest in differently healthy bodies and the methodological approach taken. In particular, studies of health and place should make more use of the technical and methodological developments in mediation analysis which are facilitating the investigation of more complex models incorporating multiple mediators, heterogeneity of associations, multiple levels and longitudinal data (Bind et al., 2016; Loeys et al., 2013; Preacher et al., 2007, 2010; Selig and Preacher, 2009; Valeri and VanderWeele, 2013; Zhang et al., 2009). Utilising such techniques will help to elucidate exposomic and biosocial geographies of place and health over time and

ally with a relational lens that points towards the analysis of dynamic process and relationships.

V Conclusion

To uncover the *how* and *when* of health and place relationships, health geographers need to engage with biosocial ideas. The missing insight into how exposure to the varied social and physical features of places come to be imprinted on and manifest in differentially healthy bodies can be gained through an understanding of biosocial relations. Integrating biosocial thought with the established social determinants of health model will allow health geographers to move the agenda forward to investigating not only the interacting processes from the macro socioeconomic climate to individual characteristics, but also to exploring biological process and its inherent connection to social context. Biosocial theorisations enable both body and environment to be repositioned as active components in fluid health and place relationships, acting in interchange and accumulation over time. In this way health geographers, and particularly quantitative researchers, can move beyond static, and at times uncritical, understandings of the determining power of place to more nuanced, critical theorisations for the marginalisation of different groups over time.

Our growing insight into the processes of epigenetics and of allostatic pathways for the embodiment of context provide novel avenues for feeding into discourses on health inequalities. These processes offer links between socially structured relations over the lifecourse and patterns of group and population health. By engaging with the expanding biodata resource across large-scale social surveys and through collaboration with epidemiologists and the biomedical community, health geographers can inform discussion on the biological embedding of disadvantage. The geographic lens is needed in this discussion to provide the more-than-individual, social perspective which has so far been largely lacking in bio-studies. The complex temporality and plasticity of bodies indicated by processes such as epigenetics invites an integration with relational theorisations of space, place and the social.

It will be beneficial to employ the concept of the exposome within health geographies. The exposome can provide a holistic framework in which to position the investigation of dynamic

relationships between heterogeneous and multi-scalar exposures, their biological imprint and health outcomes. It will be a complex and difficult task to compile biosocial geographies of health and place through the exposome. Researchers will have to take up and integrate methodological and theoretical developments in the assessment of exposures and context, of modelling lifecourse relationships, and of investigating the mechanisms of embodiment, to reveal histories of exposure, vulnerability and marginalisation to inform and act on inequalities in health.

Introduction to Chapter 3

This chapter addresses the first research question: What is the shape of age and cohort health trajectories over time? The previous chapter identified that understandings of health trajectories and long-term health dynamics – in other words, questions of *when* in health and place relationships – is a gap in the literature that remains to be addressed. To understand the complexities of relationships between a multitude of exposures and health outcomes, it is necessary to first examine how different dimensions of health are expected to change over time. This first analytical chapter draws upon the rich longitudinal data of the British Household Panel Survey and Understanding Society, covering a total period of 26 years, to assess how two major health outcomes, self-rated health and mental health, change over time. It serves as a baseline study of the temporal dynamics of these health outcomes in our datasets, before the next chapter investigates how neighbourhood and individual-level deprivation relates to subjective health over time.

The novel contribution of this analysis lies in the use of random effects modelling in an exploratory fashion to non-parametrically investigate the shape of age and cohort trends. The technique, where ages and cohorts are treated as temporal contexts in multilevel modelling – in the same way spatial contexts would be modelled – does not impose *a priori* assumptions on the shape of age and cohort trends. Rather the models allow the temporal dynamics of the data to 'speak for themselves' (Gould, 1981). Moreover, drawing upon some of the lifecourse epidemiological literature identified in the previous review chapter, we identify cohort dynamics in self-rated health and mental health. Cohort trends reflect shared experiences or characteristics of those born at a similar time, which could be the result of societal or economic shifts for example. Cohort trends, therefore, help appreciate the wider social contexts in which individuals are embedded as they progress through the lifecourse. Employing random effects modelling to non-parametrically assess cohort patterns is particularly helpful; it stands in contrast to research approaches which subjectively split populations into categories or quantiles before analysis which may not necessarily align with underlying cohort groupings.

The following analysis also explores interactive effects of age and cohort trajectories, further helping to elucidate the complex dynamism of time trends in health, in keeping with the tenets of the exposome highlighted in Chapter 2. In doing so the chapter highlights the potential of random effects modelling in exploring interaction effects. The investigation of how lifecourse trends may vary by cohorts also contributes to understandings of health inequalities. It can reveal generational differences in health trajectories. This investigation is particularly important in light of current debates over the increasing burden of ill-health for young persons, such as the growing awareness of a potential youth mental health crisis (Schraer, 2019; Siddique, 2018).

Included at the end of this chapter are supplementary results from sensitivity analyses with separate samples of men and women. These serve to illustrate any major sex differences in the patterning of the health outcomes by age and cohorts.

Chapter 3. Illness and the lifecourse: does the relationship vary by cohort?

I Introduction

The importance of appreciating how health and mortality changes as people progress through different life stages has long been recognised, across an array of demographic, health and epidemiological fields (Ben-Shlomo and Kuh, 2002; Burton-Jeangros et al., 2015; Grundy and Murphy, 2015). Examining trajectories of different health dimensions provides insight into later health outcomes and, through highlighting divergent health patterns, informs our understanding of health inequalities. Assessment of temporal trends in health can serve as a baseline to the later analysis of the factors which explain patterns of health, as is part of the lifecourse epidemiological tradition of research (Ben-Shlomo and Kuh, 2002; Elder, 1998).

Health reflects more than the absence of disease and infirmity. As such general measures of health, which represent overall appraisals of functioning, wellbeing and condition, are important tools in health research. Variation in general health is frequently captured using self-rated health measures. Subjective health assessments are extensively employed across social health research and these measures have been widely validated and consistently shown to be predictive of mortality across a range of contexts (Jylhä, 2009; Schnittker and Bacak, 2014; Wu et al., 2013). Models of self-rated health suggest that these measures involve an evaluation of diagnosed conditions, feelings and observations of illness and function, all in the context of a personal health history which is also implicitly informed by societal and cultural understandings of 'health' (Jylhä, 2009). Self-assessments of health can also be useful in identifying dysregulations pertinent to health and later mortality that may not necessarily be of clinical significance in themselves (Jylhä, 2009). For example, Stenholm et al. (2016) showed that it is possible to evidence inequalities in self-rated health related to later mortality more than a decade before death, even without a formal diagnosis in the case of cardiovascular diseases. Self-rated health is a vital tool in research into health inequalities, it provides an assessment of 'feeling' healthy, which feeds into broader definitions of health and which has relevance beyond more objective health measures.

We also assess mental health in this study. Mental health trajectories are important in their own right and provide information on a vital dimension of overall health and wellbeing. Their inclusion in this chapter has a further utility in allowing an evaluation of similarities and differences in lifecourse trajectories against the general health orientated self-rated measure. It is important to make this comparison and identify any consistent or divergent cohort interrelationships, particularly in light of the growing awareness of mental health issues and the growing body of research which highlights the burden of mental ill-health for younger persons in particular (Kieling et al., 2011; Patel et al., 2007).

When considering health and the lifecourse, isolating the change in health due to age is often the central aim; health states can change as a result of ageing processes as people grow older. For instance, there is a substantial health and ageing literature, concerned with the prospect of healthy ageing and with how different dimensions of health are expected to change for elderly individuals as they progress through the latter stages of life (Beard et al., 2016; Sowa et al., 2016; World Health Organisation, 2015). This subject is of particular importance across Western societies that have experienced demographic change, with an increasing shift towards an ageing population (Grundy and Murphy, 2015). However, broader perspectives on trajectories of health across the entire lifecourse are also essential to our understanding of health inequalities.

There is a long lineage of research on mortality models which provides an indication of how health could be expected to change with age. For instance, the Gompertz (1825), and the modified Gompertz-Makeham (Greenwood, 1922; Makeham, 1873), models suggest increasing mortality through adulthood (Olshansky and Carnes, 1997). In addition, a number of health conditions are more prevalent at older ages (Prince et al., 2015; World Health Organisation, 2015). Self-assessments of health have been shown to be predictive of mortality (Benjamins et al., 2004; Kaplan and Camacho, 1983; Mossey and Shapiro, 1982) and objective health status will feed into perceptions of overall health status (Jylhä, 2009), therefore, we may expect an accelerating decline in self-rated health with age. Longitudinal studies have evidenced such a decline by age. Andersen et al. (2007) showed that multiple variants of self-rated health measures evidenced a decline with age when examined longitudinally in a study

on Danish persons. Sacker et al. (2005) undertook an assessment of trajectories of self-rated health by social class in the BHPS, using waves from 1991 to 2001. They found evidence for a worsening trend in self-rated health as people aged. Dummy variables for period were additionally included in their assessment (for year of interview), which also showed a marginal decline over time, though they did not additionally explore interactions between these temporal terms.

However, the relationship between self-rated health and mortality or objective health may be less potent for elderly persons (Young et al., 2010), for instance, due to revised expectations of 'good' health (Leinonen et al., 1998; Vuorisalmi et al., 2006). Additionally, as a subjective measure, which incorporates elements of psychological wellbeing, self-rated health could also exhibit a similar temporal signal to measures of wellbeing. Studies have suggested wellbeing may follow a u-shaped relationship with age, where younger and older persons show higher wellbeing with a nadir in mid-life (Blanchflower and Oswald, 2008; Cheng et al., 2017; Steptoe et al., 2015). Moreover, Blanchflower and Oswald (2016) supported a u-shape of mental distress, as proxied by antidepressant use, with the peak of use in middle age. In a study using panel data from Sweden, Johansson et al. (2015) reported improving trends in self-rated health for older individuals (aged 48 or above) whilst younger age-groups showed stable or worsening trends between 1980 and 2005. This would suggest support for elements of the u-shape for self-rated health by age.

To the degree to which psychological wellbeing is represented in measures of mental health a u-shape relationship with age may also be relevant to its development over time. However, conflicting evidence has also been presented. For instance, Thomas et al. (2016) suggested a linear improvement model of a mental health composite of positive and negative attributes, in a study based on participants from San Diego, California. Others have questioned whether apparent u-shaped relationships of mental wellbeing and age are in fact an artefact of inappropriate control variables, such as marital status, which can itself be influenced by wellbeing outcomes (Glenn, 2009), rather than a genuine age trend. Dimensions of mental health which incorporate negative outcomes, such as anxiety and depressive symptoms, could be expected to worsen as people age, concurrently with declining physical health. For

example, Fiske et al. (2003) demonstrated higher depressive symptoms in older individuals in a cross-sectional examination, with a longitudinal analysis continuing to reveal worsening over time for those aged 60 and older. However, they also showed support for a u-shape relationship with age as a middle-aged group did not evidence such a decline over their 9-year follow-up.

Therefore, for both self-rated and mental health, whilst there is a long history of research which informs on potential patterns of development with age, there continues to be discussion. In particular, the continued dominance of cross-sectional studies complicates the issue; the question remains whether true age effects are being presented or whether cohort and other temporal influences are responsible. The issue of accounting for cohort influences is highlighted by studies using modelling approaches which control for all time-invariant individual-level variables which would include cohort, such as fixed effects analysis (Bell and Jones, 2015). For instance, Frijters and Beatton (2012) who do not find evidence of a u-shape relationship between life satisfaction and age in their analysis, instead reporting improving satisfaction from around age 55, followed by a decline in latter old-age from around 75 years-of-age. The research and methodological literature on age-period-cohort modelling also emphasises the risk in considering a single time dimension, with the potential for age effects to be conflated with cohort trends (Bell and Jones, 2014a, 2014b). This issue is the focus of a study by Bell (2014) who models and controls for both age and cohort effects in mental health score. Through taking simultaneous account of these temporal influences, a cubic ageing effect – with worsening over time but a plateau in mid-life – is revealed.

Cohort effects are a second temporal influence of substantive interest in studies of health over time. Cohort effects concern impacts on health which arise through the shared characteristics or experiences of those born contemporaneously, and in the following analysis cohorts are defined based on birth year. Cohort effects may reflect changes in environmental or living conditions, societal change or demographic shifts in cohort populations themselves. For instance, individuals born and growing up during economic recessions, or other periods of socioeconomic or resource uncertainty such as during a war, may suffer long-term consequences in their adult health. Analysing cohort trends helps ground health trajectories

in the social, historical and cultural context in which individuals are embedded, following lifecourse developmental theory (Elder, 1998). Identifying generational differences may also inform on how the health of different groups progresses over time, helping to understand, predict and act on health inequalities. Recent reports, such as by the Health Foundation have also sparked renewed discussion on the health of younger generations, inviting questions on cohort effects. The report suggests the current generation of young persons (aged 12-24) are likely to experience negative health consequences in their later lives due to a series of social difficulties they face today (Hagell et al., 2018). Moreover, a potential burden of mental health issues for young people is also being increasingly evidenced (Office for National Statistics, 2017b), stimulating examination of age and cohort effects.

Following cultural and societal shifts which have been hypothesised to impact on a potential burden of mental health issues for younger generations, some researchers have focused specifically on the presence of cohort effects in depression and other mental health outcomes (Twenge, 2015). For example, an increasingly individualistic society has been postulated to play a role in the rising incidence of depressive symptoms among those frequently referred to as 'millennials' (Twenge, 2015). Others have characterised trends of growing depression prevalence as a 'disease of modernity' (Hidaka, 2012). In their review of studies comparing the mental health of children and adolescents in the 20th and 21st Centuries, Bor et al. (2014) found mixed results for cohort effects. For the youngest cohorts, toddlers and children did not appear to be exhibiting worsening mental health symptoms, although a majority of reviewed studies reported an increasing burden of internalizing problems for adolescent girls (Bor et al., 2014). Twenge (2015) used repeated time-points of survey data on adolescents and young adults, and showed that later cohorts (assessed during the 2000s to 2010s) reported depressive symptoms to a higher degree than their earlier cohort counterparts (evaluated 1980s to 1990s). Additionally, adults aged 30-39 were demonstrated to report increased psychosomatic symptoms of depression over a 12-year follow-up between 1988 and 2000 (Twenge, 2015). Cohort effects may also be present in self-rated health. For example, Chen et al. (2007) found a general trend of accelerated health decline with age in a sample of women assessed between 1975 and 2004. This study also revealed cohort

differences, finding that women in the 'baby-boomers' cohort displayed an accelerated downward slope in self-rated health over the three decades of follow-up compared with those women classed as 'pre-boomers' (Chen et al., 2007).

Age and cohort are clearly two vital temporal dimensions which can influence health trends over time. As well as the methodological motivation for examining both age and cohort influences, a notable gap in the current research literature concerns the exploration of interactions between age and cohort effects (that is whether the age effect is different for different cohorts), an issue present across the study of various health outcomes. Although the evidence is yet to be seen it is clear that, were interactive processes to be present, this could have long-standing consequences for subsequent health trajectories and the development of health inequalities.

The following analysis aims to progress understanding in health demography by investigating age and cohort trajectories of self-rated health and mental health. We advocate an exploratory, non-parametric approach using the random effects modelling capabilities of multilevel models to reveal underlying temporal dynamics and systematic age and cohort variations. We aim to evaluate temporal trends in important health measures without *a priori* imposing a structure or parametric shape to the data, as would be the case with a traditional regression approach where age or cohort are included as fixed regression coefficients. The multilevel exploratory approach detailed below is also valuable in enabling a direct assessment of the degree of variation explained by age and cohort, and their interaction, as important temporal contexts for health. This analysis acts to provide an up-to-date baseline for trajectories of two major health dimensions in a nationally representative sample from Great Britain.

II Data

To evaluate age and cohort trends in health over time, this study uses the British Household Panel Survey (BHPS) and Understanding Society (also known as the UK Household Longitudinal Study – UKHLS) (Knies, 2018; Taylor et al., 2010; University of Essex et al., 2018b).

These are large scale household panel surveys and as such provide information on a nationally representative sample of individuals in the population at all ages as well as on a range of different cohorts over time.

The BHPS ran from 1991 to 2009 as a survey repeatedly interviewing adult members of households. The Survey was designed to include more than 5,000 households, providing approximately 10,000 individual interviews. The UKHLS is the successor to the BHPS, with an expanded sample of approximately 45,000 individuals. This chapter employs the first 7 waves of UKHLS data, spanning 2009 to 2017. In contrast to the annual BHPS, data collection for the UKHLS runs on a rolling two-year basis so that, for instance, Wave 1 covers 2009-2011, Wave 2 includes 2010-2012 and so on. From Wave 2 of the UKHLS, consenting members of the BHPS sample were incorporated into the UKHLS. Together the two surveys provide the potential to cover 26 years of health development. Our analysis uses the Great Britain (England, Scotland and Wales) general population samples for the BHPS and UKHLS, as well as Scotland and Wales boost samples which were added to the BHPS sample in 1999. We chose to restrict to a Great Britain sample through the 26-years of data to maintain comparability, given that a Northern Irish component was incorporated from Wave 11 (2001) and thus is much shorter in time span.

Self-rated health

The first outcome under study – self-rated health – is a subjective measure of overall health. Self-rated health is regarded as a valid and reliable measure of general health, consistently found to be a strong predictor of mortality and other health outcomes (Benjamins et al., 2004; DeSalvo et al., 2005; Kaplan and Camacho, 1983; Mossey and Shapiro, 1982; Wu et al., 2013). For all waves of the BHPS (excluding Wave 9) respondents were asked 'Please think back over the last 12 months about how your health has been. Compared to people of your own age, would you say that your health has on the whole been…', with the possible responses 'excellent', 'good', 'fair', 'poor' and 'very poor'. For Wave 9 of the BHPS and all waves of the UKHLS, self-rated health was measured by the question 'In general, would you say your health is…' with respondents scoring their health on a slightly altered 5-point scale of 'excellent', 'very good', 'good, 'fair' or 'poor'.

Two models of self-rated health measures are commonly implemented in research – age comparative and global. Age comparative refers to the process where individuals are explicitly asked to consider their health status in relation to others of a similar age and given comparative response options such as 'better' or 'worse'. By contrast global measures (such as that used throughout the UKHLS) are less specific and do not provide comparison response options. Whilst the subjective health measure used in the BHPS (other than Wave 9) does ask for a comparison with similar aged individuals, the responses are in the tradition of a global measure. Additionally, age remains a central lens for health appraisal for both types of self-rated health measures (Jylhä, 2009). For instance, a comparison between three different types of self-rated health measures by Eriksson et al. (2001) reported that age-adjustments were likely present in all measures, both comparative and non-comparative.

For the purposes of this study we have dichotomised both measures similarly, treating them as a single response. All modelling requires choices to simplify reality to allow the development of new insights (Nagin, 2005). In our approach, we wish to maintain a high temporal resolution (up to 26 data points) for as many of the participants as possible. As a consequence, we must reduce the resolution of the response to facilitate interpretation. We contrast those who rate their overall health as good or better (scored as 0), with those who consider their health as fair or worse (scored 1). As a test of the dichotomisation treatment of the two variables, we compare the age-comparative and global measures from Wave 14 of the BHPS when both were reported. The correlation between the comparative and global self-rated health measures was high (0.84, $p < 0.000$). In a cross-tabulation of the two measures we were able to reject the null hypothesis of independence ($p < 0.000$) with the majority of those respondents tracking as would be expected between the measures, for instance 93.1% of those who rated their health as 'good' on the age-comparative measure were distributed between the responses of 'very good' and 'good' on the global measure.

General Health Questionnaire (GHQ)

The second outcome considered in this study is the General Health Questionnaire (GHQ), which is a commonly used measure of psychological distress (Goldberg and Williams, 1988; Jackson, 2007; Romppel et al., 2013). This analysis employs the 'short' 12-item GHQ which

involves asking respondents a series of questions relating to how they have been feeling over the last few weeks. The 12 items cover positive aspects such as 'Have you recently been able to enjoy your normal day-to-day activities?' which are scored on a scale of 1 'more so than usual' to 4 'much less than usual', as well as negative aspects such as 'Have you recently been losing confidence in yourself' which are scored on a scale from 1 'not at all' to 4 'much more than usual'. The GHQ scale employed for this analysis is computed by re-scoring the items from 1-4, to 0-3 before summing to create an index from 0-36, where higher scores are indicative of more distress, and, therefore, a worse mental state.

Although the validity of the GHQ as a screening instrument for psychiatric morbidity has been challenged (Hankins, 2008), we do not operationalise the GHQ-12 on a case basis, rather as a continuum of mental distress for the purpose of within and between individual comparisons. Additionally, the presence of the item at every wave of the BHPS and UKHLS with consistent phrasing and scoring provides a valuable resource for exploring trajectories of mental health over a long period.

Age and cohort

The aim of this study is to evaluate health trajectories to provide a baseline knowledge of age and cohort trends over time, and to exemplify an exploratory approach that can uncover interaction effects and the variation explained by temporal contexts. As this is an exploratory analysis, we are not attempting to explain any identified trends at this stage, and so no covariates or factors are included. Sensitivity analyses using separate samples of males and females were conducted to indicate any major sex differences in the temporal patterns (see Supplementary Information). Our multilevel approach detailed below includes ages and cohorts as random effects, where the model treats them as category identifiers. The age range of the sample is restricted to those aged between 18 and 90 to cover the majority of adulthood and to ensure a large sample size at all age-points. The average age of the sample is 47.8 years. Cohorts are measured by the respondent's birth-year and we restrict the sample to cohorts where 150 or more observations are present to improve the analysis and reduce stochastic variation. The cohort range runs between 1907 and 1997, with the average cohort-year being 1959.

III Methods

Multilevel models are utilised in an exploratory approach to assess age and cohort effects in self-rated health and GHQ score over time. A multilevel logistic regression is used for the binary self-rated health measure, predicting the log-odds of being in poor health, whilst normal multilevel models are used to predict GHQ-score as a continuous outcome. This analysis seeks only to assess the baseline variability of these health measures over time in terms of age and cohort, using null models without controlling for any covariates which may explain the identified temporal patterns.

Random effects modelling is exploited to non-parametrically evaluate the shape of age and cohort trajectories over time. We treat ages and cohorts as random classifications within which individuals are nested. This technique effectively assesses the *general contextual effect* (Merlo et al., 2018) of ages and cohorts as temporal contexts, in the same way that you would evaluate a spatial context such as a neighbourhood using multilevel modelling. In this way, we can evaluate any temporal patterns in age and by cohorts through assessment of the predicted random effects without having imposed a parametric shape on the time variables, as would be the case if they were included as fixed effects. The assessment of age, cohorts and their interaction using multilevel modelling is also beneficial in allowing direct evaluation of the variation attributed to these temporal contexts.

We independently test age and cohort random effects in separate models, before jointly including them in a single model to assess their trajectories, each accounting for the influence of the other. The research and methodological literature on age-period-cohort modelling emphasises the risk in considering a single time dimension, with the potential for age effects to be conflated with cohort trends (Bell and Jones, 2014a, 2014b). To assess whether or not there are interactive effects – in other words whether there are different age effects for different cohorts – we also compute and additionally include a multiplicative age*cohort random classification. This consists of each age and cohort combination in the dataset. For the full sample there are 1,980 combinations in total – that is the range of ages present for

those born in 1907, plus the range of ages present for those born in 1908 and so on. Note that each cohort has a varying age range as the panel is unbalanced and data collection for all participants does not start at the same age. The cross-classified data-structure is detailed in Figure 3.1 and the number of units at each level is shown in Table 3.1.

Table 3.1 Number of units at each level

	Self-rated	GHQ
Level	**Units**	
Age*Cohort	1,980	1,980
Cohort	91	91
Age	73	73
Individuals	75,349	69,097
Observations	447,540	406,265

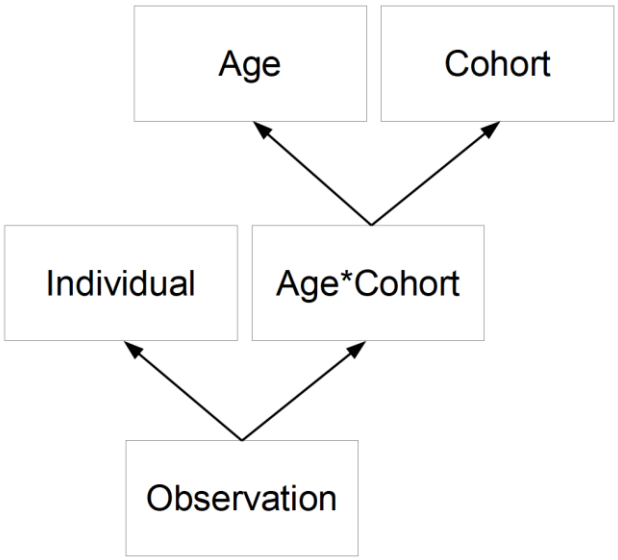

Figure 3.1 Multilevel data structure

Equations 1 and 2 detail the most complex model for self-rated health (logistic binomial specification where π represents the underlying mean propensity of being in poor health) and GHQ (normal response) respectively, with the intercept term (β_0) and all random effects (μ) included. For GHQ the lowest level random term ($e_{observation}$) is freely modelled, signifying the observation residuals. The individual random level is needed to account for the dependency in observations from the same respondent over time. This term is not included in the logistic models for self-rated health as within the binomial specification, this parameter is constrained to 1 in the logistic models. The subscripts *i*, *j*, *k*, *l* and *m* indicate the observation, individual, age, cohort, and age*cohort levels respectively.

$$logit(\pi_{ijklm}) = \beta_{0jklm} + \mu_{age*cohort} + \mu_{cohort} + \mu_{age} + \mu_{individual} \quad (1)$$

$\mu_{age*cohort} \sim N(0, {\sigma^2}_{u(5)})$, $\mu_{cohort} \sim N(0, {\sigma^2}_{u(4)})$, $\mu_{age} \sim N(0, {\sigma^2}_{u(3)})$, $\mu_{individual} \sim N(0, {\sigma^2}_{u(2)})$

$var(y_{ijklm}|\pi_{ijklm}) = \pi_{ijklm}(1 - \pi_{ijklm})/n_{ijklm}$

$$GHQ_{ijklm} = \beta_{0ijklm} + \mu_{age*cohort} + \mu_{cohort} + \mu_{age} + \mu_{individual} + e_{observation} \quad (2)$$

$$\mu_{age*cohort} \sim N\left(0, {\sigma^2}_{u(5)}\right),\ \mu_{cohort} \sim N\left(0, {\sigma^2}_{u(4)}\right),\ \mu_{age} \sim N\left(0, {\sigma^2}_{u(3)}\right),$$

$$\mu_{individual} \sim N\left(0, {\sigma^2}_{u(2)}\right),\ e_{observation} \sim N(0, {\sigma^2}_{e})$$

All models were run using Markov Chain Monte Carlo (MCMC) methods in MLwiN version 3.01 (Browne, 2017; Charlton et al., 2017). For GHQ, models were run for 50,000 iterations, with a burn-in period of 2,000. This was sufficient to achieve convergence for all parameters and to ensure a reasonable Estimated Sample Size (ESS) of over 200 for all parameters. For self-rated health, the logistic models required a longer run of 1,000,000 with a burn-in of 10,000 to achieve the same convergence and minimum ESS. To improve model run-time and convergence, all models were run using orthogonal parameterisation and hierarchical centring, centred on the level with the fewest categories (Browne, 2017). Models were sequentially fitted starting from a two-level model of observations nested within individuals, and the final models were verified through comparison of the Deviance Information Criterion (DIC), a measure of model fit penalised for complexity, which is suitable for use in the comparison of MCMC output.

IV Results

Results for the sequence of models predicting self-rated health and GHQ score are presented in Table 3.2. In both cases the best fitting model was Model 5, which included random effects for individuals, ages, cohorts, and the multiplicative age*cohort classification. This result confirms the need for including interaction effects over and above the main effects of age and cohort. The following discussion is based on the results from these most complex models.

Self-rated health

Firstly, to gain an insight into the temporal patterning of self-rated health we examine the residuals for the separate age (Figure 3.2) and cohort (Figure 3.3) random effects. Recalling that we are using a non-parametric modelling approach, which does not impose any structure

on the data, there is a remarkable degree of patterning for both ages and cohorts. For age we can see a distinct u-shaped relationship. In general, the middle-aged groups are less likely to be unhealthy, whilst the log-odds of being in poor health are higher for the youngest age groups and markedly increased for older persons. There is a noticeable drop-off in the residual for the 90-year old age group, suggesting they are less likely to report poor health than individuals in their 80s. However, over the age range there is a notable lack of noise in the residuals. This is remarkable as by treating different ages as random classifications, they are regarded in the model as simple identifiers for the different groups. More explicitly, the model does not 'know' that age 22 follows 21 and so on, as age is unstructured in the model. That the model outcomes demonstrate such a strong configuration under these assumptions demonstrates the power of this modelling technique to expose underlying trends in the data.

For self-rated health, we also find strong evidence to suggest a trend over time in cohorts, as shown in Figure 3.3. The cohort pattern operates in the opposite direction to the age trend, with younger cohorts showing lower residuals indicative of better health. Although there is more variation and noise between cohort-years than was evident between ages, in terms of effect-size the cohort trend is the stronger of the two. Comparison of the proportion of variance accounted for by age and cohort random effects also shows the strength of cohorts. Approximately 10.1% of variation in self-rated health is attributed to the cohort level, in contrast with 4.2% accounted for by the random age classification. The degree of difference between the age and cohort trends highlights the importance of simultaneously accounting for these competing time dimensions; if we had only portrayed one dimension there would be a risk of conflating these divergent patterns and reporting erroneous findings.

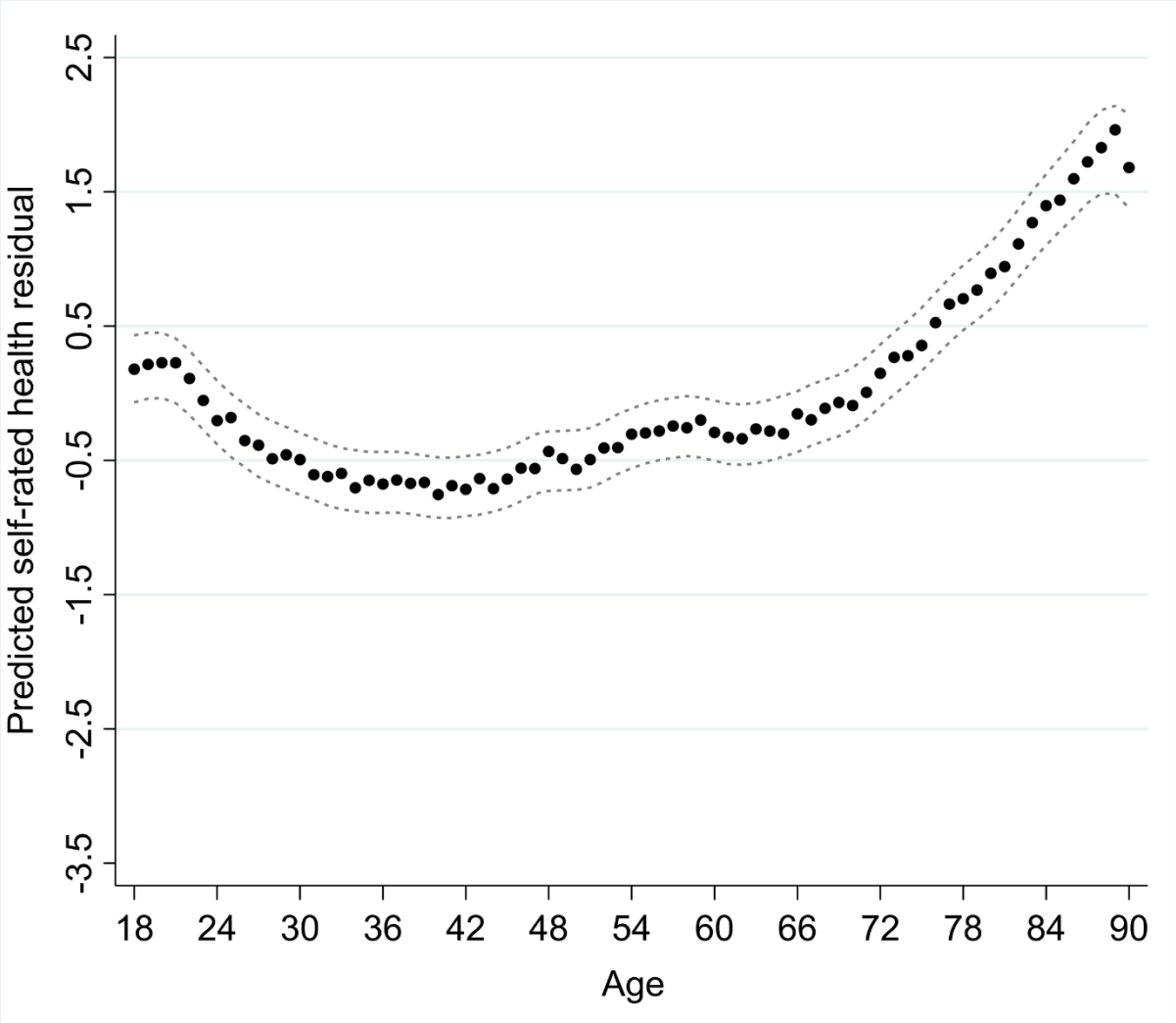

Figure 3.2 Estimated age random residuals for log-odds of poor self-rated health, dashed lines indicate 95% confidence intervals

Table 3.2 Model results including the median estimated coefficient and 95% credible intervals

	1. Individual			2.Age			3.Cohort		
		Credible Interval			Credible Interval			Credible Interval	
	β	2.5%	97.5%	β	2.5%	97.5%	β	2.5%	97.5%
Response: Self-rated health									
Fixed									
cons	-2.394	-2.425	-2.362	-1.927	-2.209	-1.645	-1.885	-2.193	-1.575
Rando									
Age*co									
Cohort							2.213	1.636	2.985
Age				1.475	1.054	2.058			
Individ	8.218	8.017	8.425	7.358	7.182	7.539	7.253	7.075	7.434
DIC	318983			315569			316608		
Response: Mental health									
Fixed									
cons	11.162	11.130	11.196	11.214	11.104	11.330	11.184	11.085	11.283
Rando									
Age*co									
Cohort							0.176	0.119	0.257
Age				0.211	0.148	0.298			
Individ	14.091	13.886	14.293	13.943	13.744	14.152	13.938	13.747	14.143
Observ	16.393	16.316	16.473	16.336	16.258	16.414	16.395	16.315	16.476
DIC	234007			233862			234000		

	4. Cohort, Age			5. Age*Cohort		
		Credible Interval			Credible Interval	
	β	2.5%	97.5%	β	2.5%	97.5%
Response: Self-rated health						
Fixed						
cons	-2.010	-2.292	-1.726	-1.945	-2.247	-1.665
Rando						
Age*co				0.088	0.078	0.099
Cohort	1.330	0.969	1.811	1.278	0.917	1.765
Age	0.522	0.366	0.739	0.538	0.372	0.766
Individ	7.413	7.232	7.600	7.519	7.337	7.706
DIC	313757			311911		
Response: Mental health						
Fixed						
cons	11.257	11.134	11.383	11.259	11.140	11.384
Rando						
Age*co				0.020	0.013	0.027
Cohort	0.066	0.036	0.107	0.062	0.033	0.102
Age	0.210	0.146	0.296	0.208	0.146	0.296
Individ	13.900	13.695	14.108	13.903	13.708	14.102
Observ	16.335	16.257	16.414	16.317	16.241	16.394
DIC	233857			233846		

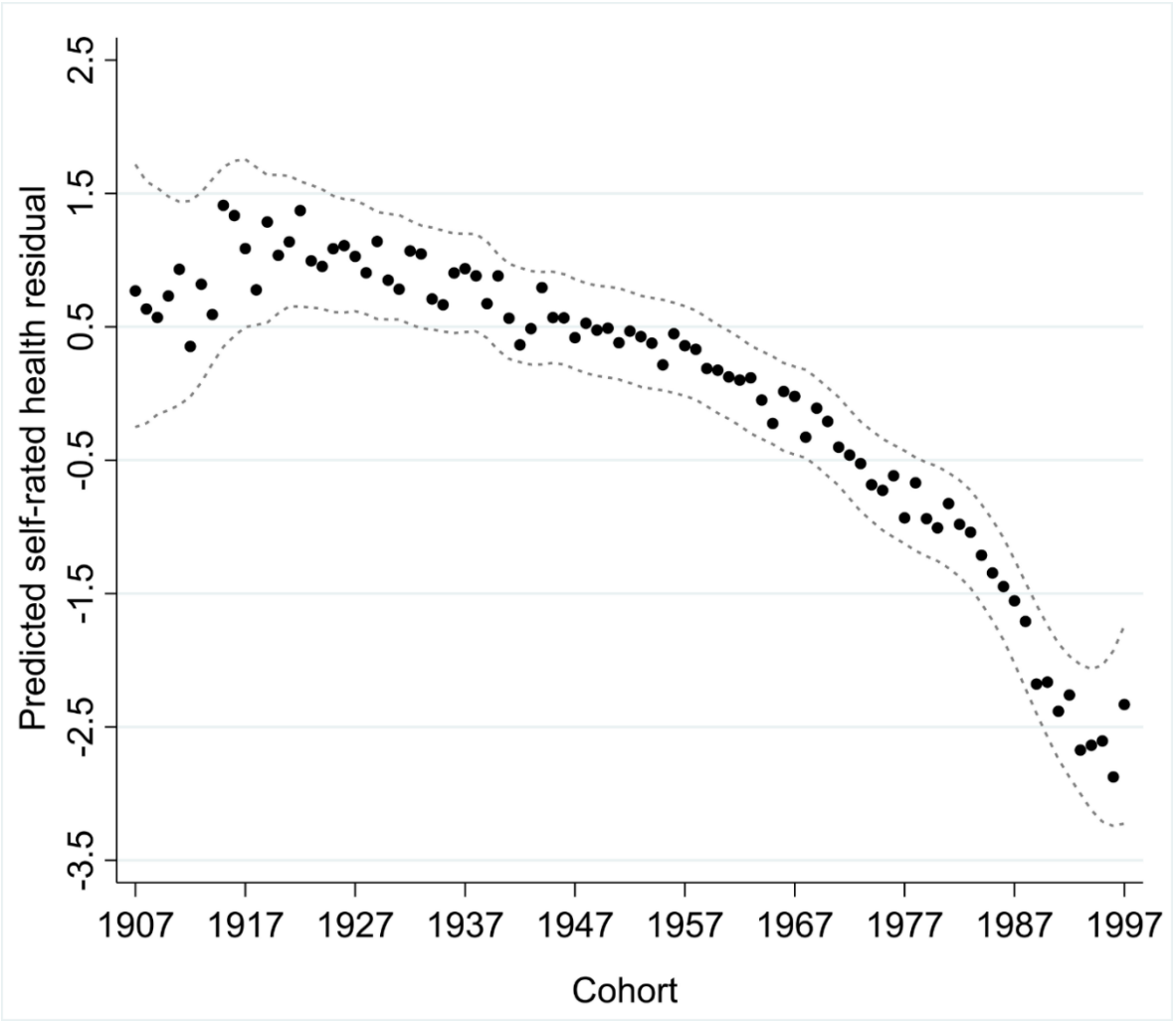

Figure 3.3 Estimated cohort random residuals for log-odds of poor self-rated health, dashed lines indicate 95% confidence intervals

Examining the variance partitioning coefficient (Goldstein et al., 2002) reveals that the multiplicative classification accounts for only 0.7% of the total variance, suggesting a small influence on self-rated health overall. However, the degree of variation of the age*cohort level is significant as inclusion of this multiplicative class improved the model fit, providing evidence of different cohort effects across age groups. To convey the interactive effect of age and cohort we provide the predicted log-odds of being in poor self-rated health by age, grouped by cohort (see Figure 3.4). To aid interpretation we have presented a trellis plot sequentially highlighting decadal groupings of cohort-years in black (note that individual age-years and cohort-years are entered in the model for the random effects classification). These

findings are the predicted log-odds of being in poor health, taking the average log-odds of being in poor health and accounting for the additional effects of being in particular age, cohort and age*cohort groupings.

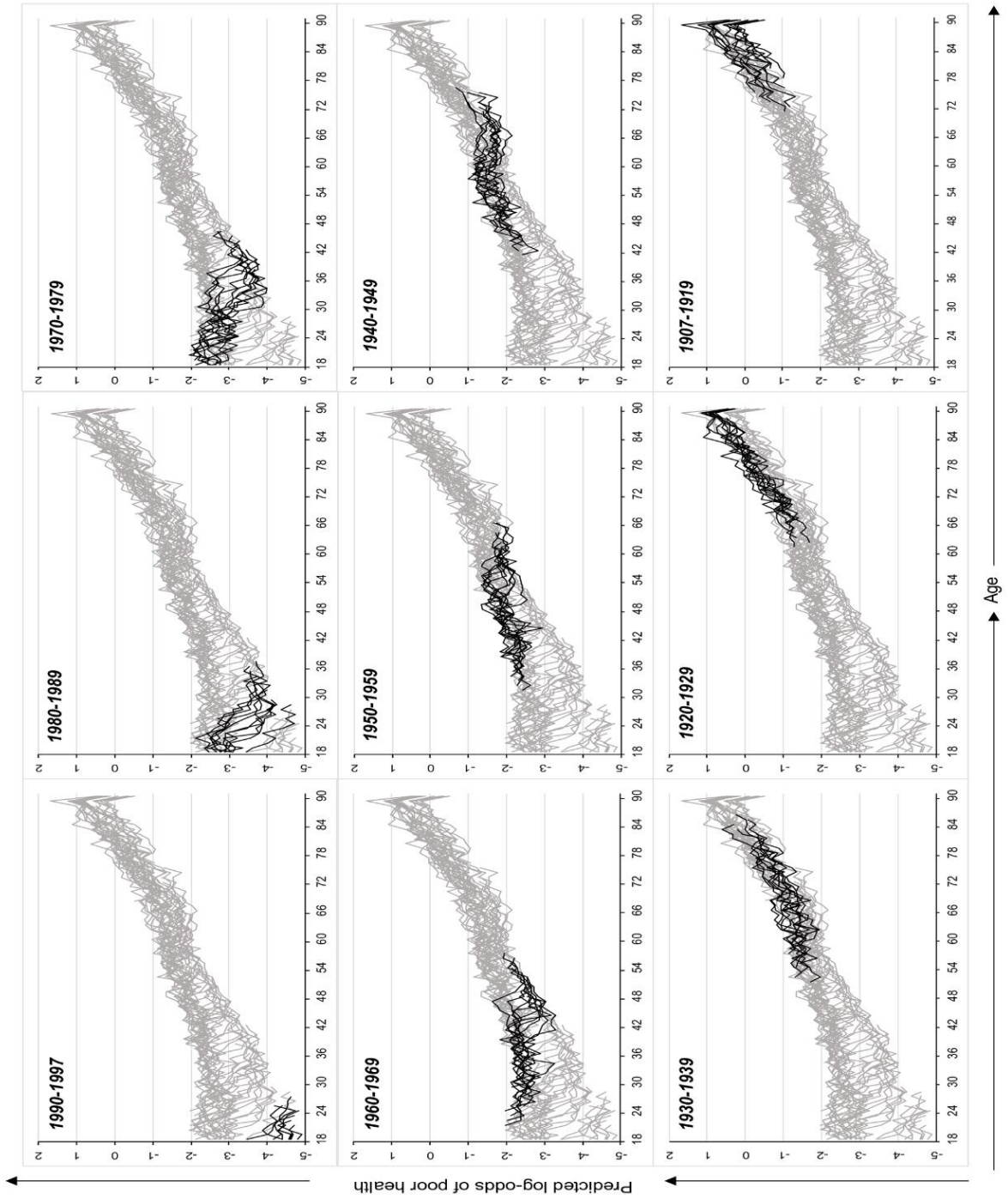

Figure 3.4 Predicted log-odds of poor self-rated health by age by cohort-year

From examination of Figure 3.4, one of the most prominent findings that emerges is that the youngest cohorts (the 1990s) are less likely to report that they are in poor health. In Figure 3.4, the cohort-years from the 1990s, and additionally the 1989 cohort, are clearly separated from older cohorts (from the 1980s, 70s and 60s) who have been assessed at the same age during the survey. This degree of separation and clustering is remarkable given we have not imposed a structure on the data, and reveals the capacity of this modelling approach to reveal inherent patterns in the data, including interactions. Figure 3.4 also shows that across the whole age range it is possible to identify a general convergence in the log-odds of being in poor health; cohort differences appear to be smaller as age progresses, with more overlap across decades.

Mental health

Results for the models predicting GHQ are presented in Table 3.2. As with self-rated health, recall that the most complex model was the best fitting to the data, and so the following results are based on this final model. The results demonstrate that there is a high degree of dependency in observations over time (53.5%), as well as a considerable degree of variation between individuals (45.6%). This means that very little of the total variation in GHQ scores is attributed to the temporal contexts of ages and cohorts (0.7% and 0.2% respectively), which is much lower than for self-rated health (4% for ages, 10% for cohorts). However, this result indicates that for mental health the lifecourse process of ageing is more relevant than any shifts contributable to cohort changes. This can more clearly be seen in Figure 3.5 and Figure 3.6 which show the estimated age and cohort random residuals from the final model respectively. There is a greater range of values present across the age values than there is present for cohorts, the residuals of which are bounded within an expected 1-point shift on the GHQ scale.

Figures 3.5 and 3.6 depict the temporal trends of GHQ by age and by cohort respectively. Again, given our non-parametric modelling strategy, there appears to be a remarkable degree of patterning, particularly for age. The estimated random residuals for age display a cubic pattern, whereby mental distress increases through to middle-age where there is an improvement to around the age of 65, where mental state appears to worsen again as people

grow elderly. It should be noted these differences across the lifecourse are relatively small in terms of expected change in GHQ score, the total range is within 2 points. Turning to the estimated random residuals for cohort effects, the patterning is less pronounced and with smaller expected variation. There does, however, appear to be improvements to mental health for some cohorts, notably the cohort-years of the 1930s, 1940s and 1970s. In contrast, later cohorts appear to be on a worsening trend in terms of mental distress.

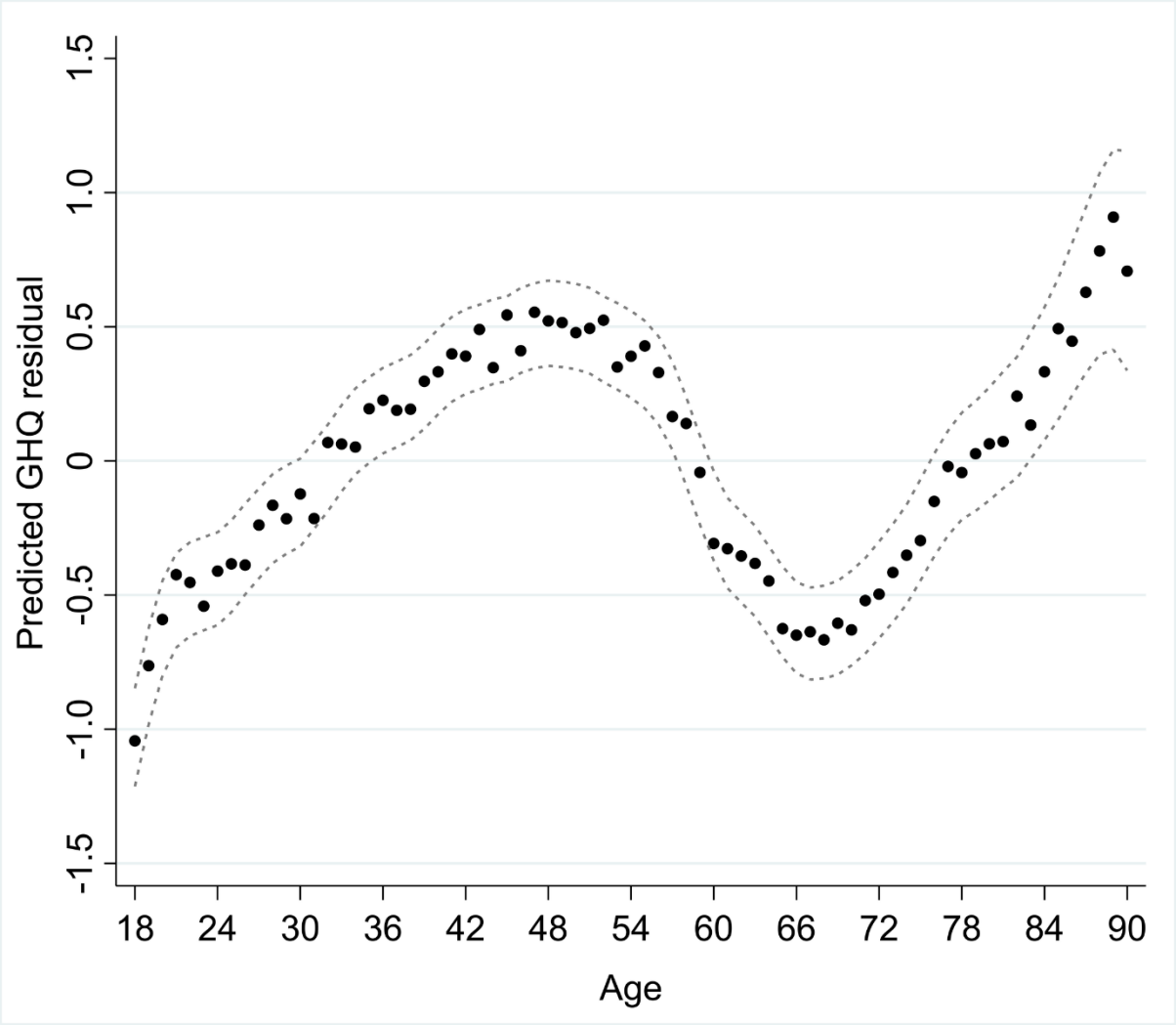

Figure 3.5 Estimated age random residuals for mental health, dashed lines indicate 95% confidence intervals

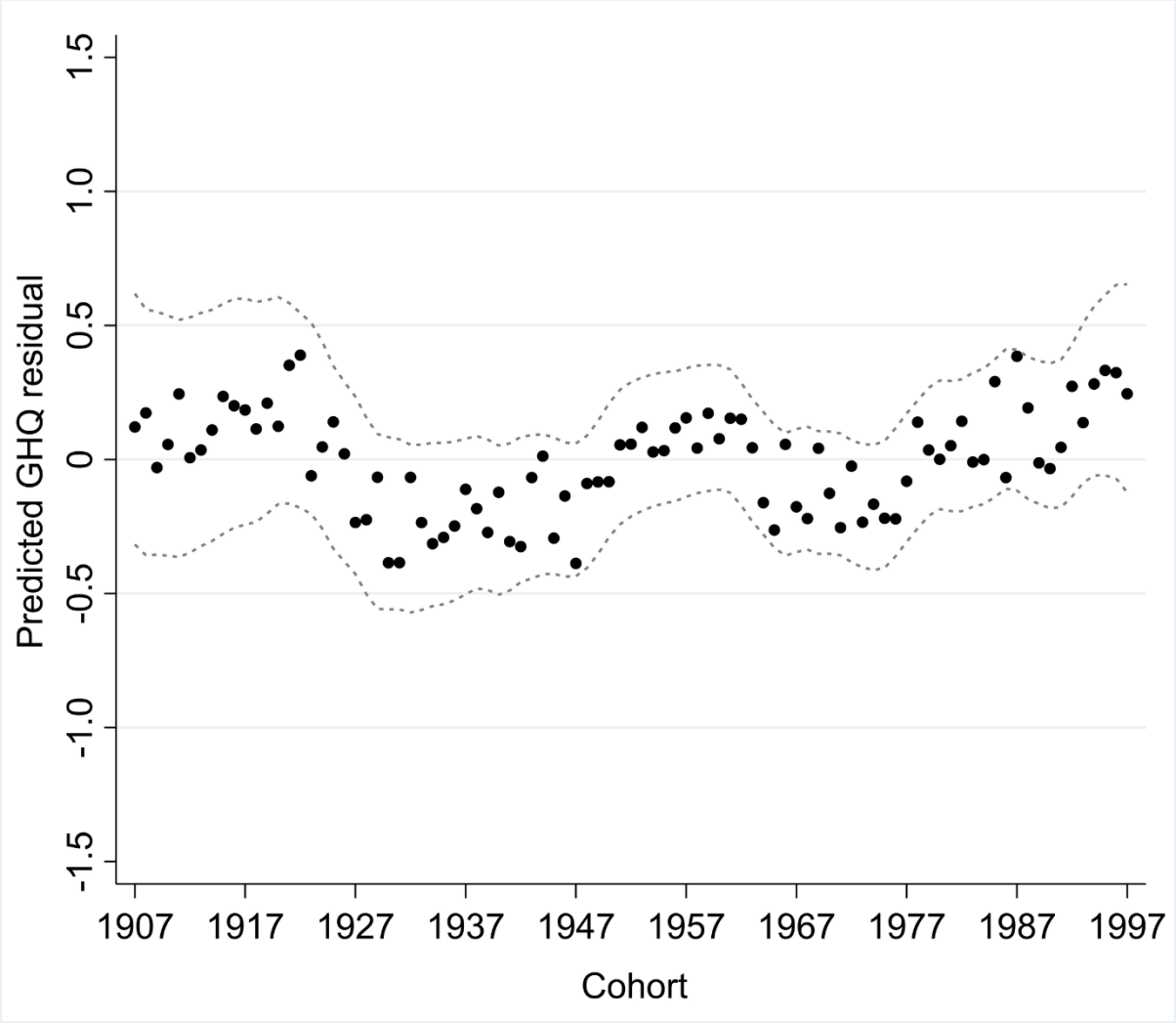

Figure 3.6 Estimated cohort random residuals for mental health, dashed lines indicate 95% confidence intervals

The evidence for an interaction between age and cohort is weaker for mental health than it was for self-rated health, with the inclusion of the multiplicative classification showing a smaller improvement in the DIC over Model 4 than the equivalent self-rated health models. Additionally, the age*cohort classification accounts for only 0.1% of the total variation, as one may expect given the small amount of variation explained by cohorts alone. However, the variance at the age*cohort level is still significant so the predicted GHQ score by age, grouped by cohort, is plotted in Figure 3.7.

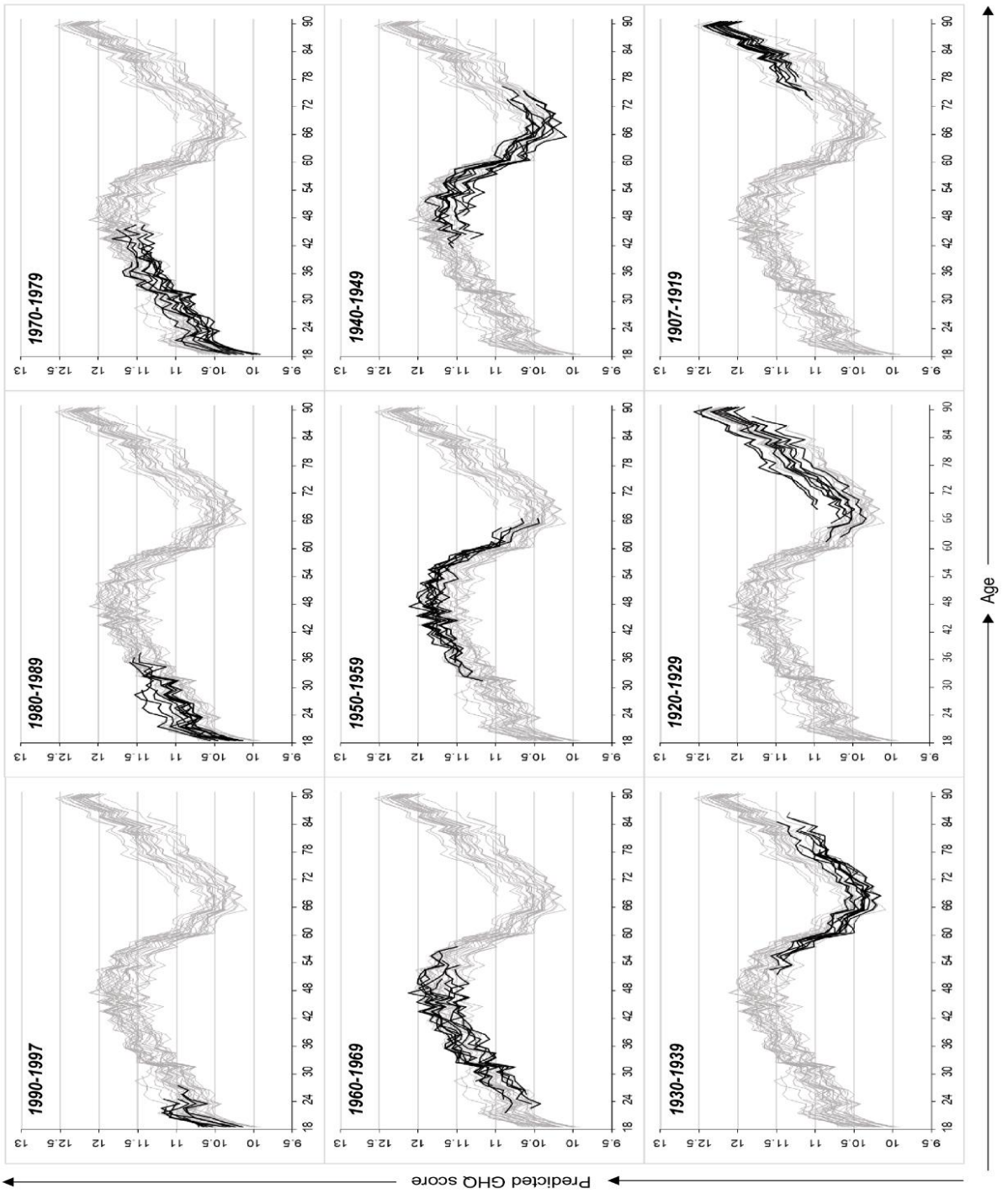

Figure 3.7 Predicted mental health score by age by cohort-year

Figure 3.7 demonstrates that overall the different cohorts follow similar trends of mental health development throughout the lifecourse. Unlike the results for self-rated, there are no clearly delineated cohort-years. However, there is some noticeable grouping by cohort, with some decades appearing to track as consistently better or worse off as they age. For instance, the 1930s, 1940s and 1970s cohorts are generally predicted to have lower GHQ scores, indicating better mental health, than younger cohorts assessed at comparable ages. This reinforces the pattern indicated in Figure 3.6. In comparison, cohort-years from the 1920s and 1950s are generally grouped towards the top side of the graph, indicating higher mental distress. In direct contrast to the results for self-rated health, the younger 1980s and 1990s cohorts seem to be doing comparatively worse in terms of mental health than their respective older cohorts when assessed at the same age. This finding is unexpected given the strong connection and often comorbidity between mental and physical health.

V Discussion

The results of this exploratory analysis reveal a powerful technique for the detection of inherent temporal patterning in survey data. The results suggest lifecourse trajectories of self-rated health are expected to take a u-shape, with improving health from young adulthood to middle-age, before a progressive decline as individuals transition through old age. The general trend of worsening health as people age aligns with previous findings from studies which assess large age-ranges. For example, Young et al. (2010) who report increasing proportions of individuals in fair or poor health for older age groups when looking cross-sectionally at Census-based data for 35 to 74-year olds, and a recent study following married Americans between 1980 and 2000 which evidenced an overall decline in self-rated health over time, with a greater deterioration for those who were older at baseline (Berdahl and McQuillan, 2018). Aligning with our results, Chen et al. (2007) and Sacker et al. (2005) also indicate curved relationships of self-rated health and age, with accelerated declines from middle to old age using longitudinal datasets. The improvement in self-rated health from young adulthood is evidenced to a lesser degree in these studies, though it must be noted that our research does not parametrically model age effects as fixed effects taking other variables into account, as

these studies do. The right-hand portion of the u-shape in Figure 3.2, representing the exponential decline in self-rated health, also suggests similarity to prominent mortality models, such as the Gompertz-Makeham (Greenwood, 1922; Makeham, 1873). This supports the relationship of self-rated health to mortality and to objective health status, with many conditions expected to worsen during old age.

However, it is important to remember that changes in self-rated health over time may also reflect shifting understandings of what it means to be in 'good' health, as well as representing changes in objective health conditions and physical illness. For instance, the phenomenon of response shift is well known in the literature on self-rated health and generally concerns the propensity of elderly individuals to revise their standards of health as they age under a constructed expectation of health decline with growing age (Eriksson et al., 2001; Galenkamp et al., 2012; Leinonen et al., 1998; Vuorisalmi et al., 2006). More generally, baseline expectations of 'good' health are likely to vary by age group and different age groups or generations may varyingly consider health factors such as behaviours in their evaluations (Jylhä, 2009). The subjective and socially constructed dimensions of self-rated health mean the degree to which these measures reflect changes in objective health could shift over the lifecourse (Vuorisalmi et al., 2005). This would problematise the use of self-rated health purely as a proxy for underlying physical illness. Similarly, the power of self-rated health in predicting mortality has been shown to be variable between populations (Young et al., 2010), and some groups may tend to downplay or overstate their health status (Ploubidis and Grundy, 2011), both of which also indicate the role of social context in health evaluations. However, this paper was concerned with the identification of baseline trajectories of self-rated health as a subjective measure, with the capacity to reflect feeling 'healthy' or 'unhealthy' viewed as an important element to investigating overall health and wellbeing.

In contrast with the declines in health expected with ageing, self-rated health appears to be better for latter-born cohorts in comparison with members of the older generations. Analysis of the random residuals and proportion of total variation explained further revealed the cohort effect was dominant over the influence of ageing for self-rated health. This serves to highlight the importance of simultaneously considering these two temporal dimensions and

provides important information for those interested in the temporal properties of self-rated health. Additionally, the illness and lifecourse relationship was demonstrated to vary by cohort, with cohort groupings making more of a difference at younger ages and with self-rated health trends converging to similar trajectories at older ages. We clearly identified the youngest birth cohorts from the 1990s as evidencing better health than their older counterparts when assessed at the same age (between 18 and around 27). It is difficult to make comparisons of this result with other studies; those studies who have reported on cohort effects and which (approximately) cover this age group have relied on older datasets and data from other national contexts (Johansson et al., 2015; Sacker et al., 2011). For instance, the cross-national study by Sacker et al. (2011) does use data from the BHPS, but presents little evidence for cohort differences over time. Additionally, they only report on data waves from 1994-2001; those born in the 1990s would only have been surveyed as adults when they reached 16 years of age so would not be covered in that sample (Sacker et al., 2011). Therefore, the separation of the 1990s cohorts as being of relatively better health could represent a novel cohort effect for this sample covering all of Great Britain. It should be noted that, as we restrict our age sample to those aged 18 or above, individuals born in the 1990s would only have been assessed via the UKHLS survey and thus only through completion of the global self-rated health question ('In general, would you say your health is…'). In contrast, individuals from older cohorts (born between 1972 and 1989) would have been assessed at age 18 via the more age-comparative question in the BHPS. It is possible, therefore, that the apparent cohort inequality we identify is, in part, an artefact of the change in operational definition of the self-rated health measures. However, given the availability of cohort and age combinations in the UKHLS and original BHPS surveys we do not have sufficient resources to test this. It is worth noting that concern over the operational differences between age-comparative and global self-rated measures is usually centred on shifts for elderly respondents (Vuorisalmi et al., 2005, 2006).

The report of better health by the youngest cohorts could reflect shifting expectations of 'good' health in relation to societal conditions or it may be that this generation incorporates different health-relevant dimensions, such as health behaviours, in their evaluation of their

health state (Jylhä, 2009). We do not explore possible explanations of the temporal patterning because it is beyond the scope of this study, which aims instead to demonstrate the power of this exploratory method in initial evaluations of underlying patterns. Future studies need to examine the impact of key factors, such as socioeconomic status and financial situation, as well as the influence of other health outcomes. Previous research has suggested sex differences in health trends, for instance, data from Northern Sweden has been used to report worsening trends in the self-rated health of women aged 24-35 over time, whilst an increasing proportion of men reported better health (Lidström et al., 2017). Separate analyses of female and male participants were investigated (results in the Supplementary Information) to indicate any preliminary differences by sex. The results replicate the common finding that on average women show worse health than men, though the differences were small. The estimated likelihood of the female sample being in poor health across all the waves was around 12.7% compared with 10.6% for the male sample. For mental health the difference was just over 1-point on the 36-point GHQ scale. Plotting the random residuals (Figures 3.S1 to 3.S4) revealed trends in both self-rated and mental health were very similar between the two groups. Investigation of broader social determinants, at varying scales from neighbourhood level to wider society (Dahlgren and Whitehead, 1991), would also be an important next step. For instance, it may be that those who are reporting better health are located in more advantaged communities, or places undergoing regeneration, where there is increased opportunity for salutogenic exposures.

The results for mental health show that when the ageing trend is non-parametrically assessed, taking account of the influence of cohort differences, a cubic-shaped pattern is exposed. Mental health worsens over time from young adulthood to around the age of 50, improving till around retirement age (~65) where it appears to decline through old age (see Figure 3.5). This trajectory is similar to that reported by Bell (2014) who also used the BHPS dataset and controlled for cohort trends; it is reassuring to replicate this pattern by age even when including the additional UKHLS sample. This analysis differs from the research of Bell (2014) by highlighting the potential of random effects modelling in uncovering potential interaction effects and for providing a direct appreciation for the variation explained by the different

temporal contexts. Age is only included in the fixed part of the work by Bell (2014) which is more specifically focused on ways of addressing the age-period-cohort issue. Additionally, this analysis extends this previous research through using the more recent UKHLS sample.

The indication of heightened mental distress at older ages supports previous research indicating depressive symptoms increase with age (Fiske et al., 2003). The trajectories for self-rated health and mental health coincide for older participants, both showing deteriorating trends from around the age of 65. It is known that there may be increased somatization of mental illness and depressive symptoms at older ages (Sheehan and Banerjee, 1999). Therefore, as our measure of mental health is the GHQ, a self-reported indicator of mental distress, this increased manifestation of physical symptoms may be influencing the trends for the more elderly participants, particularly as the models are unadjusted for covariates such as physical health status.

Outside of the worsening trends for older individuals, the difference in expected health trajectories for GHQ and self-rated health also demonstrates the complexity of health development, pointing towards heterogeneity in the responses of health dimensions to a variety of exposures. Mental health may be more highly impacted by changing personal circumstances over the lifecourse, for instance through shifting employment security and stresses, or through changing family dynamics as children grow up (World Health Organisation and Calouste Gulbenkian Foundation, 2014). Given that the available measure of mental health – the GHQ – asks participants to consider how they have been feeling over the last few weeks, this analysis could be picking up changes in life circumstances and experiences which impact on a dynamic mental response, rather than age or cohort trajectories in a longer-term underlying mental state. This may be one explanation for the distinct differences between the results for self-rated and mental health; self-rated health may have a broader range of health dimensions feeding into responses, including objective and subjective outcomes, and, therefore, may represent a more long-term health state.

Weaker evidence was demonstrated for distinct cohort trending in mental health; the estimated range in random residuals was small, and cohort as a temporal context only explained 0.2% of the total variation in GHQ score, compared with accounting for 10% of total

variation in self-rated health. However, evaluation of the combined age and cohort influences did hint at trending groups of cohort-years as either having relatively better or worse mental health over time, exposing those born in the 1930s, 1940s and 1970s as tracking over time with lower levels of mental distress. Additionally, in contrast to the results for self-rated health, the youngest cohort years do not present better mental health, rather these cohort-years tend towards higher levels of mental distress, though the differentiation from older cohorts is limited. This finding is in keeping with studies which have emphasised the current crisis in the mental health of young persons. Our results are helpful in presenting preliminary evidence for the role of cohorts in the mental health of young adults, rather than the alternative explanation that this age group has always suffered worse mental distress over time. The growing awareness of mental health issues, as well as the current economic climate in Great Britain which may put a strain on young adults entering the job market, could be possible explanations for cohort patterning in mental distress and offer avenues for future research.

The results for GHQ score further demonstrate the complexity of evaluating health trajectories over time, with the identification of potentially divergent cohort interactions between two major dimensions of health. However, we should be cautious in our interpretation of these interactive effects for mental health, as the predicted difference in GHQ score is very small and the variance partitioning coefficient shows that the age*cohort classification accounts for very little of overall variance. Indeed, all the temporal classifications (age, cohort and age*cohort) together account for 1% of total variation in mental health score. Rather, mental state is highly variable within persons as well as showing a substantial degree of variation between individuals. It is known that mental health is a labile phenomenon and responsive to recent events and experiences, which could problematise the identification of long-term trends.

This exploratory analysis focuses on ageing and cohort effects. However, it is possible that what we identify could in part reflect period effects – that is events at a certain point in time that influence all persons – regardless of their age or cohort. For example, the implementation of a distinct change in welfare policy could impart a universal effect on the life outcomes of

individuals studied before and after the shift. However, we anticipate that in examining health trajectories, continuous, trending period influences across time in mental or self-rated health are unlikely (Bell, 2014). These results could also be limited in their generalisability beyond the context in which the data were collected, particularly regarding the report of cohort influences which are highly dependent on the wider societal, cultural and economic climate within which different generations are situated in their development. More research is needed across national contexts and with up-to-date data capturing the newest generations to establish the replicability of the temporal patterning identified.

It is also important to acknowledge the potential impact of non-response and attrition on the results presented. For instance, in the results for the ageing pattern in self-rated health there was a noticeable drop-off in the residual log-odds of reporting poor health for the 90-year-old age group. This could reflect a selection effect whereby these most frail and ill persons in this most elderly group are not present in the survey to report their subjective health. A threshold response shift could also be hypothesised, whereby expectations of 'good' health are markedly changed after reaching the 90-year-old milestone. Additionally, persons suffering from more severe mental distress may exhibit higher non-response, meaning the trajectories of these individuals are not captured as fully. Therefore, the results should be treated as indicative of potential trends for further investigation, as would fit with the exploratory nature of the analysis, rather than as presenting definitive trajectories.

The strength of this analysis is in exposing the power of multilevel modelling to reveal underlying temporal trends. Applied to two major health dimensions, the technique allows the data to speak for itself without *a priori* imposing a parametric structure on expected trajectories. The results highlight the remarkable patterning present in ageing and cohort trajectories, and in examining the partitioning of variance also provide an assessment of the relative importance of these different temporal effects in explaining health variations. Additionally, we show the potential application of cross-classified multilevel models in exploring interactive effects between age and cohort influences. In particular, for self-rated health the findings distinguish greater cohort differences in illness trajectories at younger ages than later in life, with the 1990s cohort-years (along with the 1989 cohort) identified as

reporting better health than comparatively assessed older generations. Health researchers would benefit from exploiting this methodology to explore a range of health outcomes over time and contribute to broader understandings of health inequalities.

VI Supplementary Information

Table 3.S1 Results for models containing all random effects for full, female and male samples including the median estimated coefficient and 95% credible intervals

	Full Sample			Females			Males		
		Credible Interval			Credible Interval			Credible Interval	
	β	2.50%	97.50%	β	2.50%	97.50%	β	2.50%	97.50%
Response: Self-rated health									
Fixed Part									
cons	-1.945	-2.247	-1.665	-1.923	-2.217	-1.624	-2.134	-2.417	-1.846
Random Part									
Age*cohort	0.088	0.078	0.099	0.085	0.072	0.099	0.070	0.056	0.085
Cohort	1.278	0.917	1.765	1.317	0.928	1.839	1.118	0.772	1.591
Age	0.538	0.372	0.766	0.450	0.303	0.653	0.477	0.312	0.707
Individual	7.519	7.337	7.706	7.692	7.436	7.959	7.291	7.015	7.575
Variance Partitioning Coefficient									
Age*cohort	0.7			0.7			0.6		
Cohort	10.1			10.3			9.1		
Age	4.2			3.5			3.9		
Individual	59.1			59.9			59.5		
Response: Mental health									
Fixed Part									
cons	11.259	11.140	11.384	11.740	11.622	11.857	10.603	10.477	10.733
Random Part									
Age*cohort	0.020	0.013	0.027	0.023	0.011	0.036	0.019	0.009	0.031
Cohort	0.062	0.033	0.102	0.066	0.030	0.115	0.024	0.004	0.055
Age	0.208	0.146	0.296	0.141	0.094	0.204	0.249	0.169	0.355
Individual	13.903	13.708	14.102	14.587	14.294	14.877	12.355	12.089	12.619
Observation	16.317	16.241	16.394	18.198	18.085	18.314	14.003	13.906	14.103
Variance Partitioning Coefficient									
Age*cohort	0.1			0.1			0.1		
Cohort	0.2			0.2			0.1		
Age	0.7			0.4			0.9		
Individual	45.6			44.2			46.4		
Observation	53.5			55.1			52.5		

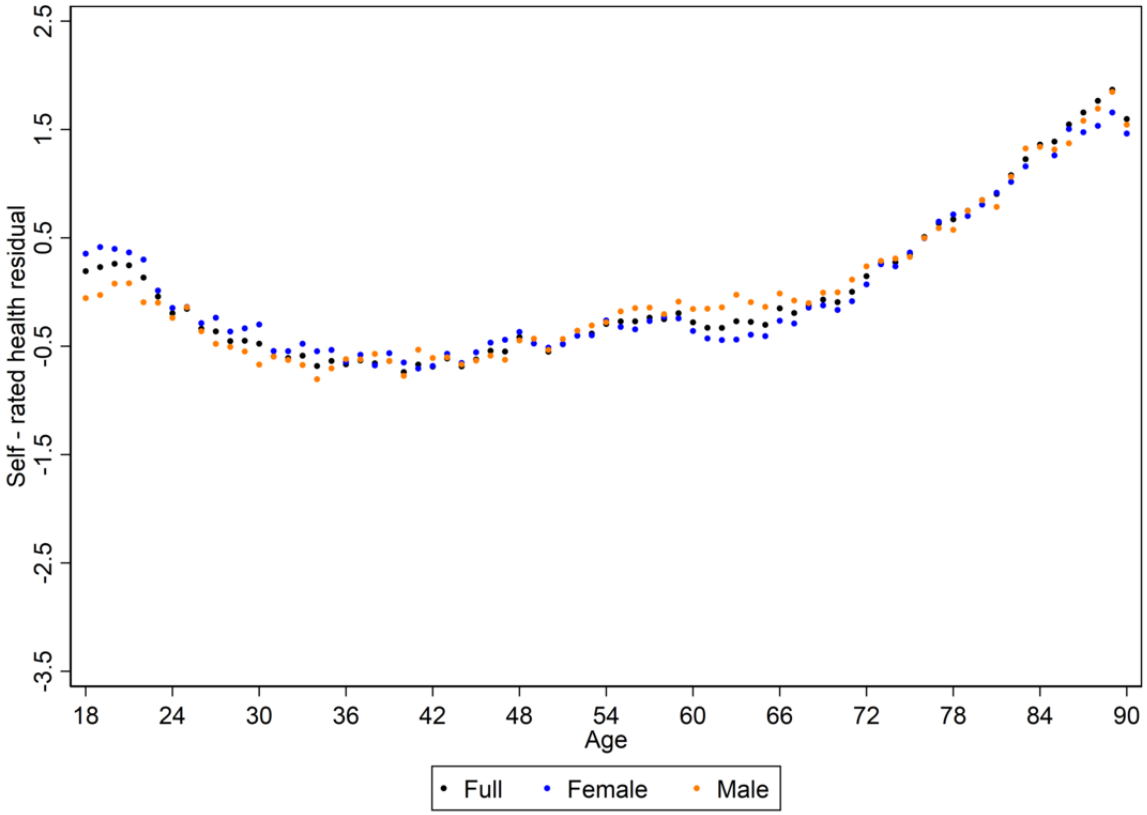

Figure 3.S 1 Estimated age random residuals for log-odds of poor health for each sample

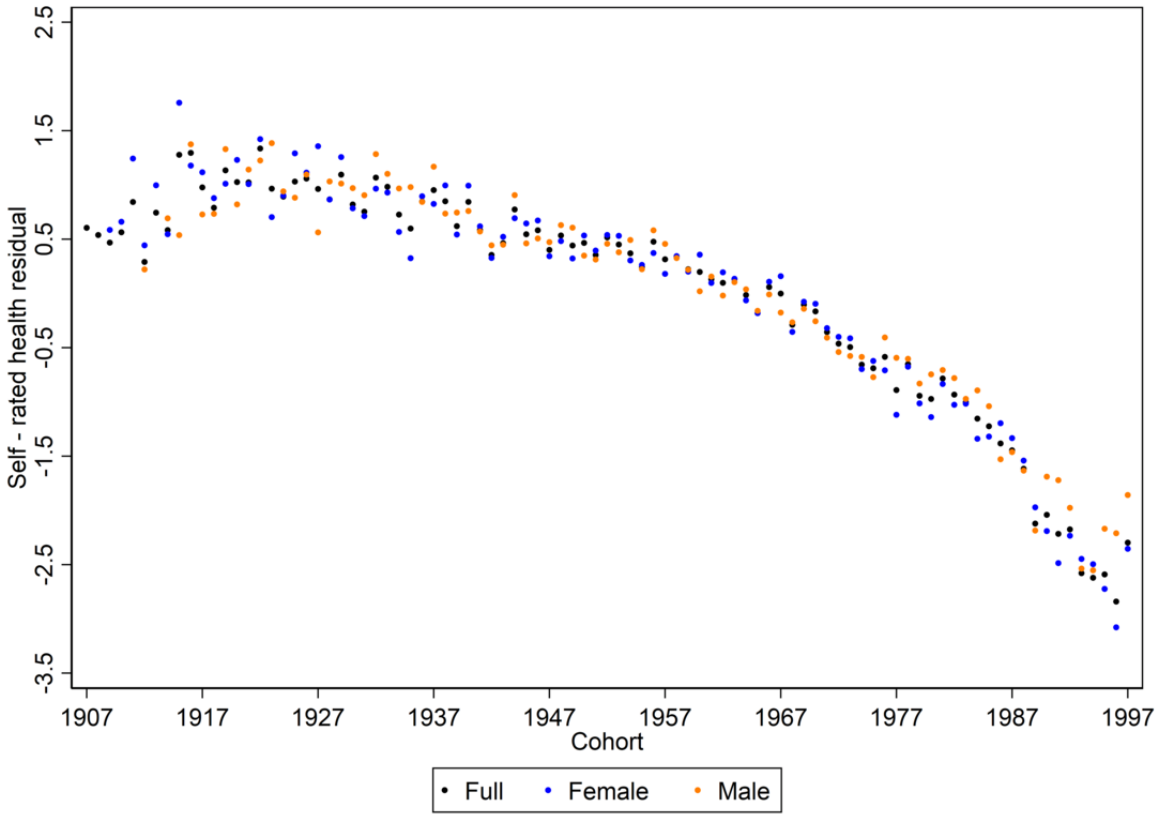

Figure 3.S 2 Estimated cohort random residuals for log-odds of poor health for each sample

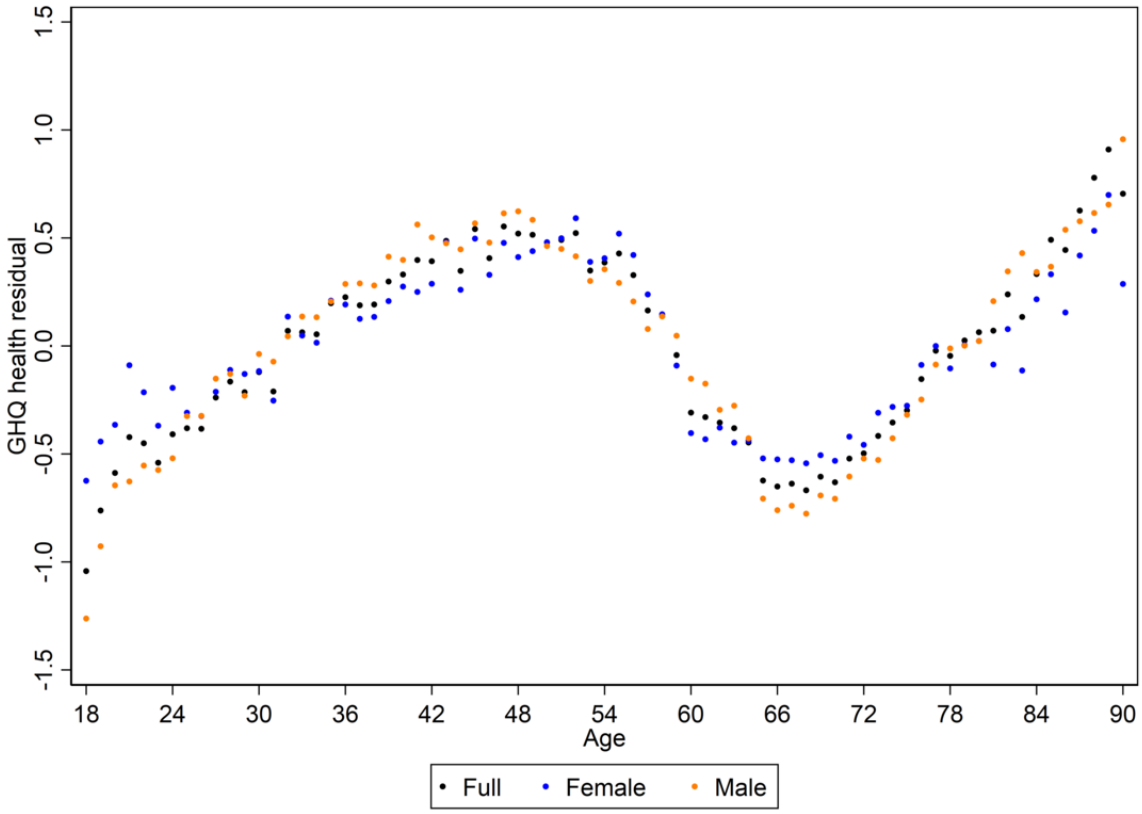

Figure 3.S 3 Estimated age random residuals for mental health for each sample

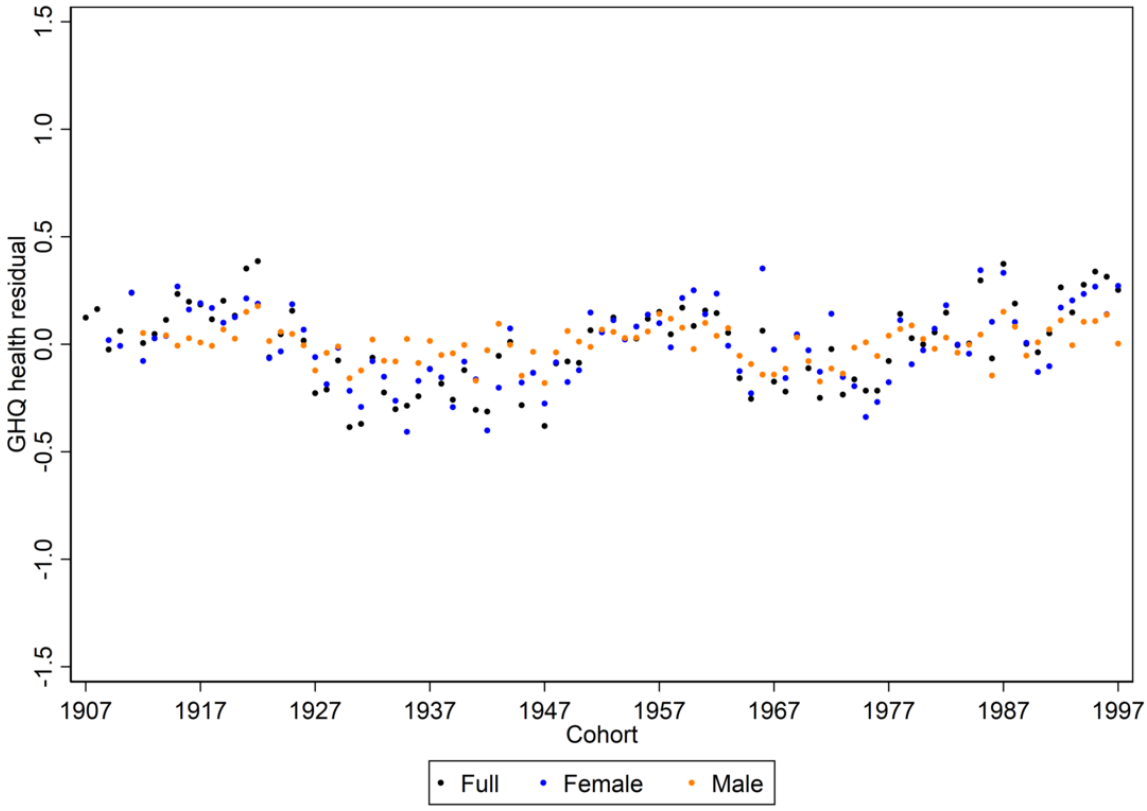

Figure 3.S 4 Estimated cohort random residuals for mental health for each sample

Introduction to Chapter 4

The previous chapter investigated the shape of age and cohort trends in self-rated health and mental health over a 26-year period. An exploratory, non-parametric approach utilising random effects modelling was employed to reveal the trends in these temporal dimensions without the need to *a priori* impose a structure on the data or expected trajectories. The second thesis research question is: Is heightened exposure to deprivation over time associated with worse general health and how does neighbourhood deprivation interact with social capital and individual-level disadvantage? To address this question, I build on the baseline understanding from the previous empirical piece and make a first exploration into how deprivation relates to health trajectories.

Exposure to neighbourhood environments is an area of long-standing interest in health research; the neighbourhood effects paradigm in particular has been predominant in assessing how the varying social and physical features of neighbourhoods and their degree of disadvantage relates to different health outcomes (Arcaya et al., 2016; Diez Roux and Mair, 2010; Kawachi and Berkman, 2003; Riva et al., 2007; Van Ham et al., 2012). Importantly for this thesis project, neighbourhood and individual-level deprivation are considered sources of stress and potentially stressful experiences. As such they are implicated in the 'stress pathway', the theoretical mechanism linking exposures to health under study in this thesis. This chapter investigates relationships with deprivation and self-rated health, drawing again on the strengths of the British Household Panel Survey (BHPS) and Understanding Society longitudinal datasets to explore heterogeneity in health relationships. Interactions between deprivation and age are explored in order to examine how trajectories may vary across the intensity of disadvantage and to explore the changing importance of neighbourhood across the lifecourse. Chapter 2 highlighted the need for nuanced understandings of health and place relationships, and the appreciation of the inherent heterogeneity in relationships and health dynamics over time. Therefore, to explicate some of the complexities of health and place relationships, this analysis explores interaction effects: between neighbourhood and individual-level disadvantage to test a 'double jeopardy' hypothesis; and between

neighbourhood deprivation and social capital. Social capital is theorised to be a resource which conveys health benefits and that can alleviate the negative impacts of deprivation through acting as a 'stress-buffer'. It is, therefore, an important component of the stress pathway to investigate, particularly as mechanisms for resilience to stress exposure over time offer potential avenues for interventions or public health planning.

Included at the end of this chapter is a supplementary table of results. These additional tests show the findings when the analysis was repeated with a sample of BHPS participants who were present and interviewed at every wave possible (24 timepoints as the BHPS sample was not joined to Understanding Society until Wave 2). This serves as a sensitivity test of the robustness of the results to selection effects and attrition bias.

Chapter 4. How does deprivation relate to health over time?

I Introduction

Health inequalities along social gradients continue to be an ever-present feature in health studies (Marmot, 2010; Prior and Manley, 2018; World Health Organisation, 2008). Personal characteristics of status as well as the deprivation and disadvantage of neighbourhoods are key factors that relate consistently to gradients in health states. Works such as the *Black Report* (Townsend and Davidson, 1982) and the project of the Commission on Social Determinants of Health (World Health Organisation, 2008) have been instrumental in highlighting the connections of social status and health gradients across a variety of outcomes. To understand how these health gradients develop it is vital to interrogate relationships between exposures and health over a long-time period. In doing so, we are better able to develop new understandings that allow enriched explanations of divergent health trajectories. Crucially, considering a longer time frame than has been done previously sheds new light on when inequalities develop, and how they persist through time.

Exposure to deprived neighbourhood environments is an oft-studied factor in health research. Theorisations such as the stress pathway hypothesis posit that area deprivation relates to health by patterning stress exposure over time, for instance through socially disordered environments, or fewer opportunities for accessing high-quality local amenities. The neighbourhood effects research paradigm has produced a plethora of research seeking to demonstrate whether or not and, if they do then how, neighbourhood circumstances relate to individual health and social outcomes. The challenge has often been to demonstrate how much of the apparent impact falls beyond the influence of individual or 'compositional' circumstances – that is the characteristics of individuals within place, as opposed to the 'contextual' features of places (Diez Roux and Mair, 2010; Kawachi and Berkman, 2003; Van Ham et al., 2012; Wilson, 1987). Many studies have shown relationships between neighbourhood socioeconomic status, deprivation or poverty and various physical and mental health outcomes (Arcaya et al., 2016; Pickett and Pearl, 2001; Riva et al., 2007). For example, Poortinga et al. (2008) demonstrated inequalities in self-rated health across a standardised

score of neighbourhood deprivation, which remained after controlling for individual-level social and economic characteristics. However, this study, and many others within the neighbourhood health literature, are cross-sectional. A dearth of longitudinal research and lifecourse perspectives, vital resources in understanding health inequalities and their progression over time, remains to be addressed in the literature.

However, there are some examples of neighbourhood-health studies which have utilised longitudinal designs. For example, baseline neighbourhood socioeconomic disadvantage was related to a higher risk of reporting worse self-rated health after a 10-year follow-up in a United States based study (Xiao et al., 2017). Similarly, in a study of elderly adults, Toma et al. (2015) reported associations between perceptions of neighbourhood disorder and mental wellbeing after 4 years, which remained significant after controlling for other sociodemographic circumstances and health conditions. In contrast, associations of a composite measure of neighbourhood deprivation with subsequent mortality in a Swedish study became insignificant on accounting for individual socioeconomic characteristics (Malmstrom et al., 2001). Despite such inconsistent evidence, studies have also shown that cumulative measures of neighbourhood circumstances are stronger predictors than single-point-in-time measures of concurrent neighbourhood exposure for BMI (Yang and South, 2018) and self-rated health (Phuong Do, 2009). These studies suggest that the influence of deprivation on health may act in an accumulative fashion, with longer exposure associated with worse outcomes.

In addition to accumulative influences of neighbourhood conditions, following the traditions of lifecourse epidemiology (Ben-Shlomo and Kuh, 2002; Elder, 1998), some studies have shown how contextual exposures at certain points in life can relate to later-life health. For example, Johansson et al. (2015) demonstrated how adolescent exposure to neighbourhood disadvantage predicted total adult alcohol consumption through to mid-life. Moreover, Dundas et al. (2014) showed that multiple childhood contexts (school and neighbourhood) were associated with adult self-rated health at 47 years. These studies point to a role of lifecourse contextual exposures in the development of adult health inequalities. Datasets from different life stages can also help to reveal when social gradients may be more important

to health inequalities. For example, Fagg et al. (2013) investigate the so-called 'socioeconomic equalisation in youth hypothesis', which posits that health inequalities in adolescence will be smaller than childhood and adulthood, thanks to the shifting importance of particular social status cues. They test the hypothesis in reference to neighbourhood deprivation throughout adolescence and find no evidence of a significant gradient in self-esteem across the deprivation spectrum (Fagg et al., 2013). Gimeno et al. (2008) used measurements of socioeconomic status and C-reactive protein (a biomarker of chronic inflammation theorised to be related to cardiovascular conditions) to show that individual-level social inequalities were only evident in adulthood. Through increasing understanding of when health inequalities related to social and contextual exposures originate and manifest, these studies highlight the benefit of longitudinal health research.

Longitudinal data can also be valuable in exploring heterogeneity in individual health trajectories, improving our understanding of how contextual exposures contribute to the progression of inequalities over time. Here again, though, there are conflicting accounts in the literature. Ellaway et al. (2012) reported that those living in deprived areas were "Getting sicker quicker" (Ellaway et al., 2012: 132) in terms of their self-rated health over a 20-year period. In contrast, results from Godhwani et al. (2018) did not show an association between baseline measures of neighbourhood deprivation and dissatisfaction and an increased chance of reporting worse health over time. Heterogeneity in deprivation-health relationships can exist along many different axes. For instance, in their study of neighbourhood deprivation and health in Canada, White et al. (2011) showed that the influence of deprivation on self-rated health, whilst consistently worsening heath, was variable in strength depending on the geographic region. Additionally, variability in deprivation itself within areas may also impact on morbidity. For example, Boyle et al. (1999, 2001) used UK Census data to demonstrate that variations of deprivation within areas related to Limiting Long-Term Illness (LLTI), as well as overall levels of deprivation. Moreover, Boyle et al. (2001) indicated that their measure of variation within areas had a stronger impact on LLTI than the absolute level of deprivation. These results suggest a role for relative deprivation in health relationships; greater variation within areas means larger inequalities.

A role for relative deprivation could also manifest through an interaction between neighbourhood and individual disadvantage, with, for instance, the health of lower status individuals being worse in more affluent areas, where their status would be in higher contrast to their neighbours. However, other studies make the case for a 'double jeopardy' of disadvantage, where the negative influence of neighbourhood circumstances is exacerbated for individuals in personally disadvantaged situations. Stafford and Marmot (2003) investigated both scenarios and found limited evidence of a 'double jeopardy' scenario where neighbourhood deprivation and low individual-level socioeconomic status interacted to predict poorer health, more financial problems and reporting more neighbourhood issues. A more recent study explored the validity of competing hypotheses for the differential impact of neighbourhood deprivation in relation to cardiovascular health outcomes and also demonstrated a case for 'double jeopardy' (Boylan and Robert, 2017).

Another sphere of literature which considers variability in the impact of disadvantage and neighbourhood deprivation is that which considers the stress-buffering role of social capital and support (Kawachi and Berkman, 2001; Uphoff et al., 2013). Neighbourhood deprivation could influence health through a variety of behavioural, social, economic and biological mechanisms. One commonly theorised pathway imagines a deprived neighbourhood environment as a context which invokes stress, with long-term and repeated exposure to stressors related to poor health (Boardman, 2004). Social capital is a multidimensional concept that has been variously defined though the central premise lies in social capital as a resource accrued, whether at the individual or collective level, through the action of social interactions and networks (Bourdieu, 1986; Coleman, 1988; Putnam, 2000). These social networks can be informal or formal, actual or virtual. Aspects of social capital are theorised to act as a resource to alleviate the detrimental impact of deprivation through stress. Most often it is facets of social capital related to support which are implicated in stress-buffering hypotheses (Cohen and Wills, 1985). For example, results from Bostean et al. (2018) supported a stress-buffering model; the negative impact of neighbourhood stressors was reduced for individuals with high social support from family. Similarly, Klijs et al. (2017) demonstrated that neighbourhood deprivation and social relations interacted, so that

deprivation predicted poorer mental health only for those with fewer and poorer social relations.

Another aspect of social capital is that of social participation, which is the aspect under consideration in this chapter. Social participation refers to engagement and activity in communities or society, for instance through interactions with community groups or through political activity such as voting. Whereas social support features in discussion of a stress-buffering model of social capital, social participation is more often considered through a main effects model – that is one in which social capital is deemed to have a direct beneficial impact on health and wellbeing (Kawachi and Berkman, 2001). For example, Giordano and Lindstrom (2010) demonstrated increasing levels of social participation over time related to improved self-rated health. However, it is still possible to hypothesise that social participation in groups and organisations may help to offset the detrimental impact of residence in more deprived neighbourhoods. Qualitative research has shown that participation can offer opportunities for socialisation and the establishment of relationships, can enhance self-esteem and a sense of control (Cattell, 2001), as well as help foster a sense of neighbourhood belonging (Elliott et al., 2014), all of which could provide resources to cope with stress. Additionally, social participation could play a role in heterogeneous neighbourhood relationships as a contextual or community resource. Aminzadeh et al. (2013) found a positive effect of high organisation membership within neighbourhoods on student wellbeing in New Zealand, with a stronger positive effect for participants with low socioeconomic status. Therefore, both main and stress-buffering effects of social capital, as represented by the dimension of social participation, will be investigated. Examining interactions of deprivation across multiple levels and with other social characteristics is, therefore, a useful tool in understanding when and for whom health inequalities exist. Neighbourhood and health associations are clearly heterogeneous and more research is needed to understand how exposures throughout time may varyingly contribute to health inequalities.

This analysis seeks to contribute to the health inequalities literature by investigating the relationship of neighbourhood deprivation and self-rated health over time in a large, nationally representative sample of adults from Great Britain. Over 25 years' worth of data is

employed to understand how exposures relate to the progression of health inequalities and to explore heterogeneity in deprivation relationships according to individual-level disadvantage and measures of social capital. The following research questions are addressed: (1) Is higher exposure to deprived environments (both at the neighbourhood and individual level) associated with worse health? (2) How does deprivation relate to temporal trends in health and do health trajectories vary between neighbourhoods? (3) Is higher social capital related to better health and does it alleviate the negative impacts of deprivation on health? (4) Is there a double jeopardy of deprivation whereby neighbourhood deprivation exacerbates individual disadvantaged status?

II Data

Data is drawn from the British Household Panel Survey (BHPS) and Understanding Society, The UK Household Longitudinal Study (UKHLS) (University of Essex et al., 2018b). These longitudinal studies provide high quality social and health data with which to investigate our questions of deprivation and health relationships over time.

The BHPS is a panel study of households, interviewing each adult household member annually, initially in 1991 and then for a subsequent 18 waves. At Wave 18 of the BHPS, participants were asked whether they would consent to continuing to be sampled as part of the larger UKHLS, and those who agreed were first interviewed at Wave 2 of UKHLS. The UKHLS follows in the scheme and purpose of the BHPS but is it much larger in scale: the first wave of the UKHLS achieved around 43,500 full (or proxy) individual interviews, in comparison with the first wave of the BHPS which totalled around 10,000 interviews. This study uses the Great Britain components of the general population samples from the UKHLS and BHPS, and additionally includes the small boost samples (~1,500) for Scotland and Wales which were recruited at Wave 9 of the BHPS. Waves 1 to 18 of the BHPS, and Waves 1 to 7 of UKHLS are used, covering the period 1991 to 2017 in total and providing a decades long time frame to assess health inequalities. More information on the studies can be found in their user guides, see Knies (2018), Fumagalli et al. (2017) and Taylor et al. (2010).

This analysis is focused on investigating relationships between health and neighbourhood deprivation. Here we consider the 'neighbourhood' to correspond to Lower Layer Super Output Area (LSOA) or the equivalent Scottish Data Zone (DZ). These are small-area geographies which were designed to improve statistics reporting. LSOAs in England and Wales have an average population of approximately 1,600 individuals (the population range is between 1,000 and 3,000 individuals) (Office for National Statistics, 2012). Scottish DZs have slightly smaller populations on average, around 750 individuals (Flowerdew et al., 2007). These statistical geographies were also designed to represent social homogeneity, within the bounds of usability and size (Flowerdew et al., 2007; Office for National Statistics, 2018a). Therefore, whilst we recognise the issues of using static, bounded units to represent neighbourhood context and real-life dynamic exposure (as noted in Chapter 2), the LSOA and DZ geographies provide a practical neighbourhood representation which is in keeping with many neighbourhood effects studies.

Neighbourhood deprivation is represented by Townsend deprivation score (Townsend, 1987). This deprivation measure summarises the z-scores of the percentage of four metrics of disadvantage within areas: non-car ownership, household overcrowding, non-home ownership and unemployment. Positive Townsend scores indicate areas which are more deprived than average, negative scores areas which are less deprived. Data from the 1991, 2001 and 2011 UK Censuses are used to calculate Townsend scores, which are harmonised so that they are provided for the 2011 LSOA or DZ units[2]. The harmonisation methodology is detailed in Norman (2010, 2016) and Norman and Darlington-Pollock (2017). Harmonised Townsend deprivation scores are matched to the main dataset by 2011 LSOA or DZ code (University of Essex et al., 2018a; University of Essex and Institute for Social and Economic Research, 2014a). For the Understanding Society waves this is a straightforward match by 2011 LSOA code (University of Essex et al., 2018a). However, the original BHPS dataset is only available matched to 2001 LSOA code (University of Essex and Institute for Social and Economic Research, 2014a), having been completed before the introduction of the new

[2] The 1991, 2001 and 2011 Townsend scores and quintiles linked with the 2011 LSOA codes were provided to the author by Paul Norman.

Census geography. Therefore, 2001 LSOA codes are matched to their 2011 counterparts (Office for National Statistics, 2018b). For England and Wales, we chose simply to keep those areas which were unchanged between 2001 and 2011 (this was 97% of the England and Wales LSOA codes in the sample). For Scotland, where the small-area geography is based on Data Zones (DZs), the shift from 2001 to 2011 involved the creation of an entirely new set of codes. Using the 2001 DZ centroids and 2011 DZ boundaries (Scottish Government, 2018a, 2018b), a point-in-polygon matching approach is taken: where the 2001 centroid fell inside the 2011 boundary (the case for 94% of Scottish DZs in the sample), those areas are kept as matched and used for linkage to the deprivation data.

The response is self-rated health, which is widely used and regarded as a valid instrument to measure overall subjective health status (Jylhä, 2009; Young et al., 2010). There were two versions of the self-rated health question which were asked during the course of the BHPS and UKHLS. Excepting Wave 9, BHPS respondents were asked "Please think back over the last 12 months about how your health has been. Compared to people of your own age, would you say that your health has on the whole been…", scoring their responses as "Excellent", "Good", "Fair", "Poor" or "Very Poor". In Wave 9 of the BHPS and all waves of the UKHLS, participants were asked "In general, would you say your health is…", possible responses were "Excellent", "Very good", "Good", "Fair" and "Poor". At Wave 14 of the BHPS both measures were reported, and given that the correlation between the measures was high (0.84, $p < 0.000$), they are similarly dichotomised in this analysis (0 represents health which is good or better, 1 indicates fair or worse health status). Therefore, this study is modelling the underlying probability of being in poor health compared with good health. The dichotomisation treatment affords investigation of health trajectories in subjective health over the 26-year period.

Temporal trends are captured through age and cohort variables. Age is continuous, ranging between 18 and 90 years old, and centred around the mean age (in full years) of 48. Cohort is defined by birth year and is also treated as continuous, centred around the average year 1959. In the previous chapter, the non-parametric exploratory analysis of age and cohort

trends revealed distinct curvilinear patterning. Therefore, quadratic terms are also included for both age and cohort.

To assess individual-level deprivation, a subjective measure of current financial situation is employed. Throughout the BHPS and UKHLS, respondents were asked "How well would you say you yourself are managing financially these days? Would you say you are…", scoring their answers as "Living comfortably", "Doing alright", "Just about getting by", "Finding it quite difficult" or "Finding it very difficult". These responses are grouped into three categories; 'doing alright' and 'living comfortably' are clustered into the top category, with those finding it quite or very difficult grouped into the bottom category. A subjective measure of financial situation is chosen over representing individual disadvantage through income. The relative buying power and status associated with a particular absolute income may have changed over the course of the surveys, whereas a subjective evaluation is more likely to naturally account for shifting economies over time.

Social capital is assessed by a social participation dimension, as capture by two variables: membership in organisations and activity in organisations. Participants were asked whether they were currently a member of any of a list of organisations, and the subsequent variable was a count of the number of organisations respondents reported being a member of, using the 13 organisation types that were asked consistently throughout the survey[3]. Participants were also asked whether they joined in the activities of the same list of organisations, whether or not they were a formal member, and this was summarised by a count of organisation activity. These questions were asked at the first 5 waves of the BHPS and then bi-annually, and in Waves 3 and 6 of UKHLS. Where the questions were not asked in a wave the information from the previous wave is substituted. Both the membership and activity variables range between 0 and 10.

Other sociodemographic characteristics that may be important to health and which could themselves account for apparent deprivation-health associations are also included as covariates. Education is assessed through highest educational qualification, input as the

[3] The full list and their occurrence in the dataset can be accessed online (www.understandingsociety.ac.uk).

following categories: Degree or other higher, A-Level or GCSE equivalent, and other or no qualifications. Employment status is another categorical variable, comprising: employed (including self-employed, part-time employed and government training scheme or apprenticeship), retired, and inactive (which includes the unemployed, full-time students, long-term sick or disabled, unpaid work in a family business, those on maternity leave or doing something else). Household tenure consists of three categories: owner occupied, socially rented and privately rented. Marital status is a dichotomous variable, comparing those who are married or living together with those who are single, separated, divorced or widowed. Sex is another binary variable, where female is the reference category. Before analysis, correlations between the sociodemographic characteristics were assessed to gauge whether there were issues of multicollinearity. The highest correlation was between subjective financial situation and tenure at 0.25 suggesting multicollinearity was unlikely to be an issue for these individual characteristics. The full table of correlations is available in the Supplementary Information.

III Methods

To investigate the relationship between health and deprivation trajectories, this chapter employs multilevel modelling. Multilevel models can account for the complex structure of data, simultaneously modelling at different levels of analysis (Goldstein, 1994; Snijders and Bosker, 2012; Steele, 2008). In addition, a multilevel approach enables assessment of cross-level interactions, investigating for instance the question of a double jeopardy of neighbourhood and individual deprivation, as well as the exploration of complex heterogeneity in temporal trends (Duncan et al., 1998; Jones, 1991). The data here have a three-level cross-classified structure: measurement occasion is the lowest level (Level 1), and these occasions are nested within both individuals (Level 2) and neighbourhoods (Level 3).

The response is binary requiring a multilevel logistic regression (see Equation (1)), where the response is the logit of the underlying probability of being in poor health. The subscripts *i*, *j*, and *k* indicate the occasion, individual and neighbourhood level respectively, and *X*, *W*, and *Z*

represent sets of time-varying (occasion level), time-invariant (individual level) and neighbourhood level variables respectively.

$$logit(\pi_{ijk}) = \beta_0 + \beta_1 X_{ijk} + \beta_2 W_{jk} + \beta_3 Z_k + u_j + u_k \quad (1)$$
$$u_j \sim N(0, \sigma^2{}_{u1})$$
$$u_k \sim N(0, \sigma^2{}_{u2})$$
$$var(y_{ijk} | \pi_{ijk}) = \pi_{ijk}(1 - \pi_{ijk})/n_{ijk}$$

A series of models are run to investigate the research questions. Model 0 is a null model which partitions the variance in self-rated health between the three levels. Secondly, a model including the age, cohort and sex terms is run, to establish the relationship of these basic demographic and temporal variables to self-rated health. The next step, Model 2, involves the initial assessment of how neighbourhood deprivation relates to self-rated health through the addition of Townsend deprivation to the model. This is followed by Model 3 which tests variability in the age and health relationship between neighbourhoods and whether neighbourhood deprivation interacts with age. Model 4 includes all the sociodemographic covariates and social capital to assess how the relationship of Townsend deprivation with self-rated health is impacted by compositional characteristics. This model also serves to test a main effects model for the relationship of social participation with self-rated health. Next, a series of cross-level interaction terms are tested. These investigate whether there is a double jeopardy of neighbourhood and individual-level deprivation whereby the negative impact of living in a deprived area is worse for those who are personally struggling financially. Another cross-level interaction tests whether social capital has a stress-buffering effect where having high social capital alleviates the effects of deprivation.

Dataset preparation is carried out in Stata version 15 (StataCorp, 2017) and analysis completed in MLwiN version 3.01, using Markov Chain Monte Carlo (MCMC) estimation (Browne, 2017; Charlton et al., 2017). Models are run for 500,000 iterations, with a burn-in of 5,000, in order to achieve convergence on all parameters and an estimated sample size of at least 200 on all parameters. Orthogonal parameterisation and hierarchical centring on the neighbourhood level are used to help achieve convergence and improve model run-time (Browne, 2017).

IV Results

The response is self-rated health. Around 75% of the observations showed good or better health, compared with approximately 25% which displayed fair or worse health. As demonstrated in Table 4.1, across all waves the majority of respondents were: male; living comfortably or doing alright financially; educated to A-Level or GCSE level; employed; owner occupiers; and married or living together with a partner. The mean Townsend deprivation score across all waves is -0.66, suggesting the typical neighbourhood in the sample is slightly less deprived than the national average. There is a slight positive skew in Townsend scores; the majority of areas are relatively less deprived with a smaller number of more highly deprived neighbourhoods.

Results from the models are presented in Table 4.2. Calculating the Variance Partitioning Coefficient (VPC)[4] (Goldstein et al., 2002) for Model 0, the null model without covariates, reveals that the majority of variation in self-rated health (65%) lies between individuals. Almost 7% of the variation lies between neighbourhoods in Model 0. Given that our neighbourhood units are relatively small, our sample covers a long time period and that health can be influenced by many varied factors, 7% of variation lying at the neighbourhood level is substantial. Moreover, when compared to a simple two-level hierarchical model of occasions and individuals, the addition of the neighbourhood classification resulted in a significant model improvement as measured by the Deviance Information Criterion (DIC).

Model 1 shows the results for adding the age and cohort variables. Following the results of the previous chapter where interactive effects of these temporal effects were present, an interaction term is also included. The age by cohort influence on the log-odds of poor health is shown in Figure 4.1: younger cohorts are less likely to be in poor health than their older generation counterparts. It also shows a trend of declining health by age, with elderly persons showing higher log-odds of being in fair or worse health. Figure 4.1 additionally demonstrates how the development of self-rated health by age changes over the lifecourse. For the youngest cohorts, health appears to improve as these groups age. However, through the

[4] The occasion level residuals follow a standard logistic distribution where the variance is equal to $\pi^2/3$, here rounded to 3.29.

middle-aged cohorts the pattern reverses so that the oldest cohorts from the start of the 20th Century demonstrate declining self-rated health with age.

Table 4.1 Descriptive statistics

		N	%
Self-rated health	Good	432,274	75.26
	Poor		24.74
Sex	Male	438,530	53.76
	Female		46.24
Subjective Financial Situation	Comfortable/Doing alright	416,076	65.79
	Just getting by		25.23
	Finding it difficult		8.98
Education Level	Degree/Other higher	433,658	29.19
	A Level/GCSE		42.74
	Other/No qual.		28.07
Employment Status	Employed	438,088	58.19
	Retired		23.18
	Unemployed/Inactive		18.63
Tenure	Owned	435,888	73.48
	Socially rented		10.48
	Privately rented		16.04
Marital Status	Married/Living together	438,182	67.17
	Single/SDW		32.83
		N	Mean (SD)
Townsend Deprivation		438,457	-0.66 (2.99)
Age		438,531	47.88 (17.90)
Cohort		438,531	1958.74 (18.55)
Organisation Membership		310,772	1.11 (1.06)
Organisation Activity		411,636	0.68 (0.95)

Table 4.2 Estimated median MCMC parameter coefficients, standard errors and their 95% credible intervals

	Model 0			Model 1			Model 2		
		Credible Interval			Credible Interval			Credible Interval	
	Beta	2.5%	97.5%	Beta	2.5%	97.5%	Beta	2.5%	97.5%
Fixed Part									
Sex									
Male				-0.221	-0.273	-0.170	-0.212	-0.263	-0.161
Age				-0.021	-0.024	-0.018	-0.021	-0.024	-0.018
Age^2				-0.003	-0.003	-0.002	-0.004	-0.004	-0.003
Cohort				-0.078	-0.081	-0.075	-0.079	-0.082	-0.075
Cohort^2				-0.005	-0.005	-0.005	-0.006	-0.006	-0.006
Age*Cohort				-0.008	-0.009	-0.008	-0.010	-0.011	-0.010
Deprivation							0.117	0.110	0.125
Deprivation*Age									
Financial situation									
Just getting by									
Finding it difficult									
Education level									
A Level/GCSE									
Other/No qual.									
Employment status									
Retired									
Unemployed/Inactive									
Tenure									
Privately rented									
Socially rented									
Marital status									
Single/SDW									
Org. Membership									
Org. Activity									
Deprivation* Just getting by									
Deprivation* Finding it difficult									
Cons	-2.432	-2.466	-2.398	-2.179	-2.228	-2.129	-2.055	-2.104	-2.006
Random Part									
Level: Neighbourhood									
Var(cons)	0.797	0.733	0.858	0.738	0.677	0.801	0.622	0.57	0.678
Covar(age/cons)									
Var(age)									
Level: Individual									
Var(cons)	7.582	7.384	7.785	6.839	6.659	7.024	6.596	6.422	6.776
DIC:	306389			300831			301293		
Units									
Neighbourhood	22604			22604			22600		
Individual	73380			73380			73374		
Observation	432274			432273			432199		

Table 4.2 continued. Estimated median MCMC parameter coefficients, standard errors and their 95% credible intervals

	Model 3			Model 4			Model 5		
		Credible Interval			Credible Interval			Credible Interval	
	Beta	2.5%	97.5%	Beta	2.5%	97.5%	Beta	2.5%	97.5%
Fixed Part									
Sex									
Male	-0.213	-0.263	-0.163	-0.086	-0.141	-0.033	-0.087	-0.140	-0.032
Age	-0.021	-0.024	-0.017	-0.035	-0.039	-0.031	-0.035	-0.039	-0.031
Age^2	-0.004	-0.004	-0.003	-0.005	-0.006	-0.005	-0.005	-0.006	-0.005
Cohort	-0.079	-0.082	-0.075	-0.083	-0.088	-0.079	-0.083	-0.088	-0.079
Cohort^2	-0.006	-0.006	-0.006	-0.007	-0.008	-0.007	-0.007	-0.008	-0.007
Age*Cohort	-0.010	-0.011	-0.010	-0.013	-0.014	-0.012	-0.013	-0.014	-0.012
Deprivation	0.131	0.123	0.138	0.069	0.060	0.077	0.073	0.063	0.083
Deprivation*Age	0.002	0.002	0.003	0.002	0.001	0.002	0.002	0.001	0.002
Financial situation									
Just getting by				0.398	0.365	0.431	0.395	0.362	0.428
Finding it difficult				0.738	0.687	0.789	0.740	0.688	0.791
Education level									
A Level/GCSE				0.438	0.377	0.500	0.438	0.376	0.499
Other/No qual.				0.925	0.850	1.001	0.925	0.850	1.000
Employment status									
Retired				0.204	0.144	0.264	0.205	0.145	0.265
Unemployed/Inactive				0.710	0.666	0.753	0.712	0.668	0.756
Tenure									
Privately rented				0.247	0.183	0.310	0.246	0.182	0.310
Socially rented				0.594	0.530	0.658	0.596	0.533	0.659
Marital status									
Single/SDW				0.098	0.053	0.144	0.098	0.053	0.143
Org. Membership				-0.046	-0.066	-0.025	-0.046	-0.066	-0.025
Org. Activity				-0.091	-0.111	-0.071	-0.091	-0.112	-0.071
Deprivation* Just getting by							-0.007	-0.018	0.004
Deprivation* Finding it difficult							-0.018	-0.033	-0.003
Cons	-2.021	-2.069	-1.972	-2.705	-2.777	-2.633	-2.702	-2.775	-2.630
Random Part									
Level: Neighbourhood									
Var(cons)	0.579	0.522	0.637	0.393	0.342	0.447	0.389	0.337	0.445
Covar(age/cons)	0.009	0.007	0.011	0.005	0.003	0.007	0.005	0.003	0.007
Var(age)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Level: Individual									
Var(cons)	6.438	6.267	6.616	4.693	4.541	4.853	4.695	4.540	4.853
DIC:	300196			216999			217006		
Units									
Neighbourhood	22600			19692			19692		
Individual	73374			52290			52290		
Observation	432199			300549			300549		

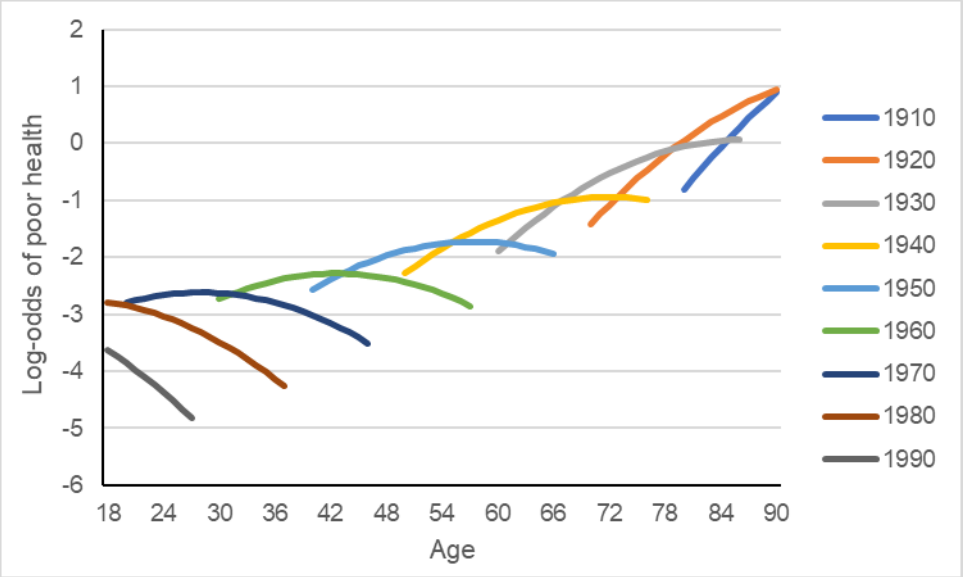

Figure 4.1 Predicted log-odds of poor self-rated health by age and 10-year cohort groups

Model 2 shows the results for when Townsend deprivation is added. A simple linear term is used to describe the relationship of neighbourhood deprivation with self-rated health. When quintiles of deprivation are included (results not presented) – allowing the deprivation relationship to exhibit non-linearity – a linear pattern was still shown demonstrating that our simple parameterisation adequately summarises the deprivation-health relationship. Townsend deprivation is significantly associated with self-rated health, ranging between around a 5% probability of being in poor health for the least deprived, compared with an approximate 30% probability of poor health for the most deprived areas. The addition of neighbourhood deprivation in Model 2 explains 16% of the between neighbourhood variation in self-rated health that was present in Model 1. However, comparison of the DIC between Model 2 and Model 1 shows that the addition of the Townsend score does not significantly improve model fit, despite the association running in the hypothesised direction.

Model 3 explores variability in the neighbourhood deprivation and health relationship by age. An interaction is present as demonstrated in Figure 4.2. It shows that for younger ages there is little effect of neighbourhood deprivation on the predicted log-odds of being in poor health. In comparison, at older ages the gradient in predicted health across the range of

Townsend scores is much steeper, with relatively more deprived areas associated with worse health. This interaction continues to be significant even after accounting for the sociodemographic and economic characteristics of individuals in subsequent models.

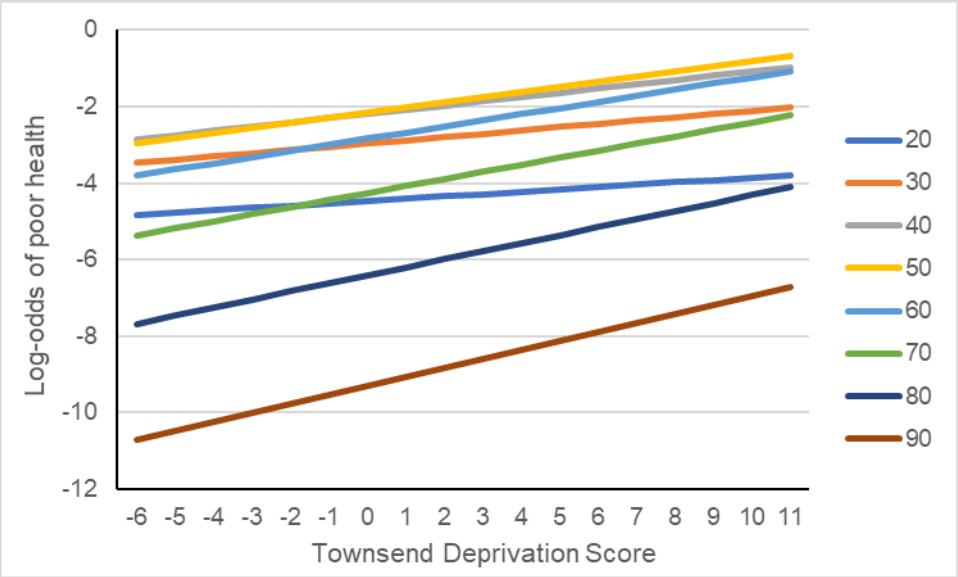

Figure 4.2 Predicted log-odds of poor self-rated health by neighbourhood deprivation and 10-year age groups

Model 3 also allows the linear effect of age to vary between neighbourhoods. The between neighbourhood variance by age is presented in Figure 4.3. This shows that variation in the effect of age on self-rated health is highest for older ages, with less variation between neighbourhoods around early middle-age (35 to 40 years of age). Therefore, while the interaction of neighbourhood deprivation and age shows that deprivation is more strongly related to worse health for older persons, the impact of old age on self-rated health is also more variable between neighbourhoods. The addition of the deprivation-age interaction and the age random slope term results in a significant improvement over Model 2 and Model 1.

When the sociodemographic and social capital variables are added in Model 4, the relationship of neighbourhood deprivation and self-rated health remains significant, though it is diminished in size. As expected, the results for Model 4 show individual-level disadvantage is associated with poorer health. Subjective financial situation displays a clear

gradient, with those who are living comfortably or doing alright having a predicted 11% probability of poor health, compared with an almost 15% probability for those who are just getting by, and an approximate 20% probability for those finding it difficult to get by financially. The other socioeconomic variables also show graded associations with health: those individuals with the fewest or lowest level qualifications, who are unemployed or inactive, who are living in socially rented housing and who are single, separated, divorced or widowed demonstrate the worst self-rated health.

The measures of structural social capital, referring to formal relationships and networks, also display the expected relationships to self-rated health. Being a member of more organisations, as well as being active in a greater number of institutions is associated with a significantly decreased likelihood of reporting poor health. Activity in organisations appears to be the stronger effect. These result supports a direct beneficial influence of social participation on health and the main effects remain similarly patterned when we test cross-level interactions with Townsend deprivation and subjective financial situation in Model 5. However, whilst the main effects of social capital are significant and consistent with health benefits, cross-level interactions between neighbourhood deprivation and organisation membership or activity were not significant (results not shown). The impact of neighbourhood deprivation on self-rated health did not vary with social capital. Only the main effects of the structural social capital variables are, therefore, included in the model results.

Next, Model 5 tests the double jeopardy hypothesis by including a cross-level interaction between neighbourhood deprivation and subjective financial situation. A significant interaction is identified, as portrayed in Figure 4.4. However, the results run contrary to the double jeopardy scenario, where we would expect a stronger impact of neighbourhood deprivation for those that are also struggling financially. Figure 4.4 instead shows that while those who are finding it difficult financially show the worse self-rated health, the gradient across Townsend deprivation scores is slightly steeper for those who are doing alright or living comfortably. The results also demonstrate that as neighbourhood deprivation increases, the difference between the classes of financial situation decreases.

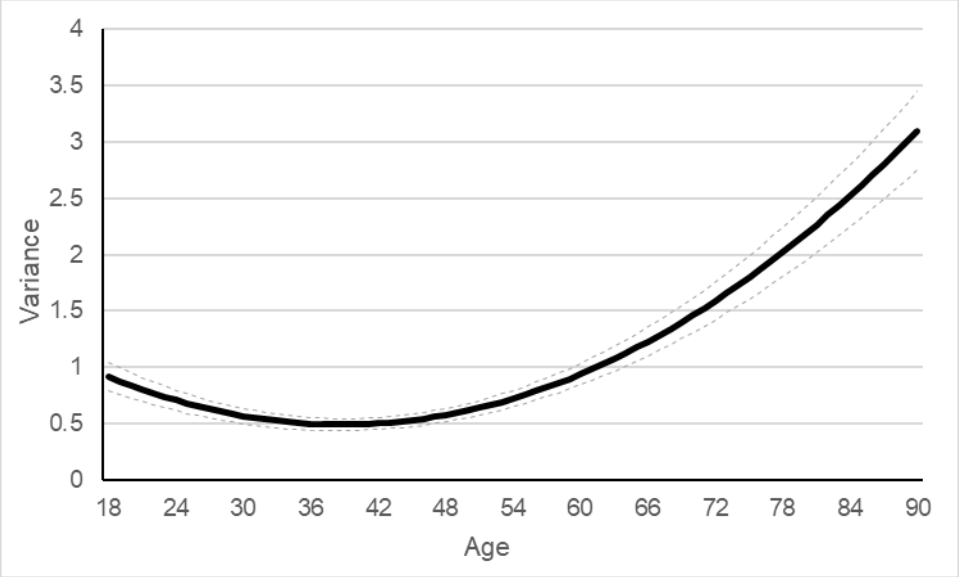

Figure 4.3 Estimated variance between neighbourhoods by age, dashed lines indicate 95% confidence intervals

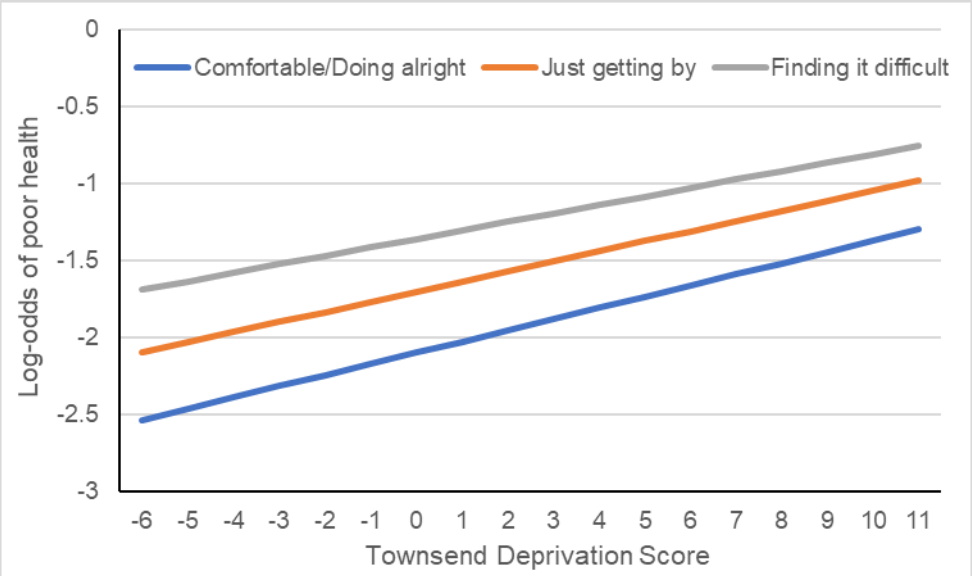

Figure 4.4 Predicted log-odds of poor self-rated health by neighbourhood deprivation and subjective financial situation

V Discussion

This analysis explored how neighbourhood deprivation relates to self-rated health over time. In answer to the first research question, concerning the association of deprivation with worse health, a gradient in health status across the range of Townsend deprivation scores was found. This association was robust to controlling for a range of pertinent individual characteristics that themselves impact on general health. This result joins a plethora of other neighbourhood studies which have indicated associations of neighbourhood disadvantage and various health outcomes (Arcaya et al., 2016; Diez Roux and Mair, 2010; Pickett and Pearl, 2001; Riva et al., 2007). Additionally, in line with previous studies, gradients in health were present across all measures of socioeconomic circumstance (Marmot, 2010; Townsend and Davidson, 1982). Those who were financially struggling, less educated, economically inactive and living in socially rented housing were all more likely to have worse self-rated health. The reflection of social status and neighbourhood disadvantage in self-rated health consolidates the persistent nature of health inequalities. The results also align with the basic premise of the stress-pathway hypothesis: neighbourhood deprivation should be associated with poorer health, thanks to the heightened stress exposure deprived areas convey through the lack or poor-quality of services and amenities, as well as through physical and social disorder (Boardman, 2004; Daniel et al., 2008; Ross and Mirowsky, 2001; Taylor et al., 1997).

Heterogeneity in the relationship between deprivation and health over time was also demonstrated. Firstly, a cross-level interaction was identified between Townsend score and age, which showed that neighbourhood deprivation was more strongly related to self-rated health at older ages, compared with younger ages where the gradient across the Townsend scores was much flatter. Additionally, a random slope for the age effect was also shown to be significant, suggesting the lifecourse ageing effect varied significantly between neighbourhoods. Examination of the variance function showed that neighbourhood variability in the influence of age on self-rated health was greatest for older ages, with middle-age associated more consistently with health across neighbourhoods. Together, these findings represent greater importance of the neighbourhood environment for elderly persons. This result could reflect differences in the relative mobility of older versus younger

persons; older people are more likely to have conditions which limit their mobility (Gould and Jones, 1996) and to have generally more restricted activity spaces (Milton et al., 2015; Temelová and Slezáková, 2014). This means they will be more reliant on local services and amenities, having fewer opportunities for accessing resources beyond the neighbourhood (Milton et al., 2015). For example, Elliott et al. (2014) demonstrated the relationship of neighbourhood cohesion and wellbeing was stronger at older ages, and indicated through qualitative interviews that the relative importance of local groups to older persons and differences in mobility between younger and older persons could play a role in explaining the association. The finding that the difference between deprived and non-deprived areas is more impactful for older persons is, therefore, particularly relevant in light of austerity cuts to health and other local services. Such cuts may disproportionately disadvantage the elderly population and other subsets of the populace who are more reliant on local services, which would work to exacerbate health inequalities (Loopstra et al., 2016; Stuckler and Basu, 2013). Moreover, in light of demographic changes in the United Kingdom and Great Britain, which is increasingly characterised by an ageing population (Bloom et al., 2015; Grundy and Murphy, 2015), the finding that neighbourhoods become increasingly important with age has important policy implications.

Partial support was found for the third research question, which concerned relationships with social capital. The two measures of structural social capital tested in this analysis – summarising the number of organisations people were a member of, or regularly active in – were both significantly related to self-rated health. Greater social participation was related to better health, in line with the conceptualisation of social capital as a beneficial health resource (Kawachi and Berkman, 2001; Moore and Kawachi, 2017) and previous research. For example, Eriksson and Ng (2015) demonstrated that low levels or decreasing social participation was associated with a negative impact on self-rated health, using longitudinal data from northern Sweden. Giordano and Lindstrom (2010) showed that increasing social participation – as measured by being active members of voluntary, community, or leisure groups – was related to improved self-rated health. It should be noted that the influence of both social capital measures on self-rated health was relatively small: the difference in the

predicted probability of being in poor health for being a member of between 0 and 10 organisations was 4%; being active in between 0 and 10 organisations related to a 7% change in the probability of poor health.

The results did not indicate that either of the social capital measures interacted with neighbourhood deprivation. Therefore, it is not possible to offer support for a stress-buffering influence: the effect of neighbourhood deprivation on self-rated health was similar for those participating in few or many organisations. This result stands in contrast to previous research, such as a qualitative study based in East/North East London which indicated participation in organisations was beneficial to health and wellbeing, buffering some of the negative effects of poverty (Cattell, 2001). Other studies have shown that structural components of social capital – that is formal participation in institutions and networks (Moore and Kawachi, 2017) – may be less pertinent to alleviating the negative impacts of deprivation or generally less relevant to health. For example, Yip et al. (2007) demonstrated cognitive measures of social capital were related to self-rated health, psychological health and wellbeing, with little support or consistency shown for relationships of structural social capital with the same outcomes. Additionally, Cohen and Wills (1985) emphasise the importance of matching relevant social resources to particular stressors; social participation in formal organisations may not provide the social resources to effectively alleviate neighbourhood stressors as captured by the Townsend index. However, in this analysis we were limited in the dimensions of social capital we could assess due to the availability of consistent measures at multiple timepoints throughout both surveys.

It may also be that the individual-level is not the scale at which stress-buffering effects of social capital operate to mitigate the impact of neighbourhood deprivation. Multiple studies have shown stress-buffering impacts when investigating neighbourhood-level social capital environments. For example, Aminzadeh et al. (2013) found that higher organisation membership in the community offset the negative impact of individual-level socioeconomic deprivation on the wellbeing of adolescents. Stafford et al. (2008) also showed that measures of neighbourhood social capital comprising both structural and cognitive aspects were related to common mental disorders only in the presence of household or neighbourhood

deprivation. Additionally, Fone et al. (2007) demonstrated that neighbourhood-level cohesion modified the deprivation-mental health relationship but did not evidence a similar interaction for individual-level cohesion.

Moreover, both the social capital measures analysed here are concerned with degrees of participation in organisations. It is likely that these are situated within the local area, with the availability, quality and funding of organisations also varying between neighbourhoods by deprived status (Browne-Yung et al., 2013). Therefore, participation in multiple organisations within your local area could act as a mechanism of the deprivation-health relationship. Indeed, research has suggested that measures of social capital partially mediate neighbourhood deprivation and self-rated health relationships in an English sample (Verhaeghe and Tampubolon, 2012). Further research would be needed to explore this question further and to investigate heterogeneous relationships of social capital and health at multiple scales.

The final research question explored in this analysis dealt with the potential interplay of deprived status at the neighbourhood and individual level. A double jeopardy scenario was hypothesised, where the impact of living in deprived neighbourhoods would be more severe for those who were themselves personally disadvantaged in terms of their subjective financial situation (Barber et al., 2016; Boylan and Robert, 2017). The results did show a cross-level interaction between Townsend score and financial situation. However, this did not operate in line with a double jeopardy scenario: the gradient in the log-odds of being in poor self-rated health was steeper for those who were living comfortably or doing alright, and shallower for those who were struggling financially. This suggests a relationship more akin to the relative deprivation scenario, which posits that the impact of low (high) personal status will be intensified for those living in higher (lower) status areas – where their *relative* circumstance is more in contrast to the community (Parkes and Kearns, 2006; Stafford and Marmot, 2003). In Figure 4.4, the difference between those doing comfortably and those finding it difficult was larger in less deprived neighbourhoods compared with more deprived, supporting a relative deprivation hypothesis. Though significant, the interaction is very small in scale, however, and comparison of the DIC between Model 4 and 5 shows its addition did not

significantly improve model fit. There are also potential limitations from the use of a subjective measure of individual financial status. The subjective measure was chosen as it was deemed likely to reflect the stress associated with struggling financially and to naturally account for situations such as where individuals have a higher income but are living beyond their means. However, as a judgement on their own status the measure could have been influenced by other individual traits not accounted for in the modelling, for instance personality type, leading to potential bias. Additionally, the subjective measure may not represent relative status in society to the same degree as a measure such as income quintiles which could have contributed to the relatively small interaction observed.

Overall, the results of this analysis do provide support for a role of neighbourhood deprivation in self-rated health inequalities over time. Neighbourhood deprivation was evidenced as being particularly relevant to older persons, who also showed greater variability in their self-rated health between neighbourhoods. However, adding the Townsend score in Model 2 explained a small proportion of the between neighbourhood variation in self-rated health, around 16% compared with Model 1. Additionally, comparison of the DIC between Model 1 and 2 indicated that accounting for Townsend deprivation score did not significantly improve the model fit. Together these results challenge the proposed importance of neighbourhood deprivation to self-rated health. It may be the dimensions of Townsend deprivation, comprising largely structural aspects of disadvantage, are not the most relevant neighbourhood exposures to subjective health evaluations. A measure such as the Index of Multiple Deprivation (IMD) (Noble et al., 2006), which combines information on a broader set of dimensions, including the living environment and crime for example, may offer more potent relationships with health. The IMD was not used for this Chapter or Chapter 6 (which also analyses deprivation over time). The IMD is not sufficiently comparable over time due to changes in the indicators used to compile it and the relative nature of the measure (Smith et al., 2015). As a result, the analysis would be restricted to a single timepoint measure of deprivation over the entire 26 years of data. In contrast, the Townsend deprivation score was available as a time comparative index that enabled a more realistic appraisal of deprivation over time. Moreover, Townsend scores are, in general, highly correlated with IMD scores, for

instance the correlation between 2010 IMD scores and Townsend scores derived from the 2011 Census for LSOAs in England was 0.84, $p<0.00$. As such we would not expect the findings to be substantially different from what we would have observed if we had been able to use the IMD. Another possibility is that the neighbourhood units employed are not the phenomenon scale (Montello, 2001) at which the components of Townsend deprivation operate or show the most variation, helping to explain the diminished findings.

In this analysis, we have also not considered causal interpretations of the identified associations. What we identify may be the result of selection effects for example, with those in better health more likely to move to less deprived areas for instance (Norman et al., 2005). To help identify the impact of potential selection effects in this chapter, the analysis was repeated with the BHPS sample who were present at every possible timepoint between 1991 and 2017. This balanced sample of 1,755 individuals showed essentially the same pattern of results in terms of the association of neighbourhood deprivation and self-rated health; higher deprivation was associated with worse self-rated health (see Supplementary Information). The effect of deprivation was smaller in size, however, suggesting that the main analysis using the full unbalanced panel could be overestimating the size of the deprivation effect. Further analysis is needed to explore the competing contribution of social causation or selection hypothesis, which is not possible within the scope of this analysis. The story of this chapter is one of heterogeneity in health relationships and development over time, though the underlying proposition that deprivation relates to health inequalities is corroborated.

VI Supplementary Information

Table 4.S1 Estimated median MCMC parameter coefficients, standard errors and their 95% credible intervals for balanced BHPS sample

	Model 0			Model 1			Model 2		
		Credible Interval			Credible Interval			Credible Interval	
	Beta	2.5%	97.5%	Beta	2.5%	97.5%	Beta	2.5%	97.5%
Fixed Part									
Sex									
Male				-0.315	-0.525	-0.099	-0.310	-0.532	-0.091
Age				0.009	0.005	0.014	0.014	0.009	0.019
Age^2				-0.004	-0.005	-0.003	-0.005	-0.006	-0.004
Cohort				-0.016	-0.027	-0.005	-0.013	-0.024	-0.001
Cohort^2				-0.006	-0.007	-0.005	-0.007	-0.008	-0.006
Age*Cohort				-0.011	-0.012	-0.009	-0.012	-0.013	-0.010
Deprivation							0.065	0.040	0.090
Deprivation*Age									
Financial Situation									
Just getting by									
Finding it difficult									
Education level									
A Level/GCSE									
Other/No qual.									
Employment status									
Retired									
Unemployed/Inactive									
Tenure									
Privately rented									
Socially rented									
Marital status									
Single/SDW									
Org. Membership									
Org. Activity									
Deprivation* Just getting by									
Deprivation*Finding it difficult									
Cons	-1.872	-1.994	-1.750	-1.562	-1.759	-1.362	-1.446	-1.647	-1.250
Random Part									
Level: Neighbourhood									
Var(cons)	0.990	0.803	1.198	0.993	0.806	1.202	0.972	0.789	1.167
Level: Individual									
Var(cons)	4.277	3.843	4.733	4.310	3.872	4.785	4.204	3.783	4.661
DIC	31320			30975			30988		
Units									
Neighbourhood	2248			2248			2247		
Individual	1755			1755			1755		
Observation	41957			41957			41956		

Notes: MCMC models were run for 100,000 iterations, with a burn-in of 5000.

Table 4.S1 continued. Estimated median MCMC parameter coefficients, standard errors and their 95% credible intervals for balanced BHPS sample.

	Model 3			Model 4			Model 5		
		Credible Interval			Credible Interval			Credible Interval	
	Beta	2.5%	97.5%	Beta	2.5%	97.5%	Beta	2.5%	97.5%
Fixed Part									
Sex									
Male	-0.314	-0.528	-0.104	-0.199	-0.405	0.006	-0.198	-0.416	0.018
Age	0.015	0.010	0.020	0.017	0.010	0.023	0.017	0.010	0.023
Age^2	-0.005	-0.006	-0.004	-0.005	-0.006	-0.005	-0.005	-0.006	-0.005
Cohort	-0.013	-0.024	-0.002	-0.013	-0.024	-0.001	-0.013	-0.024	-0.002
Cohort^2	-0.007	-0.008	-0.006	-0.008	-0.009	-0.006	-0.008	-0.009	-0.006
Age*Cohort	-0.012	-0.013	-0.010	-0.013	-0.015	-0.011	-0.013	-0.015	-0.011
Deprivation	0.077	0.051	0.103	0.066	0.039	0.093	0.071	0.043	0.099
Deprivation*Age	0.002	0.001	0.003	0.003	0.001	0.004	0.002	0.001	0.004
Financial Situation									
Just getting by				0.263	0.176	0.350	0.256	0.167	0.342
Finding it difficult				0.475	0.331	0.617	0.469	0.325	0.610
Education level									
A Level/GCSE				0.227	0.027	0.438	0.229	0.024	0.441
Other/No qual.				0.468	0.217	0.712	0.471	0.223	0.721
Employment status									
Retired				-0.042	-0.185	0.098	-0.042	-0.183	0.103
Unemployed/Inactive				0.600	0.480	0.722	0.603	0.482	0.723
Tenure									
Privately rented				0.249	0.022	0.474	0.247	0.024	0.472
Socially rented				0.340	0.129	0.554	0.338	0.123	0.559
Marital status									
Single/SDW				0.107	-0.028	0.241	0.106	-0.025	0.238
Org. Membership				0.003	-0.047	0.053	0.003	-0.047	0.052
Org. Activity				-0.082	-0.132	-0.031	-0.082	-0.131	-0.031
Deprivation* Just getting by							-0.009	-0.037	0.018
Deprivation* Finding it difficult							-0.036	-0.078	0.008
Cons	-1.426	-1.623	-1.232	-1.843	-2.088	-1.596	-1.844	-2.095	-1.592
Random Part									
Level: Neighbourhood									
Var(cons)	0.964	0.782	1.173	0.861	0.693	1.051	0.855	0.684	1.042
Level: Individual									
Var(cons)	4.191	3.780	4.643	3.666	3.288	4.072	3.670	3.288	4.080
DIC	30982			28190			28189		
Units									
Neighbourhood	2247			2193			2193		
Individual	1755			1750			1750		
Observation	41956			38177			38177		

Notes: MCMC models were run for 100,000 iterations, with a burn-in of 5000.

Table 4.S2 Correlations between sociodemographic covariates used in analysis

	Financial situation	Education level	Employment status	Tenure	Marital status
Financial situation	1				
Education level	0.119	1			
Employment status	0.1851	0.2252	1		
Tenure	0.2534	0.2072	0.2319	1	
Marital status	0.1129	0.0569	0.1689	0.2004	1

Introduction to Chapter 5

Having explained health trends over ages and cohorts, and explored the association between neighbourhood deprivation and health, the next stage in investigating the puzzle of health and place relationships is to delve into the action of potential mechanisms that explain the identified associations. The theoretical background of the stress pathway provides an underlying explanation for the identified associations of deprivation and poor health: deprived neighbourhood environments are posited to be more stress inducing, impacting on health long term through chronic exposure. Chapter 4 demonstrated support for this underlying proposition: exposure to a higher degree of neighbourhood deprivation over time was related to a higher probability of being in poor health. This chapter furthers the investigation of the stress pathway in a more explicit fashion, by exploration of whether and how a biological measure of chronic stress burden (allostatic load) mediates relationships of neighbourhood deprivation with physical and mental health. This following chapter addresses the thesis research question: Are relationships of deprivation and health mediated by allostatic load as a measure of cumulative biological weathering in response to stress?

This chapter will directly assess a biological mechanism of the stress pathway, in relation to chronic exposure to deprivation and the resultant physiological weathering. By testing a biosocial pathway of health and place relations, this chapter fits directly into 'biosocial health geography' as proposed in Chapter 2. It also helps to address one of the two key research gaps that were identified in the literature review: the need to explore mechanisms of exposure-health relationships. This analytical chapter offers a novel assessment of relationships between the neighbourhood environment and health in testing allostatic load as a mediator. Mediation analysis, as identified in Chapter 2, provides a technique to investigate the mechanisms by which contextual exposures become manifest in health. Therefore, it is a well-suited methodology for demonstrating the mechanism of the stress pathway in an explicit fashion, and one which is comparatively underused in neighbourhood and biosocial studies.

The supplementary tables at the end of this chapter demonstrate the results of the mediation analysis under different sensitivity tests which assess the robustness of the findings to different formulations of allostatic load. This includes testing the decision to treat missing biomarker information as 'not at risk' through repeating the mediation with only those participants with complete non-missing information across all biomarkers. Additionally, the results are presented for three operationalisations of allostatic load, serving to show that the general patterning of the relationships and conclusions drawn remain similar.

Chapter 5. An investigation of whether allostatic load mediates associations between neighbourhood deprivation and health

I Introduction

There is a long history of research seeking to better understand how where you live interacts with your health and wellbeing (Brown et al., 2010; Jones and Moon, 1992). Persistent health inequalities between areas mean local context (commonly referred to as 'the neighbourhood') remains a focal point of interest in health relationships (Office for National Statistics, 2014; World Health Organisation, 2008). It is widely acknowledged that living in disadvantaged areas negatively impacts your life chances. This idea underlies much of the neighbourhood effects research paradigm and has generally found support in the literature (Kawachi and Berkman, 2003; Van Ham et al., 2012). Given this consistency of findings, interest has turned towards investigating the mechanisms that may explain relationships between deprivation and health.

Within the literature which has unpacked the 'black-box' of neighbourhood effects (Macintyre et al., 2002), a developing area is concerned with biological plausibility. There is an extensive literature detailing how features of the social and physical environment may play a role in contextual relationships with health and wellbeing (see Diez Roux and Mair, 2010; Rosenberg, 2017). Now researchers are turning their attention to the question of how environments 'get under the skin'. The complexity of environment-health interactions, and their potential to accumulate over the lifecourse, makes research at the dynamic interface of the biological and social a fruitful avenue of inquiry. Considering biological plausibility in the embodiment of context can provide insight into pathways that are credible for a range of processes. Tracing the imprint of disadvantage also offers a powerful tool to comprehend histories of vulnerability, and thus to inform policy on health inequalities.

As yet, this literature has not been fully developed and further research is needed to understand processes of health and place relationships and to explore biosocial links in an explicit manner (see Chapter 2). This chapter contributes a test of the stress pathway model,

which posits that living in disadvantaged areas increases the stress burden residents are exposed to, raising the likelihood of poor health. To address some of the key gaps in the emergent biosocial literature, we adopt a multilevel perspective concerned with neighbourhood in combination with biodata and examine the role of a stress burden *within* relationships of place and health, using mediation analysis. We assess whether allostatic load, marking a cumulative biological weathering in response to chronic stress, mediates the association between neighbourhood deprivation and individual health.

II Background

Previous studies have indicated the presence of associations between deprived neighbourhoods and health outcomes across a range of national contexts (Adams et al., 2009; Arcaya et al., 2016; Sundquist et al., 2004). Such studies have been instrumental in demonstrating the impact of neighbourhood on individual health and the inequalities of health status between areas (Wilson et al., 2010). However, many of these studies do not directly address the question of how the neighbourhood would impact the individual. Quasi-experimental studies, such as the Moving to Opportunity (MTO) and Gautreaux residential mobility programs in the US, provide insight into neighbourhood and health relationships (Ludwig et al., 2012; Rosenbaum and Zuberi, 2010). For example, improvements in the mental health of those who moved to lower poverty neighbourhoods under MTO have been attributed to reductions in stress exposure (Katz et al., 2001). The role of perceptions and experiences of stress in deprivation-health relationships is a recurring theme in the neighbourhood literature and offers a pathway for exposing the mechanisms of neighbourhood effects.

The increased incorporation of biomarkers within large social surveys is facilitating analysis which appreciates the entanglement of biological and social phenomena. The stress pathway is one theorised biosocial model drawn upon to link places and health. It postulates that the fewer and poorer quality social and physical resources that characterise deprived areas shape exposure to stressful experiences, as well as restricting opportunities for wellbeing. The

resulting stress burden is proposed to negatively impact health (Daniel et al., 2008). The biological response to chronic stress can be captured using the concept of allostatic load, which represents a weathering on physiological functioning resulting from repeated and prolonged exposure to stressors (McEwen and Seeman, 1999; McEwen and Stellar, 1993). Whilst the acute stress response is adaptive in the short-term, chronic activation stimulates a cascade of dysregulations across multiple physiological systems. These dysregulations ultimately increase the chances of morbidity and mortality, contributing to allostatic load and the common language feeling of being 'stressed out' (Juster et al., 2010; McEwen, 2008).

To operationalise allostatic load, a set of biomarkers is typically used to construct a composite index, for instance, summarising the number of biomarkers falling into high risk quartiles (Seeman et al., 1997). Factor analysis has shown that biomarkers used to construct allostatic load measures tend to load onto a single common factor, suggesting this summary approach to be sufficient (Howard and Sparks, 2016; Wiley et al., 2016). Results by Wiley et al. (2016), comparing factor loadings of their full model with a series of models where different sub-systems and their associated biomarkers were dropped, were consistent with item parameter invariance. This implies the same latent factor representing allostatic load may be identified even if the underlying set of biomarkers varies (Wiley et al., 2016). Higher allostatic load has consistently been found to relate to mortality and worse health outcomes (Hwang et al., 2014; Juster et al., 2010). For example, allostatic load has been shown to be predictive of cognitive and physical functioning decline (Seeman et al., 1997), chronic diseases (Mattei et al., 2010) and depressive symptoms (Seplaki et al., 2006). Allostatic load therefore provides a valid tool to trace the biological memory of disadvantage over time and link neighbourhood circumstances to individual health.

Studies which have implicated stress exposure using allostatic load have focused on individual-level factors, such as socioeconomic status, poverty and adverse experiences (Barboza Solís et al., 2015; Gruenewald et al., 2012; Gustafsson et al., 2012; Kakinami et al., 2013). Others have invoked neighbourhood by examining how individual perceptions of neighbourhood features relate to allostatic load (Van Deurzen et al., 2016). By focusing on individual-level perspectives, researchers are missing the context of health relationships and

are not recognising the inherently social construction of life (Krieger, 1994). Where place or neighbourhood characteristics have been explored, allostatic load has been positioned as an outcome rather than as an intervening variable in environment-health pathways. These studies have generally corroborated the negative health consequences of adverse neighbourhood circumstances on allostatic load (Bird et al., 2010; Brody et al., 2014; Theall et al., 2012). However, there remains a need for more studies examining the neighbourhood space, allostatic load and health in other national contexts; research using data from US studies has dominated the literature so far. Xu (2018), for example, demonstrates the importance of national context: circumstances indicative of higher socioeconomic status, such as high income and higher-level occupations, were associated with worse allostatic load in the Chinese context of rapid social and health transformation. This chapter considers how allostatic load acts in pathways from neighbourhood circumstance to general states of health and functioning, for a nationally representative sample of Great Britain. Note that for this analysis we primarily view allostatic load as a predictor of physical and mental health, rather than considering the biomarker summary as a representation of those health outcomes in itself. Allostatic load captures a body out of balance, with dysregulations across physiological systems that feed into later health complications but may not in themselves be indicative of clinically diagnosed conditions.

The potential of mediation analysis in helping to disentangle the mechanisms linking gradients in circumstance to health inequalities has been recognised. For example, Schulz et al. (2012) used the causal steps criteria (Baron and Kenny, 1986) to show the relationship of neighbourhood poverty to allostatic load was mediated by psychosocial stress for residents of Detroit. However, there have been very few studies to date which assess allostatic load as a mediator of health relationships. For instance, Hu et al. (2007) were not able to support allostatic load as a mediator of the relationship of socioeconomic status to self-rated health and activity limitations. In contrast, Sabbah et al. (2008) provided evidence of a mediating influence of allostatic load on socioeconomic gradients in periodontal and ischaemic heart disease. However, both studies relied on the attenuation of a previous relationship to evaluate the presence of mediation, an approach which is problematic as it does not allow

researchers to distinguish a mediator from a confounder. This technique also does not follow recommendations for conducting mediation analysis which require that the indirect effect – that is the effect that travels through the mediator – must be investigated (Hayes, 2009). Moreover, investigations that explicitly explore the role of allostatic load, and which do so in multilevel frameworks, are currently lacking.

This chapter aims to address these limitations by employing large-scale data from Great Britain to investigate the stress pathway, placing allostatic load as a mediator in the proposed causal pathway from neighbourhood deprivation to health. Figure 5.1 demonstrates the model of the stress pathway conceptualised in this study. As part of this assessment we hypothesise: (1) higher deprivation predicts worse allostatic load; (2) higher allostatic load is associated with worse physical and mental health; (3) higher deprivation relates to worse physical and mental health. To the author's knowledge this will offer a novel test of whether and how allostatic load acts as a mediator in a multilevel, neighbourhood framework.

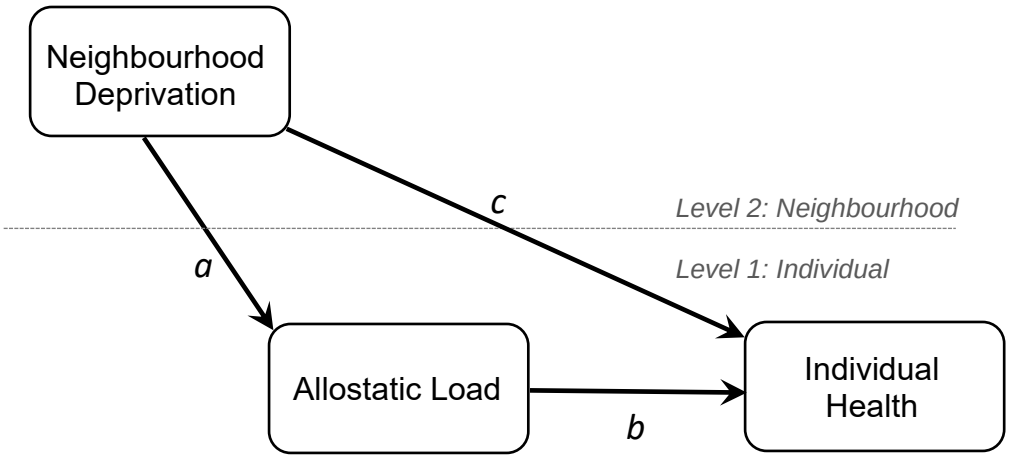

Figure 5.1 Diagram of the stress pathway

III Methods

This study uses data from Understanding Society (Knies, 2018; University of Essex et al., 2018b). At Waves 2 and 3 (collected between 2010-2012) separate nurse health assessments were carried out and blood samples collected (University of Essex and Institute for Social and

Economic Research, 2014b). The Wave 2 nurse assessment was undertaken on a subset of the General Population Sample component, with 10,175 persons consenting to have a blood sample taken. At Wave 3 the health survey was assessed on a subset of the former British Household Panel Survey sample: a smaller sample of 3,342 adults had a blood sample taken. Documentation of the nurse assessment and the biomarker data is available in McFall et al. (2014) and Benzeval et al. (2014). This chapter combines the two biomarker samples, treating them as a single cross-sectional sample for the purpose of this analysis. Respondents from Northern Ireland were not included in the nurse health assessments; therefore, our sample is representative of Great Britain only.

Individual-level data was linked to neighbourhood context in the form of Lower Layer Super Output Areas (LSOAs and the equivalent Scottish Data Zones, DZs) using the 2011 Census boundaries (University of Essex et al., 2018a). The conceptualisation of neighbourhoods is a contested issue (Galster, 2001) and although employing this statistical unit may not be an ideal representation of an individual's context, employing statistical or administrative geographies is common practice in the neighbourhood literature. We elected to keep the neighbourhood unit similar to that adopted most commonly in the literature to aid comparisons as we are exploring an innovative means of understanding how neighbourhood context transmits to individuals. LSOAs and DZs are small geographical units, with around 1,600 and 800 individuals on average for LSOAs and DZs respectively (Flowerdew et al., 2007; Office for National Statistics, 2016). This offers a reasonable approximation to colloquial understandings of 'neighbourhood'. All models had 11,387 individuals nested within 6,629 neighbourhoods.

Health Outcomes

We report on two outcome variables, the 12-Item Short Form Health Survey (SF-12) physical and mental health component scores. The SF-12 physical health score covers physical functioning, limitations due to physical health, bodily pain, and general health. The mental health score addresses vitality, social functioning, limitations due to emotional problems, and mental health. Valid answers to source questions covering these features are converted to the SF-12 physical and mental health functioning scores, which are continuous scales running

between 0 and 100, where higher scores are representative of better health (Ware et al., 2002). The SF-12 was developed as a measure of generic health status, and is a shorter alternative to the SF-36 health measure (Ware et al., 1995).

Neighbourhood Deprivation

Neighbourhood deprivation is measured using the Index of Multiple Deprivation (IMD, see Noble et al., (Noble et al., 2006) for detail). The IMD serves to identify areas of concentrated deprivation at the small-area (LSOA) level. Whilst it would be ideal to measure deprivation at a consistent point in time, the devolved administrations within the UK run separate programs and as a result, data come from the 2015 English IMD (GOV.UK, 2015), the 2016 Scottish IMD (Scottish Government, 2016) and the 2014 Welsh IMD (StatsWales, 2015). The majority of indicators for the three measures are sourced from 2011 to 2015 (National Statistics for Scotland, 2016; Smith et al., 2015; Statistics for Wales, 2014). Each country's IMD is compiled in similar ways, producing a relative ranking of deprivation of small areas. However, the exact data sources and module content varies between countries so that each measure better reflects the national context. Therefore, quintiles of deprivation were calculated separately within each country. Here it is assumed that the relative nature of deprivation is captured similarly by the three national measures. Country of origin is additionally included in the models to account for differences between the English, Scottish and Welsh measures. The highest rates of deprivation are indicted by quintile 5.

Allostatic Load

Allostatic load represents a physiological 'wear-and-tear', characterised by dysregulation across multiple systems of body as a consequence of chronic exposure to stressful experiences (McEwen and Seeman, 1999). To represent allostatic load, this study uses 13 biomarkers from the cardiovascular, inflammatory, lipid and glucose metabolism systems, and the hypothalamic-pituitary (HPA) axis. Summaries are presented in Table 5.1. The biomarkers represent a similar suite to those used by previous studies with each marker utilised regularly in analyses (Schulz et al., 2012; Seeman et al., 1997; Wiley et al., 2016).

Information on the analysis and measurement procedure for each biomarker can be found in the Biomarker User Guide (see Benzeval et al., 2014).

Table 5.1 Biomarker summaries and high-risk quartile cut-off values

System	*Biomarker*	N	Mean (SD)	High Risk Cut-off Values
Cardiovascular	*Systolic Blood Pressure*	10,891	126.54(16.60)	≥136.5 mmhg
	Diastolic Blood Pressure	10,891	73.12(10.77)	≥80 mmhg
	Pulse Rate	10,891	68.84(10.74)	≥75.5 bpm
Lipid Metabolism	*HDL cholesterol*	12,858	1.55(0.46)	<1.2 mmol/l
	Total: HDL cholesterol ratio	12,857	3.75(1.36)	≥4.42
	Triglycerides	12,880	1.79(1.21)	≥2.2 mmol/l
	BMI	12,844	27.95(5.56)	≥30.8 kg/m^2
	Waist Circumference	13,060	93.82(14.45)	≥103 cm
Glucose Metabolism	*HbA1c*	12,145	37.25(8.19)	≥39 mmol/molhb
Inflammatory	*C-Reactive Protein*	12,513	3.26(7.14)	≥3.2 mg/l
	Fibrinogen	12,819	2.79(0.61)	≥3.2 g/l
	Albumin	12,902	46.78(2.95)	<45 g/l
HPA-axis	*DHEAs*	12,855	4.60(3.24)	<2.2 mol/l

A system risk score of allostatic load was created by calculating the proportion of biomarkers within each of the subsystems that fell into high-risk quartiles (this was the top quartile for every biomarker except for HDL cholesterol, albumin and DHEAs where the lowest quartile represents those most at risk), before combining the proportions across the systems to create a continuous score ranging from 0 to 5, where higher scores represent worse outcomes. This method accounts for the unequal number of biomarkers representing the different systems

(Read and Grundy, 2014; Seeman et al., 2014). Measures were calculated for every participant, except where an individual lacked data on all biomarkers: where individuals were missing data on a biomarker this was treated as 'not at risk' in a maximum bias approach (Barboza Solís et al., 2015). Results were not significantly different using measures created only with those participants with non-missing information across all biomarkers (see Supplementary Information). We also explored two additional constructions of allostatic load: a simple risk score and a total allostatic load score. The simple risk score was a count of the number of biomarkers for which participants fell into high-risk quartiles. The total allostatic load score was created by standardising each of the biomarkers into a z-score and taking the average of these z-scores. Sensitivity analyses (see Supplementary Information) showed findings were comparable across the three allostatic measures so only results for the system risk score are presented.

Individual Socio-demographics

To control for the action of individual characteristics that may confound the neighbourhood deprivation effect and act as predictors of health status, the individual covariates of age, sex, ethnicity, employment status, marital status, education, welfare status and housing tenure were included in this analysis. Binary variables included sex, ethnicity, marital status and welfare status. Ethnicity was a comparison of non-white to white. Marital status compared those who were single, divorced, separated or widowed with those married, in a civil partnership or living as a couple. Welfare status was calculated by combining the main means-tested benefits relating to disadvantaged status (Unemployment and National Insurance benefits, Income support, and Housing and Council Tax benefits), and recoding to receiving any of these benefits or none. Employment status was recoded to three categories: employed, retired, and inactive (composed of unemployed, long term sick or disabled, those caring for family or home, full-time students and other non-employed statuses). Education was captured through the highest educational qualification. Housing tenure was a categorical variable comprising: owned, socially rented, privately or other rented. See Table 5.2 for summaries of the variables.

Table 5.2 Descriptive summaries of outcomes and covariates

	N		
Physical Health	11540	Mean (SD)	49.65(11.00)
Mental Health	11540	Mean (SD)	50.30(9.45)
Neighbourhood Deprivation	13228	Q1*	22.20%
		Q2	22.03%
		Q3	21.75%
		Q4	17.89%
		Q5	16.12%
Country	13228	England*	83.97%
		Wales	7.26%
		Scotland	8.76%
System Risk Allostatic Load	13226	Mean (SD)	1.15(0.97)
Simple Risk Allostatic Load	13226	Mean (SD)	3.02(2.40)
Total Allostatic Load Score	13226	Mean (SD)	0.00(0.46)
Age	13228	Mean (SD)	51.97(17.20)
Sex	13228	Male*	44.64%
		Female	55.36%
Ethnicity	13150	White*	95.29%
		Non-White	4.71%
Marital Status	13228	Married*	68.30%
		Single	31.70%
Employment Status	13228	Employed*	54.85%
		Retired	28.80%
		Inactive/Other	16.35%
Education	13095	Degree*	34.68%
		A Level	19.11%
		GSCE	20.83%
		Other	11.06%
		None	14.32%
Welfare Status	13213	Not Receiving*	87.79%
		Receiving	12.21%
Tenure	13211	Owned*	76.50%
		Socially Rented	13.54%
		Privately Rented	9.95%

Notes: * indicates reference category.

Analysis

To unpack the black-box of neighbourhood effects we adopt a mediation approach. Mediation is conceived as a causal phenomenon, whereby the relationship between two variables is accounted for by a variable that is conceptually on the causal pathway between the exposure and the outcome – a mediator (Baron and Kenny, 1986). Here a multilevel analysis is used to investigate whether allostatic load mediates the association of neighbourhood deprivation with physical and mental health. A multilevel framework is required to simultaneously estimate at different levels of analysis and account for the clustering of individuals within neighbourhood units (Duncan et al., 1998; Jones and Duncan, 1995). Assessing the hypothesised model in Figure 5.1 requires fitting two multilevel equations for each health outcome, *i* and *j* subscripts indicate individual-level and neighbourhood-level respectively.

$$M_{ij} = \beta_1 0 + aX_j + \mu_{Mj} + e_{Mij} \quad (1)$$

$$Y_{ij} = \beta_2 0 + cX_j + bM_{ij} + b_1 MX_{ij} + \mu_{Yj} + e_{Yij} \quad (2)$$

Equation (1) predicts the mediator (M) by neighbourhood deprivation (X), assessing pathway *a* in Figure 5.1 and the first hypothesis. The second equation fits a two-level model predicting the health outcome of interest (Y) by neighbourhood deprivation (X) and allostatic load (M). This second equation assesses whether hypotheses (2) and (3) are supported; it provides information on pathways *b* and *c* in Figure 5.1. An interaction between neighbourhood deprivation and allostatic load is additionally included in the second equation. Insights from the causal inference literature have emphasised the importance of accounting for potential interactions between the exposure and the mediator to making correct mediation inferences (Valeri and VanderWeele, 2013).

The effect of deprivation that travels through allostatic load, the indirect effect (*IE*), is calculated as the product of the effect of X on M in equation (1) and M on Y from equation (2), as in equation (3).

$$IE = a(b + b_1 X) \quad (3)$$

If no interaction is present (if b_1 was zero), the equation for the indirect effect reduces to the simple *ab* product. The product method was chosen as an intuitive measure of the indirect effect, and one which facilitates explicit examination of the pathways of interest (Krull and MacKinnon, 2001; VanderWeele, 2016). Additionally, the difference method for identifying indirect effects, comparing the effect of the exposure before and after controlling for the mediator, has been criticised in the presence of exposure-mediator interactions (Kaufman et al., 2004).

As our measure of neighbourhood deprivation is categorical (with dummy variables included for quintiles 2 to 5 in the models) we identify four indirect effects, which we term *relative indirect effects* following the convention introduced by Hayes and Preacher (2014). Estimates of each of these indirect effects and their 95% confidence intervals were obtained from an iterated bias-corrected bootstrapping procedure creating 5,000 resampled estimates, for 10 replicate sets to achieve convergence (see the MLwiN user's guide (Rasbash et al., 2019) for details of the bootstrapping process). Bias-corrected bootstrapping is considered an appropriate method to evaluate the indirect effect of a mediation analysis (MacKinnon et al., 2004; Pituch et al., 2006). The mean value of the *IE* calculated from the final iteration sets of 5,000 is taken as the coefficient estimate of the relative indirect effects, and the 95% confidence intervals are obtained by finding the values of the 2.5th and 97.5th percentiles of the estimated *IE* distributions. Bootstrapped estimates of the relative total effects, the sum effects of neighbourhood deprivation on health, are also reported as a comparison to the mediated effects.

Data preparation was conducted in Stata Version 14 (StataCorp, 2017), and analysis was carried out in MLwiN version 3.01 (Charlton et al., 2017) using the runmlwin command (Leckie and Charlton, 2012) in Stata. All models were conducted with the final sample of 11,387 participants who had full data across all variables.

IV Results

In a null model predicting allostatic load, the variance partitioning coefficient (VPC) indicated 14.8% of the variation lay between neighbourhoods. Significant higher-level variation remains in the fully adjusted model. The inclusion of neighbourhood deprivation and compositional characteristics reduced the variance at the neighbourhood-level to 7.8% in the final model.

Table 5.3 presents the results where the mediator, allostatic load, is the outcome: this is the assessment of pathway *a* on Figure 5.1. The first hypothesis is supported; areas characterised as more deprived are associated with higher, and therefore worsening, allostatic load scores. This relationship is significant having controlled for socio-demographic characteristics. The results signal that neighbourhood deprivation acts most strongly through a heightened stress burden for those residing in areas in the most deprived circumstances. Figure 5.2 highlights the marked difference in predicted allostatic load score for someone resident in Q5 of neighbourhood deprivation, representing the most deprived areas, compared with Q4.

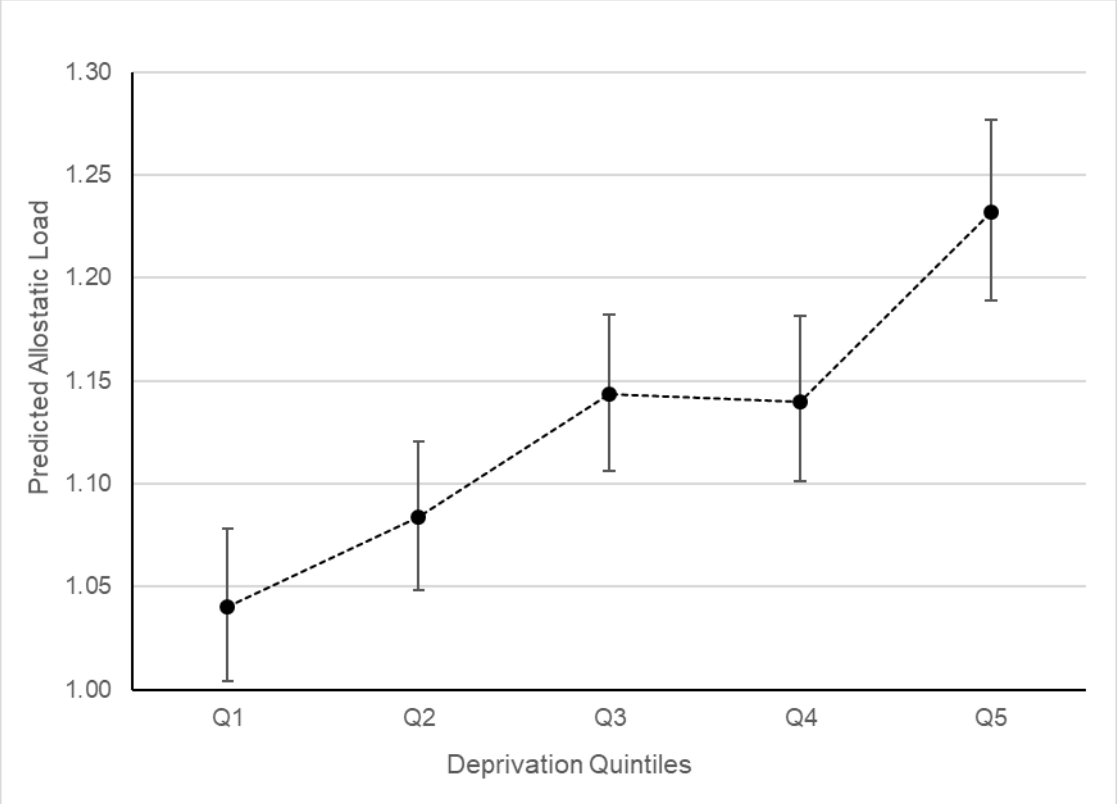

Figure 5.2 Mean predicted allostatic load score with 95% confidence intervals by quintiles of neighbourhood deprivation, other covariates are held at their average values

Table 5.3 also presents results of models predicting the health outcomes, assessing pathways *b* and *c* in Figure 5.1, and the second and third hypotheses. In null models containing no covariates (not shown) the VPC showed 13.5% of the variation in physical health lay between neighbourhoods. For mental health, the VPC was slightly lower (11.9%). In the fully adjusted models, significant higher-level variation remains for both physical and mental health, with VPCs of 5.2% and 8.1% respectively. The larger proportion of variation explained by the inclusion of neighbourhood deprivation and individual characteristics suggests a stronger impact of deprivation on physical health than mental.

Table 5.3 Model results predicting physical health, mental health, and allostatic load

		Physical Health			*Mental Health*			*Allostatic Load*		
		β	S.E.		β	S.E.		β	S.E.	
Fixed Part										
Cons		60.574	0.877	**	55.420	0.811	**	-0.472	0.074	**
Neighbourhood Deprivation	*Q1 (ref)*									
	Q2	-0.362	0.405		-0.463	0.263		0.044	0.024	
	Q3	-0.274	0.410		-0.567	0.267	*	0.103	0.024	**
	Q4	-0.705	0.440		-0.853	0.286	**	0.100	0.026	**
	Q5	-1.509	0.479	**	-1.495	0.314	**	0.192	0.029	**
Country	*England (ref)*									
	Wales	-0.869	0.355	*	-0.749	0.345	*	0.006	0.031	
	Scotland	-0.373	0.314		-0.062	0.303		0.053	0.028	
Allostatic Load (AL)		-1.834	0.208	**	-0.461	0.103	**			
Neighbourhood Deprivation* Allostatic Load (AL)	*Q1*AL(ref)*									
	Q2*AL	-0.428	0.283							
	Q3*AL	-0.732	0.278	**						
	Q4*AL	-0.869	0.297	**						
	Q5*AL	-0.935	0.304	**						
Random Part										
Level 2 Variance		4.607	1.091	**	6.496	1.026	**	0.052	0.009	**
Level 1 Variance		83.447	1.504	**	73.511	1.343	**	0.616	0.011	**

Notes: Models adjusted for age, age2, sex, ethnicity, marital status, employment status, education level, welfare and tenure. ** and * indicate significance at 99% and 95% confidence levels respectively.

Allostatic load demonstrates a weaker association to mental health than to physical health. The expected decline in health status across the allostatic range is 11.92 points on the physical health scale, compared with 2.29 points on the mental health measure, holding other covariates at their average values[5]. This result could suggest a deficiency of the allostatic load measure employed to capture the biological dysregulations pertinent to mental health. Otherwise, given the reasonably high proportion of neighbourhood-level variation remaining in the final model for mental health (recall the VPC is 8.2%), there could be other processes at work not accounted for in this model, for instance psychosocial stress buffering through social capital and support. The associations of allostatic load to health are significant in all cases having controlled for individual-level confounders, however, and run in the theorised direction, supporting hypothesis (2).

Having adjusted for individual characteristics, higher levels of deprivation are associated with poorer mental and physical health (evidenced by increasingly negative coefficients), and so hypothesis (3) is supported. The association manifests primarily through an effect of residing in areas characterised as the most deprived (Q5) for both physical and mental health. The results also show that the predicted health status of individuals living in Scotland or Wales is worse than for a person living in England, though this effect only appears significant for Wales.

An interaction was additionally identified between neighbourhood deprivation and allostatic load for physical health. As shown in Figure 5.3 the relationship of allostatic load with physical health is more pronounced for quintiles characterising neighbourhoods which are more deprived. For clarity 95% confidence intervals are not shown; if present they would show a significant difference between Q5 and the quintiles of lowest deprivation (Q1 and Q2). This interaction matches the theoretical background provided by the stress pathway: the negative health impact of a cumulative stress burden (allostatic load) is greater in more deprived areas. An interaction was tested for mental health but was not found to be significant or improve model fit so was therefore not included in the final models.

[5] Predictions obtained using the 'Customised Predictions' facility in MLwiN version 3.01, calculated for values from 0 to 5 on the allostatic load scale.

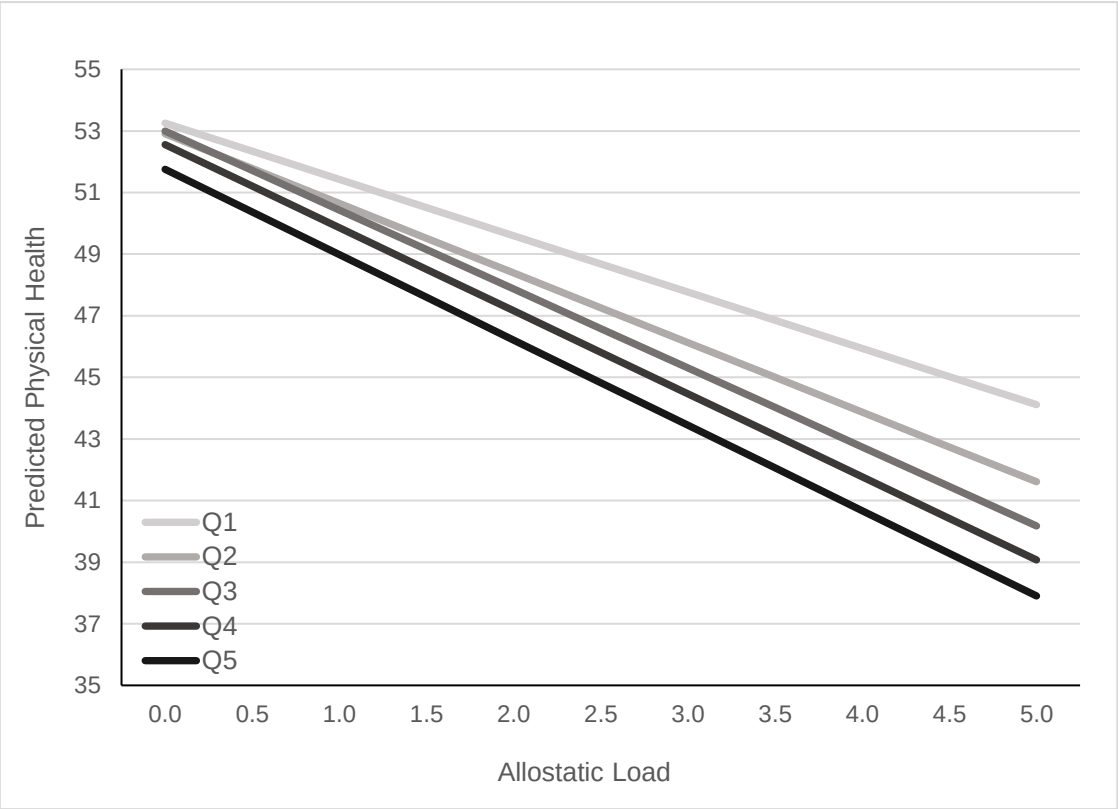

Figure 5.3 Mean predicted health scores by allostatic load and neighbourhood deprivation quintiles with other covariates held at their average values

Finding evidence for pathways linking deprivation to allostatic load, and allostatic load to physical and mental health supports a mediation pathway acting through a chronic stress burden. This result is substantiated by the relative indirect effects presented in Table 5.4. The majority of the relative indirect effects for both physical and mental health are significant; except for the indirect effect of being in Q2 compared to Q1, none of the confidence intervals include zero. The relative indirect effects are strongest for those in the most deprived areas (Q5) compared to the reference group. This gradient in the strength of the mediation is in line with the theoretical background of the stress pathway. Those residing in more deprived areas would be expected to experience increased exposure to stressful experiences, for instance from higher prevalence of crime or lack of social amenities, heightening the burden on their health (Ross and Mirowsky, 2001).

The relative indirect effects on mental health follow the same pattern as that for physical health. However, the strength of the mediation is weaker for mental health than physical health. Partially standardised indirect effects are presented (IE_{ps}), these provide a measure of mediation effect size by giving the ratio of the indirect effect to the standard deviation of the response (Hayes, 2018; Miočević et al., 2018). This measure shows the insubstantial nature of the mediation effect for mental health; the largest expected decline in health status from living in the most deprived neighbourhoods is 0.009 of a standard deviation on the mental health score. For physical health in comparison, the predicted effect that travels indirectly through allostatic load of residing in areas characterised as the most deprived compared to the least deprived is a decrease of 0.048 standard deviations in health score. The indirect effects for mental health are also relatively smaller in comparison to their total effects than for physical health.

Table 5.4 Bootstrapped relative indirect effects (*IE)* and partially standardised indirect effects (IE_{ps}) and total effects *(TE)*.

Indirect Effects							
		IE	95% CI	IE_{ps}	95% CI	*TE*	95% CI
Physical	Q2	-0.100	(-0.210, 0.006)	-0.009	(-0.019, 0.001)	-0.900	(-1.443, -0.370)
Health	Q3	-0.264	(-0.402, -0.137)	-0.024	(-0.037, -0.012)	-1.298	(-1.858, -0.740)
	Q4	-0.273	(-0.420, -0.130)	-0.025	(-0.038, -0.012)	-1.873	(-2.482, -1.280)
	Q5	-0.528	(-0.713, -0.358)	-0.048	(-0.065, -0.033)	-3.010	(-3.665, -2.331)
Mental	Q2	-0.020	(-0.047, 0.001)	-0.002	(-0.005, 0.000)	-0.481	(-0.993, 0.020)
Health	Q3	-0.047	(-0.081, -0.021)	-0.005	(-0.009, -0.002)	-0.616	(-1.147, -0.087)
	Q4	-0.046	(-0.080, -0.019)	-0.005	(-0.009, -0.002)	-0.897	(-1.469, -0.338)
	Q5	-0.088	(-0.137, -0.045)	-0.009	(-0.015, -0.005)	-1.589	(-2.202, -0.946)

V Discussion

This chapter is concerned with unpacking the black-box of neighbourhood effects through a biosocial lens. Often the literature reporting neighbourhood effects presents analysis in which the link between context and outcome is implicitly explored rather than explicitly tested. By investigating a proposed stress pathway acting between neighbourhoods and health we have

moved forward to connect context and outcome directly in a biologically plausible manner. This was achieved by exploring whether allostatic load mediated the relationship between neighbourhood deprivation and both physical and mental health. The results support the three hypothesised pathways and our analysis of the relative indirect effects provides evidence to demonstrate allostatic load acts as a mediator within the deprivation-health relationship in Great Britain. Overall, our results support the stress pathway theorisation, and substantiate the potential role of allostatic load in health relationships illustrated by previous studies.

This study adds to the growing body of literature which cites the neighbourhood space and brings forward a concern for biological plausibility. We provide evidence for contextual associations of neighbourhood circumstances in Great Britain on allostatic load, corroborating the hypothesised stress pathway and the biological embedding of place in health. Health patterns routinely reflect gradients of status and resources, and this extends to contextual conditions (Marmot, 2010; Theall et al., 2012). We found a gradient in the association of neighbourhood deprivation to allostatic load and our health outcomes; the strongest associations were consistently shown for the most deprived areas. The gradient in effect indicates the suitability of biosocial pathways to the investigation of health inequalities. It is possible to trace the imprint of varying exposures in the health states of different groups, by interrogating how the conditions of place are embodied through accumulated 'weathering' processes (Geronimus, 1992; McEwen and Stellar, 1993).

More generally, we have also highlighted the potential of mediation frameworks as a relevant technique to explore the complex pathways between neighbourhood conditions and health. By directly interrogating the indirect effect, this study improves on previous attempts to assess the potential of allostatic load to explain health gradients (Hu et al., 2007; Sabbah et al., 2008). This study thus expands the biosocial literature by assessing the action of allostatic load *within* the stress pathway, in a multilevel mediation study design. Allostatic load did significantly mediate the relationship of neighbourhood deprivation with physical and mental health, but with stronger support for the pathway to physical health. The mediating influence of allostatic load was strongest for areas characterised as the most deprived. Indeed, for

physical health an interaction was present whereby the detrimental impact of allostatic load was heightened in more deprived compared with less deprived neighbourhoods.

It is important to recognise some of the limitations of this study, particularly regarding the allostatic load measure. For instance, whilst the approach taken in this chapter follows previous research (Gruenewald et al., 2012; Read and Grundy, 2014; Seeman et al., 2014), the measure does not include many of the primary stress biomarkers, such as cortisol or adrenaline (McEwen and Seeman, 1999) as these are not available in Understanding Society. As a result the allostatic measure is capturing more 'downstream' biomarker disturbances and may not reflect more immediate dysregulations related to stress-exposure (Read and Grundy, 2014). However, the use of secondary indicators from the allostatic pathway, such as those from the cardiovascular and metabolic systems, does align with theorising exposure to neighbourhood stressors as operating through the long-term accumulation of experience. The lack of primary stress biomarkers in the allostatic load index may help to explain the discrepancy between the strength of association for physical and mental health. The downstream indicators utilised are closer in nature to physical health than mental health outcomes.

Additionally, allostatic load as a concept more widely could be criticised for the lack of consensus over how to operationalise indices and the variety of biomarkers utilised (Szanton et al., 2005). However, despite these inconsistencies, review studies have highlighted a considerable degree of uniformity in the patterning of relationships of allostatic load with various health and social features (Beckie, 2012; Dowd et al., 2009; Juster et al., 2010). We believe the concept has value in social science and health geography research where the evaluation of singular mechanisms that could have salience for multiple outcomes can offer useful insights for potential policy interventions.

There are also limitations to the mediation method employed in this chapter. The restriction to a cross-sectional design placed on the analysis by the biomarker sample prevents establishment of temporal ordering. Therefore, we cannot rule out reverse causation. Additionally, insights from the causal inference literature have stressed the importance of controlling for mediator-outcome confounders; the assumption of no confounding of this

nature is required in order to make causal interpretations of indirect and direct effects (Pearl, 2001; Robins and Greenland, 1992; VanderWeele, 2016). By including key socio-demographic characteristics we control for some potential mediator-outcome confounders – that is features which would affect both allostatic load and health status. For instance, those with higher allostatic load and those with poorer health are both more likely to be in worse social positions, for instance receiving welfare benefits or having fewer qualifications. However, there may be other unmeasured factors that act to confound the mediator-outcome relationship and so there remains the possibility for bias in the interpretation of the results.

The indirect effects for both health outcomes were statistically significant, however the indirect effects for mental health were on the margin of insignificance and not substantial in size. Results by Seplaki et al. (2006) suggest the association of allostatic load to different health outcomes can vary by the type of allostatic load, in terms of the distribution of sets of biomarkers in high or low risk categories. It may be that by not differentiating between forms of allostatic load in the present study we are missing out on some of the relationship with mental health. Our sensitivity analyses using simple risk and total indices of allostatic load did demonstrate similarity in the pattern of results between measures, which gives confidence in the results found here. However, Howard and Sparks (2016) indicated the specific biological pathways through which allostatic load arises may vary by individual characteristics. Their study highlighted differences in the relative importance of the metabolic, inflammatory and cardiovascular subsystems by race/ethnicity and education. Future research would benefit from exploring different formulations of allostatic load that may account for the heterogeneity of pathways. Structural equation modelling would be a useful tool in this task, as it allows allostatic load to be formulated as a latent factor which could then be simultaneously evaluated for its role in pathways of interest.

The heterogeneity we identified between the physical and mental health outcomes may also reflect that the action of the stress pathway as we have operationalised it is more relevant to physical health than mental health. This analysis took a strictly biosocial approach to summarising the response to chronic stress, using the biomarker summary of allostatic load. However, this approach may not be the most pertinent for offering insight to the mechanisms

of the stress pathway hypothesis for mental health. A psychosocially inspired viewpoint on 'stress', giving more precedence to perceptions, thoughts and feelings could offer further understanding of the interplay of neighbourhood context and mental health. Other contextual characteristics than deprivation, for instance segregation and neighbourhood stigma, alongside individual factors, particularly personality traits and psychological pathways that account for the perception of different situations, may also be more germane to mental health. Future research would benefit from deeper analysis of more complex mediating and interacting pathways. Researchers should bring factors that have previously been identified as important in the health and place literature, for instance disorder, social cohesion, and the role of green space, into a biosocial framework. Building on recent work such as a study by Robinette et al. (2018) which demonstrated higher perceived cohesion in the local area was related to lower cardiometabolic risk for older adults in the US, additionally implicating anxiety and physical activity in the pathway from cohesion to cardiometabolic risk.

Additionally, mental health is more transient in nature than physical health, incurring a higher degree of measurement error. This difficulty in capturing mental health may contribute to the diminished association we find in comparison to the physical health measure. The temporal variability of mental health may also mean that the impact of chronic stress exposure on mental health does not operate in the same cumulative fashion as for physical health and functioning. There is a clear need for longitudinal perspectives on biosocial pathways.

Longitudinal research is also needed to establish the order of causation and to take account of health-selective migration patterns which offer a competing hypothesis to the causal pathway proposed in this paper. For instance, Jiménez et al. (2015) did not evidence a relationship between baseline neighbourhood socioeconomic status and allostatic load at two years follow-up in a sample of older Puerto Ricans. The use of a longitudinal design in this study would have ruled out reverse causation due to the migration of those in poorer health to lower status neighbourhoods. We are not able to do this in the current study due to the cross-sectional nature of the biomarker data. Single-point-in-time measures may also underestimate the total, accumulated contribution of area conditions (Murray et al., 2013).

Future research should interrogate the temporality of relationships between neighbourhood characteristics, allostatic load and health. A lifecourse perspective which appreciates the importance of timing and the embedding of personal experience in the wider social and economic climate would be a fruitful avenue for inquiry. It would be beneficial to integrate the multilevel biosocial thinking advocated by this chapter with methods and insights from the lifecourse epidemiological literature, which has interrogated different lifecourse models of health relationships. For instance, Ploubidis et al. (2014) employed structural equation modelling to quantify the direct and indirect pathways of critical period, chains of risk, accumulation of risk and social drift hypotheses for the influence of socioeconomic position on later-life biomarkers. Gustafsson et al. (2014) exemplified the benefit of integrating lifecourse epidemiology and neighbourhood frameworks with the concept of allostatic load, demonstrating an accumulating impact of neighbourhood disadvantage on allostatic load.

In conclusion, this chapter has provided a demonstration of the stress pathway through an interrogation of whether allostatic load acts as a mediator of neighbourhood circumstances on health. The results indicate support for an indirect pathway acting through allostatic load for adults in Great Britain, with a stronger and more substantial association demonstrated for physical health. Consistent gradation in the strength of effects across increasing quintiles of neighbourhood deprivation additionally corroborates the action of an enhanced stress burden for those living in more disadvantaged circumstances. The salience of biosocial ideas to health and place research is clear, particularly the importance of considering pathways for the cumulative influence of disadvantage on health. More research is needed to expose further discourses of marginalisation and inequality, and to understand histories of poor health for vulnerable groups. In this study, a substantial degree of higher-level variation remained unexplained for mental health, and for physical health the partially standardised indirect effects showed the largest effect was relatively small in comparison to the overall variation in physical health, around one twentieth of a standard deviation. These results show that while the pathway through allostatic load may be important it is not the whole story. Integrating biosocial ideas with insights from the place and health literature may reveal other important pathways for the embodiment of context. Longitudinal and lifecourse research

exploring direct and indirect pathways will also be vital to researchers interested in the nature of place and health relationships.

VI Supplementary Information

Table 5.S1 Model results predicting physical health, mental health, and allostatic load for measures created with complete non-missing information across all biomarkers

		Physical Health			*Mental Health*			*Allostatic Load*		
		β	S.E.		β	S.E.		β	S.E.	
Fixed Part										
Cons		60.317	1.058	**	54.796	0.976	**	-0.408	0.094	**
Neighbourhood Deprivation	*Q1 (ref)*									
	Q2	-0.530	0.474		-0.441	0.299		0.040	0.028	
	Q3	-0.392	0.487		-0.304	0.306		0.108	0.029	**
	Q4	-0.920	0.533		-0.783	0.334	*	0.107	0.031	**
	Q5	-1.311	0.582	*	-1.288	0.366	**	0.218	0.034	**
Country	*England (ref)*									
	Wales	-0.763	0.422		-0.731	0.415		0.020	0.039	
	Scotland	-0.320	0.365		0.142	0.354		0.078	0.033	*
Allostatic Load (AL)		-1.824	0.231	**	-0.439	0.116	**			
Neighbourhood Deprivation*Allostatic Load (AL)	*Q1*AL(ref)*									
	Q2*AL	-0.395	0.317							
	Q3*AL	-0.635	0.315	*						
	Q4*AL	-0.681	0.341	*						
	Q5*AL	-0.974	0.350	**						
Random Part										
Level 2 Variance		3.556	1.379	**	7.983	1.315	**	0.040	0.012	**
Level 1 Variance		80.157	1.830	**	67.602	1.594	**	0.656	0.015	**

Table 5.S2 Relative indirect effect (*IE*) results and partially standardised relative indirect effects (IE_{ps}) for system risk allostatic load calculated with non-missing information across all biomarkers

Indirect Effects					
		IE	95% CI	IE_{ps}	95% CI
Physical	Q2	-0.088	(-0.216, 0.035)	-0.008	(-0.020, 0.003)
Health	Q3	-0.265	(-0.415, -0.122)	-0.024	(-0.038, -0.011)
	Q4	-0.266	(-0.436, -0.108)	-0.024	(-0.040, -0.010)
	Q5	-0.609	(-0.847, -0.402)	-0.055	(-0.077, -0.037)
Mental	Q2	-0.017	(-0.048, 0.006)	-0.002	(-0.005, 0.001)
Health	Q3	-0.047	(-0.087, -0.016)	-0.005	(-0.009, -0.002)
	Q4	-0.047	(-0.087, -0.015)	-0.005	(-0.009, -0.002)
	Q5	-0.095	(-0.157, -0.043)	-0.010	(-0.017, -0.005)

Table 5.S3 Full model results predicting physical health for system risk, simple risk, and total score allostatic load measures

Physical Health		*System Risk*			*Simple Risk*			*Total Score*		
		β	S.E.		β	S.E.		β	S.E.	
Fixed Part										
Cons		60.574	*0.877*	**	60.828	0.879	**	56.896	0.884	**
Neighbourhood Deprivation	*Q1 (ref)*									
	Q2	-0.362	*0.405*		-0.246	0.417		-0.835	0.272	**
	Q3	-0.274	*0.410*		-0.205	0.423		-1.073	0.276	**
	Q4	-0.705	*0.440*		-0.777	0.454		-1.571	0.297	**
	Q5	-1.509	*0.479*	**	-1.708	0.495	**	-2.528	0.327	**
Country	*England (ref)*									
	Wales	-0.869	*0.355*	*	-0.844	0.354	*	-0.785	0.353	*
	Scotland	-0.373	*0.314*		-0.307	0.314		-0.290	0.313	
Allostatic Load		-1.834	*0.208*	**	-0.673	0.083	**	-3.485	0.430	**
Age		-0.004	*0.033*		0.025	0.033		0.099	0.033	**
Age^2		-0.002	*0.000*	**	-0.002	0.000	**	-0.003	0.000	**
Sex	*Male (ref)*									
	Female	-0.216	*0.178*		-0.684	0.179	**	-0.844	0.180	**
Neighbourhood Deprivation* Allostatic Load (AL)	*Q1*AL (ref)*									
	Q2*AL	-0.428	*0.283*		-0.189	0.115		-1.387	0.598	*
	Q3*AL	-0.732	*0.278*	**	-0.285	0.113	*	-1.807	0.587	**
	Q4*AL	-0.869	*0.297*	**	-0.277	0.119	*	-1.775	0.611	**
	Q5*AL	-0.935	*0.304*	**	-0.275	0.122	*	-1.827	0.624	**
Ethnicity	*White (ref)*									
	Non-White	-1.364	*0.461*	**	-1.590	0.461	**	-1.542	0.460	**
Employment Status	*Employed (ref)*									
	Retired	-1.640	*0.324*	**	-1.729	0.324	**	-1.793	0.324	**
	Inactive/Other	-3.866	*0.285*	**	-3.827	0.285	**	-3.779	0.285	**
Marital Status	*Married (ref)*									
	Single	-0.334	*0.212*		-0.427	0.212	*	-0.423	0.212	*
Education	*Degree (ref)*									
	A Level	-0.932	*0.251*	**	-0.945	0.252	**	-0.956	0.251	**
	GCSE	-0.819	*0.247*	**	-0.786	0.247	**	-0.782	0.247	**
	Other	-1.896	*0.318*	**	-1.902	0.318	**	-1.844	0.318	**
	None	-2.879	*0.324*	**	-3.001	0.324	**	-2.966	0.324	**
Welfare Status	*Not receiving (ref)*									
	Receiving	-2.196	*0.344*	**	-2.287	0.344	**	-2.226	0.343	**
Tenure	*Owned (ref)*									
	Social Rented	-2.149	*0.321*	**	-2.089	0.321	**	-2.023	0.321	**
	Private Rented	-1.263	*0.320*	**	-1.226	0.320	**	-1.244	0.319	**
Random Part										
Level 2 Variance		4.607	*1.091*	**	4.283	1.087	**	4.249	1.084	**
Level 1 Variance		83.447	*1.504*	**	83.907	1.509	**	83.746	1.506	**

Table 5.S4 Full model results predicting mental health for system risk, simple risk, and total score allostatic load measures

Mental Health		*System Risk*			*Simple Risk*			*Total Score*		
		β	S.E.		β	S.E.		β	S.E.	
Fixed Part										
Cons		55.420	0.811	**	55.451	0.811	**	54.400	0.843	**
	Q1 (ref)									
	Q2	-0.463	0.263		-0.454	0.263		-0.449	0.263	
	Q3	-0.567	0.267	*	-0.558	0.267	*	-0.545	0.267	*
Neighbourhood	Q4	-0.853	0.286	**	-0.837	0.286	**	-0.813	0.286	**
Deprivation	Q5	-1.495	0.314	**	-1.486	0.314	**	-1.462	0.314	**
	England (ref)									
	Wales	-0.749	0.345	**	-0.744	0.345	*	-0.730	0.345	*
Country	Scotland	-0.062	0.303		-0.048	0.303		-0.037	0.303	
Allostatic Load		-0.461	0.103	**	-0.166	0.038	**	-1.084	0.205	
Age		-0.159	0.031	**	-0.153	0.031	**	-0.133	0.032	**
Age^2		0.002	0.000	**	0.002	0.000	**	0.002	0.000	**
Sex	*Male (ref)*									
	Female	-1.627	0.169	**	-1.718	0.169	**	-1.768	0.170	**
Ethnicity	*White (ref)*									
	Non-White	-0.658	0.441		-0.701	0.441		-0.685	0.440	
Employment Status	*Employed (ref)*									
	Retired	1.362	0.309	**	1.346	0.309	**	1.333	0.309	**
	Inactive/Other	-2.850	0.271	**	-2.845	0.271	**	-2.829	0.271	**
Marital Status	*Married (ref)*									
	Single	-1.135	0.202	**	-1.152	0.202	**	-1.153	0.202	**
Education	*Degree (ref)*									
	A Level	0.230	0.239		0.224	0.239		0.229	0.239	
	GCSE	0.352	0.235		0.353	0.235		0.365	0.235	
	Other	0.193	0.303		0.189	0.303		0.212	0.303	
	None	-0.397	0.308		-0.417	0.308		-0.392	0.308	
Welfare Status	*Not receiving (ref)*									
	Receiving	-2.992	0.327	**	-3.004	0.327	**	-2.984	0.327	**
Tenure	*Owned (ref)*									
	Social Rented	-1.135	0.307	**	-1.125	0.307	**	-1.095	0.307	**
	Private Rented	-0.462	0.306		-0.457	0.306		-0.454	0.306	
Random Part										
Level 2 Variance		6.496	1.026	**	6.487	1.025	**	6.504	1.025	**
Level 1 Variance		73.511	1.343	**	73.527	1.343	**	73.449	1.341	**

Table 5.S5 Full model results predicting system risk, simple risk, and total score allostatic load measures

Allostatic Load		*System Risk*			*Simple Risk*			*Total Score*		
		β	S.E.		β	S.E.		β	S.E.	
Fixed Part										
Cons		-0.472	0.074	**	-1.120	0.200	**	-1.141	0.037	**
Neighbourhood Deprivation	*Q1 (ref)*									
	Q2	0.044	0.024		0.171	0.065	**	0.032	0.012	**
	Q3	0.103	0.024	**	0.340	0.066	**	0.064	0.012	**
	Q4	0.100	0.026	**	0.374	0.071	**	0.079	0.013	**
	Q5	0.192	0.029	**	0.588	0.078	**	0.112	0.014	**
Country	*England (ref)*									
	Wales	0.006	0.031		0.045	0.086		0.019	0.016	
	Scotland	0.053	0.028		0.231	0.075	**	0.046	0.014	**
Age		0.023	0.003	**	0.100	0.008	**	0.033	0.001	**
Age^2		0.000	0.000		-0.001	0.000	**	0.000	0.000	**
Sex	*Male (ref)*									
	Female	0.055	0.015	**	-0.394	0.041	**	-0.107	0.008	**
Ethnicity	*White (ref)*									
	Non-White	0.159	0.040	**	0.179	0.109		0.043	0.020	*
Employment Status	*Employed (ref)*									
	Retired	0.051	0.028		0.041	0.076		-0.005	0.014	
	Inactive/Other	0.069	0.025	**	0.223	0.067	**	0.049	0.012	**
Marital Status	*Married (ref)*									
	Single	0.030	0.018		-0.020	0.050		-0.004	0.009	
Education	*Degree (ref)*									
	A Level	0.109	0.022	**	0.261	0.059	**	0.045	0.011	**
	GCSE	0.119	0.021	**	0.335	0.058	**	0.062	0.011	**
	Other	0.121	0.028	**	0.307	0.075	**	0.068	0.014	**
	None	0.256	0.028	**	0.590	0.076	**	0.114	0.014	**
Welfare Status	*Not receiving (ref)*									
	Receiving	0.121	0.030	**	0.263	0.081	**	0.059	0.015	**
Tenure	*Owned (ref)*									
	Social Rented	0.158	0.028	**	0.503	0.076	**	0.104	0.014	**
	Private Rented	0.058	0.028	*	0.191	0.076	*	0.032	0.014	*
Random Part										
Level 2 Variance		0.052	0.009	**	0.451	0.063	**	0.014	0.002	**
Level 1 Variance		0.616	0.011	**	4.414	0.081	**	0.153	0.003	**

Table 5.S6 Indirect effect results on physical health for system risk, simple risk, and total score allostatic load measures

Physical Health: Indirect Effects					
		IE	95% CI	IE_{ps}	95% CI
System Risk	Q2	-0.100	(-0.210, 0.006)	-0.009	(-0.019, 0.001)
	Q3	-0.264	(-0.402, -0.137)	-0.024	(-0.037, -0.012)
	Q4	-0.273	(-0.420, -0.130)	-0.025	(-0.038, -0.012)
	Q5	-0.528	(-0.713, -0.358)	-0.048	(-0.065, -0.033)
Simple Risk	Q2	-0.148	(-0.264, -0.038)	-0.013	(-0.024, -0.003)
	Q3	-0.325	(-0.471, -0.195)	-0.030	(-0.043, -0.018)
	Q4	-0.357	(-0.510, -0.215)	-0.032	(-0.046, -0.020)
	Q5	-0.555	(-0.745, -0.384)	-0.050	(-0.068, -0.035)
Total Score	Q2	-0.154	(-0.275, -0.040)	-0.014	(-0.025, -0.004)
	Q3	-0.337	(-0.484, -0.205)	-0.031	(-0.044, -0.019)
	Q4	-0.418	(-0.576, -0.271)	-0.038	(-0.052, -0.025)
	Q5	-0.595	(-0.786, -0.420)	-0.054	(-0.071, -0.038)

Table 5.S7 Indirect effect results on mental health for system risk, simple risk, and total score allostatic load measures

Mental Health: Indirect Effects					
		IE	95% CI	IE_{ps}	95% CI
System Risk	Q2	-0.020	(-0.047, 0.001)	-0.002	(-0.005, 0.000)
	Q3	-0.047	(-0.081, -0.021)	-0.005	(-0.009, -0.002)
	Q4	-0.046	(-0.080, -0.019)	-0.005	(-0.009, -0.002)
	Q5	-0.088	(-0.137, -0.045)	-0.009	(-0.015, -0.005)
Simple Risk	Q2	-0.028	(-0.057, -0.007)	-0.003	(-0.006, -0.001)
	Q3	-0.056	(-0.094, -0.026)	-0.006	(-0.010, -0.003)
	Q4	-0.062	(-0.102, -0.030)	-0.007	(-0.011, -0.003)
	Q5	-0.097	(-0.151, -0.050)	-0.010	(-0.016, -0.005)
Total Score	Q2	-0.034	(-0.066, -0.009)	-0.004	(-0.007, -0.001)
	Q3	-0.069	(-0.110, -0.036)	-0.007	(-0.012, -0.004)
	Q4	-0.086	(-0.134, -0.047)	-0.009	(-0.014, -0.005)
	Q5	-0.121	(-0.181, -0.071)	-0.013	(-0.019, -0.008)

Introduction to Chapter 6

This empirical chapter addresses the final research question: How are different exposure profiles of deprivation and social capital related to later allostatic load? So far, a biosocial test of the stress pathway has shown that allostatic load mediated the relationship of neighbourhood deprivation with physical health. A mediation effect was also suggested for mental health, though this was marginal and small in effect size; mental health showed smaller associations with allostatic load overall. Support for the biosocial action of the stress pathway mechanism, as conceptualised through the burden of allostatic load, was provided. The mediation analysis results, therefore, bolstered the arguments from Chapter 4 which demonstrated how exposure to a higher degree of deprivation was related to poorer self-rated health, in line with the stress pathway theorisation.

What I want to do now is extend the investigation of the stress pathway and additionally integrate aspects of dynamic exposure from the exposome. In doing so we move from a static conceptualisation of biosocial exposure to a dynamic one that is more representative of the exposure people experience over time. This is achieved through investigation of long-term trajectories of deprivation and social capital and how these different histories of disadvantage relate to later allostatic load. Therefore, this chapter serves to address both the need for understanding of the temporality of exposure-health relationships, and the need to investigate biologically relevant mechanisms for the embodiment of contexts. It sits within the framework of a biosocial and 'exposomic' health geography as put forward in Chapter 2.

The following analysis explores trajectories of neighbourhood deprivation and structural social capital over a 20-year period. Latent class growth analysis is employed to identify distinct subgroups of exposure histories. These are then related to allostatic load as a distal outcome, testing the proposed accumulative process of allostatic load and the stress pathway hypothesis. This analysis contributes to the literature as studies which consider neighbourhood exposures and social capital over time rarely consider more than a few timepoints over the lifecourse or have a short time frame. The examination of how particular latent trajectories of deprivation and social capital relate to allostatic load also allows insight

into how the *dynamics* of exposure relate to health weathering, rather than simple cumulative measures of exposure.

Included at the end of this chapter are two tables of supplementary results which demonstrate the associations of the latent classes of deprivation and social capital exposure to allostatic load when a fully balanced sample is used. This included those BHPS participants who are present at all used waves of data. These supplementary results are included to demonstrate the impact of potential selection and attrition biases on the conclusions drawn, in comparison to the main analysis which used all information with a Full Information Maximum Likelihood estimator and under a Missing At Random (MAR) assumption.

Chapter 6. Allostatic load and exposure histories of disadvantage

I Introduction

The persistence of health inequalities across contexts and scales means understanding the processes of exposure-health relationships is an important area of research. Biosocial perspectives on health geography (Guthman and Mansfield, 2012; Krieger, 1994) offer new avenues for investigating the mechanisms by which gradients of status and disadvantage become manifest in the health of bodies as shown in Chapter 2. Concerned with the dynamic entanglements of social and biological processes, biosocial research can give insight into how environments 'get under the skin' (Taylor et al., 1997). Explaining social inequalities in health involves understanding the embodiment of the environment; biosocial data provides objective measures of the biological embedding of multiple exposures (Delpierre et al., 2016).

Pathways related to stress are relevant processes for understanding the transition from exposure to health. The social and physical environments which characterise different places and environments can be varyingly perceived as threatening or stressful (Boardman, 2004; McEwen, 2017). For example, the disordered and deteriorated environments that may typify deprived areas are commonly theorised to impact health through the incitation of stress (Dulin-Keita et al., 2012; Robinette et al., 2018; Ross and Mirowsky, 2001). Quotidian and repeated exposure to such stressful environments can result in 'wear and tear' on the body and this weathering through chronic stress can negatively influence health, a process captured through the concept of allostatic load (McEwen, 2008; McEwen and Seeman, 1999; McEwen and Stellar, 1993). Moreover, other experiences may impart a stress-buffering influence, working to alleviate the negative impact of disadvantage. For example, the beneficial health effects of green space are often linked to stress reduction (De Vries et al., 2013; Finlay et al., 2015; Hordyk et al., 2015). The stress-buffering hypothesis is also a major theoretical underpinning for positive associations of social capital with health (Kawachi and Berkman, 2001; Stafford et al., 2008; Uphoff et al., 2013). These ideas feed into the so-called 'stress pathway', a biosocial mechanism by which to understand how different exposure histories are embodied over time in the varying health states of individuals.

Investigating how exposures through the lifecourse relate to later health states is a vital component to understanding health inequalities. The biosocial viewpoint, appreciating the importance of heterogeneous exposures and processes, allies with another major health concept, that of the exposome (Wild, 2005, 2012). The exposome, designed as a conceptual complement to the genome, is focused on environmental exposures: considering the 'environment' to encompass factors within and outside the body. Hence, the exposome is clearly aligned with the biosocial ideas presented in Chapter 2. Similar to a biosocial lens on health, the dynamism of exposure and mutability of the body to experience is central to the exposome. It considers the whole lifecourse and places exposure within a space-time framework of trajectories, rather than as static factors (Jacquez et al., 2015). Therefore, it is a useful framework in the investigation of the stress pathway, where repeated exposure over time to situations perceived as stressful is vital to the allostatic process (Delpierre et al., 2016).

To investigate how stress-related exposures relate to a cumulative marker of biological weathering, it is therefore important to consider long-term environmental histories, appreciating the changing nature of exposure over time. This study will identify trajectories of neighbourhood deprivation and social capital over a 20-year period, and relate these histories to allostatic load. Therefore, this analysis offers a test of the chronic accumulation theory of the stress pathway through the lens of a biosocial and exposomic conceptual framework.

II Background

The stress pathway has long been posited as a critical element of individual outcomes in social health research. Previously this tended to be implicit, with a stress mechanism acting as an underlying theoretical proposal for explaining associations. For example, the income inequality hypothesis relies on conceptualising relative deprivation as a source of chronic stress to explain its relevance to health gradients (Singh et al., 2016; Wilkinson and Pickett, 2007). However, increasing availability of biodata within social surveys means a growing number of studies are explicitly investigating stress-related pathways for the embodiment of

exposures (Taylor et al., 1997). For example, studies have shown differences in cortisol levels and reactivity – cortisol being a primary stress hormone – by the intensity of neighbourhood disadvantage, social control and poverty (Barrington et al., 2014; Hajat et al., 2015; Rudolph et al., 2014). Dowd et al. (2009) reviewed studies examining associations of socioeconomic status with cortisol and allostatic load. Overall, they found inconsistent evidence for associations of status and different cortisol measures. The labile nature of cortisol, which shows a high degree of intra-individual variation, problematises measurement (Dowd et al., 2009). In contrast, more agreement was found in relationships of socioeconomic status and allostatic load, which summarises a long-term, accumulative response to stress exposure (Dowd et al., 2009; McEwen and Stellar, 1993).

Allostatic load is a prominent concept drawn upon in the burgeoning biosocial literature. Fitting with the 'weathering hypothesis' (Geronimus, 1992), allostatic load captures the cost of chronic stress, with health implications for a variety of biological systems (McEwen and Seeman, 1999; McEwen and Stellar, 1993). As a concept it reflects persistent exposure to stressful stimuli and the resultant physiological processes, but also the impact of behavioural habits, as well as developmental processes that pattern exposure responses (McEwen and Seeman, 1999). Allostatic load provides a useful tool in explaining social health inequalities over the lifecourse. For instance, Geronimus et al., (2015, 2010) draw on the theorised framework of allostatic load in evidencing accelerated biological ageing through perceived stress and exposure to poverty, neighbourhood dissatisfaction and negative social interactions.

Combining information on biomarkers from across physiological systems involved in allostatic pathways enables allostatic load to be operationalised in quantitative social research. In this way, allostatic load has been corroborated as predictive of mortality and a variety of morbidities, such as cardiovascular disease, physical and cognitive decline, and depressive symptoms (Juster et al., 2010; Mattei et al., 2010; Seeman et al., 1997, 2001). A growing number of studies investigate how allostatic load relates to measures of socioeconomic status, with allostatic load proposed as a biosocial link between social and health gradients. Johnson et al. (2017) reviewed 26 studies, and found that, while the operationalisation of

allostatic load varied in terms of the calculation method and biomarkers used, there was general consensus in low socioeconomic status relating to worse allostatic load.

Turning to contextual exposures, recent work has explored biosocial pathways that may explain the 'black-box' of how neighbourhoods influence health. The neighbourhood effects research paradigm has long called for the exploration of the mechanisms of effects (Van Ham et al., 2012). To date, studies have largely substantiated the proposed conceptual framework of the stress pathway in relation to neighbourhood socioeconomic status, poverty, segregation, as well as social and physical environment 'riskscapes' (Bellatorre et al., 2011; Bird et al., 2010; Mair et al., 2011; Schulz et al., 2012, 2013; Seeman et al., 2014; Stein Merkin et al., 2009; Theall et al., 2012). Recent work has further corroborated the biosocial processes of the stress pathway, providing evidence that allostatic load mediated relationships between neighbourhood deprivation and health (Chapter 5 published as Prior et al. (2018a)). However, as highlighted in a review by Ribeiro et al. (2018) the majority of studies examining allostatic load and contextual exposures are cross-sectional in nature and many rely on the same datasets from the US, limiting generalisability across different national contexts where particular societal conditions can produce difference patterns of association (Xu, 2018).

Longitudinal data is a vital resource in understanding health pathways, helping to establish the temporal ordering of exposure then outcome and help rule out alternative explanations such as selection effects. Jiménez et al. (2015) for instance, demonstrated that individuals with higher income relative to the rest of their neighbourhood had lower allostatic load at two years follow-up, but they did not show statistically significant support for a longitudinal impact of neighbourhood socioeconomic status on allostatic load. In contrast, Chen et al. (2015) reported that young African Americans who had resided in neighbourhoods of higher poverty had worse allostatic load at one-year follow-up, compared with those from less disadvantaged neighbourhoods. Longitudinal studies that consider longer multi-year to decadal time-frames, are also important in enabling a wider variety of research questions concerning dynamism, lifecourse hypotheses and exposure-health trajectories.

Studies of lifecourse epidemiology (Ben-Shlomo and Kuh, 2002) have produced a suite of research on how individual-level experiences throughout life relate to later health states.

Following a history of developmental research, such as that on the foetal origins hypothesis (Barker, 1995; Barker et al., 1989, 1993, 2002), a variety of early-life experiences and stressors have been shown to have long-standing influences on later-life biomarkers. For example, Barboza Solís et al. (2015, 2016) found associations of childhood socioeconomic position and adverse childhood experiences (factors such as parental separation, being in care and neglect) with allostatic load at 44 years old in the 1958 British birth cohort. Using retrospective reports, Friedman et al. (2015) evidenced an association between early-life adversity and allostatic load later in life. Similarly Non et al. (2014) found social adversity assessed in childhood was significantly associated with cardiometabolic risk in mid-life. Therefore, these studies suggest an early-life biological embedding of disadvantage which can have long-term consequences for health inequalities.

Moreover, research has also explored the contribution of different lifecourse hypotheses for the relationship of social status and health over time. For example, Walsemann et al. (2016) investigated sensitive period, accumulation, social mobility and pathway models for the association of socioeconomic status in adolescence and adulthood with biomarkers of cardiovascular risk. Social mobility and pathway lifecourse models both involve the indirect impact of early-life exposures on health through later status, but the social mobility model incorporates the potential for resilience through upward mobility (Walsemann et al., 2016). They found that support for each of these lifecourse hypotheses varied by gender and ethnicity: for example, all four models were supported for white women, whereas they were unable to demonstrate the influence of any of the models among black participants. Additionally, Yang et al. (2017) showed direct and indirect pathways from early-life socioeconomic status to biomarker summaries of inflammatory and metabolic burdens, as well as finding evidence for an accumulative impact of disadvantage. A potential sensitive period at the transition to adulthood was demonstrated by Gustafsson et al., (2012) for the influence of social adversity on mid-life allostatic load, with an accumulative model also supported.

An accumulative impact of disadvantage over time is a commonly theorised lifecourse model for linking social and health inequalities, and one which fits well with allostatic weathering as

a representation of the total cost of adapting to the environment over time (Delpierre et al., 2016). Lifecourse accumulation models exploring neighbourhood conditions are rare, given the operational difficulties of collecting or linking geographic data over long histories. Lemelin et al. (2009) obtained 20-year residential histories for participants, using Census tract information to create measures of average exposure to neighbourhood poverty over time. In subsequent analyses, they found that greater cumulative exposure to neighbourhood poverty was associated with a biomarker of subclinical atherosclerosis, but only for women (Lemelin et al., 2009). Another example used Swedish cohort data to demonstrate how cumulative neighbourhood disadvantage, summarising a range of socioeconomic characteristics at 16, 21, 30 and 43 years of age, significantly predicted allostatic load in mid-life (Gustafsson et al., 2014). However, the sporadic and sometimes unclear direction and strength of outcomes means that further research exploring associations of neighbourhood-level circumstances and biomarkers over long time periods is still needed. In particular, following the framework provided by the exposome, exploring the dynamics of change over time, for instance through study of exposure trajectories, would facilitate insight into the biological embedding of stressors.

In addition to the consideration of contextual exposures, there are also more limited studies which analyse aspects of social capital in relation to biosocial mechanisms. In view of the entanglement of social capital with stress-related theorisations this is a gap which needs addressing. Robinette et al. (2018) drew upon the neighbourhood health literature in showing that perceptions of neighbourhood cohesion predicted a biomarker summary of cardiometabolic risk four years later. Psychosocial processes of social support and isolation were also implicated in work by Stafford et al. (2013), who showed that older persons who had recently become widowed or were newly living alone had higher night-time cortisol levels that those married or living with others respectively. However, both these studies have relatively short time frames and only two points of social capital or support data. In a study of childhood maltreatment, Horan and Widom (2015) found that lower perceived social support throughout the life span was related to higher allostatic load and partially mediated the association of maltreatment with allostatic load. Capitalising on the social data resource

of longitudinal studies in the UK to explore the dynamics of social capital over a long time period and their relationship to biodata can clearly contribute to our understanding of stress-related health pathways.

The dynamics of the 'non-genetic' environment are of central concern in exposome studies (Wild, 2012). This points towards thinking about exposure to different trends of factors over time. Analysing exposure trajectories can further our understanding of health inequalities through appreciating heterogeneity in heath states between those who have experienced a dynamically changing environment and those who have a more static exposure history. Variety in trajectories can also be exploited to explore lifecourse models. For example, Gruenewald et al. (2012) compared the degree of allostatic load between trajectories of socioeconomic status from childhood to adulthood. They reported that those with persistently low status had the highest allostatic load, suggesting a cumulative association, followed by those experiencing a downward trend in status, potentially indicating a negative impact from loss of status (Gruenewald et al., 2012). Lin et al. (2017) reported that older persons with consistently high socioeconomic position over their lifecourse had significantly lower levels of two inflammatory biomarkers than those who had constantly low status, or those who had experienced upward social mobility. Therefore, a model of social mobility may not always impart a biological health benefit. However, both these studies rely in part on retrospective reporting which can introduce bias. Studies which investigate trajectories of multiple exposures measured across a series of timepoints would, therefore, be a valuable contribution to the literature on health inequalities. Moreover, the social sphere is largely underrepresented in exposome research currently, meaning studies of dynamic exposure histories and their relation to biosocial processes are needed.

This analysis investigates the stress pathway by examining how long-term exposure histories of neighbourhood deprivation and social capital relate to later allostatic load. A latent class approach to defining the exposure histories will be taken, accounting for heterogeneous trajectories in unobserved (latent) sub-groups of the population. It is hypothesised that the identified exposure trajectories will follow graded associations with allostatic load. Higher or worsening deprivation exposure is expected to be related to increased allostatic load, in

comparison to trajectories that reflect less disadvantaged histories. According to the stress-buffering hypothesis, higher or increasing social capital, in comparison with lower or decreasing social capital, is anticipated to be associated with lower allostatic load.

III Data

Data for this analysis is drawn from the British Household Panel Survey (BHPS) and the follow-on UK Household Longitudinal Study (UKHLS commonly referred to as Understanding Society) which as well as enrolling new participants continued to sample consenting BHPS participants from Wave 2 onwards (University of Essex et al., 2018b). At Wave 3 of Understanding Society (collected between 2011 and 2012) a nurse-based health assessment was carried out for eligible participants of the BHPS sample, taking a blood sample from which a range of biomarkers could be extracted (Benzeval et al., 2014; McFall et al., 2014; University of Essex and Institute for Social and Economic Research, 2014b). Our sample consists of 3,210 individuals who had non-missing information on at least one of the biomarkers used to construct allostatic load.

Allostatic load

The response is allostatic load, marking physiological weathering due to chronic stress exposure. An index of allostatic load is constructed from 13 biomarkers (see Table 6.1), encompassing measures from the HPA-axis and cardiovascular, lipid and glucose metabolism, and inflammatory systems. The index is a summary risk-score counting the number of biomarkers for which participants fell into high-risk quartiles (this was the lowest quartile for DHEAs, HDL cholesterol and albumin, elsewise the highest quartile). Quartile cut-offs are presented in Table 6.1; though sample-based these cut-offs correspond well to clinical cut-points, where these are known for the biomarkers (Benzeval et al., 2014). This operationalisation follows previous established conventions in constructing allostatic load measures (McEwen and Seeman, 1999; Seeman et al., 1997).

Table 6.1 Biomarker summaries and high-risk quartile cut-off values

System	*Biomarker*	N	Mean (SD)	High Risk Cut-off Values
Cardiovascular	*Systolic Blood Pressure*	2628	126.44(16.64)	≥136.5 mmhg
	Diastolic Blood Pressure	2628	73.01(10.84)	≥80 mmhg
	Pulse Rate	2628	68.79(10.93)	≥75.5 bpm
Lipid Metabolism	*HDL cholesterol*	3138	1.53(0.45)	<1.2 mmol/l
	Total: HDL cholesterol ratio	3137	3.75(1.35)	≥4.42
	Triglycerides	3144	1.79(1.27)	≥2.2 mmol/l
	BMI	3112	28.02(5.52)	≥30.9 kg/m^2
	Waist Circumference	3161	93.70(14.52)	≥103.1 cm
Glucose Metabolism	*HbA1c*	2969	37.30(8.67)	≥39 mmol/molhb
Inflammatory	*C-Reactive Protein*	3019	3.24(6.60)	≥3.2 mg/l
	Fibrinogen	3121	2.81(0.62)	≥3.2 g/l
	Albumin	3139	46.62(2.94)	<45 g/l
HPA-axis	*DHEAs*	3137	4.74(3.36)	<2.2 mol/l

Deprivation

Townsend deprivation scores (Townsend, 1987) are used to construct neighbourhood disadvantage exposure histories. The Townsend index is calculated based on four measures: unemployment; non-car ownership; non-home ownership; and household overcrowding. Z-scores are calculated for the percentage of each of the four measures within small-area units (logged percentages are used for the indicators of unemployment and overcrowding to account for skew). The Townsend deprivation score is the sum of these z-scores. Positive Townsend deprivation scores indicate more deprived areas, whilst negative values represent relatively less deprived areas than average.

This analysis uses Townsend deprivation scores derived from the 1991, 2001 and 2011 UK Censuses harmonised to 2011 Lower Layer Super Output Areas (LSOAs) boundaries, providing a time-comparable index (for details on the harmonisation methodology see Norman, 2016, 2010; Norman and Darlington-Pollock, 2018)[6]. Scores are matched to the main dataset by

[6] The 1991, 2001 and 2011 Townsend scores and quintiles linked with the 2011 LSOA codes were provided to the author by Paul Norman.

2011 LSOA or DZ code (University of Essex et al., 2018a; University of Essex and Institute for Social and Economic Research, 2014a). For the BHPS waves we first had to match the 2001 LSOA and DZ codes to their 2011 counterparts. A simple approach is taken, keeping those LSOAs in England and Wales that were unchanged between 2001 and 2011 (97% of areas in the sample) (Office for National Statistics, 2018b), and for Scotland we kept those areas where the 2001 centroid fell inside the 2011 boundary (95% of Scottish DZs in our sample) (Scottish Government, 2018a, 2018b).

To account for change in deprivation over time, the Townsend deprivation scores are linked to every other wave of the BHPS, and additionally to Wave 2 of Understanding Society, creating 10 timepoints of exposure history. The scores were applied to the 10 timepoints, with census years as mid-points: thus, 1991 Townsend deprivation scores were assigned to BHPS Waves 1, 3 and 5; 2001 scores to BHPS Waves 7, 11 and 13; and 2011 scores covered the final 4 timepoints (BHPS Waves 15 and 17 and Wave 2 of Understanding Society).

To facilitate descriptive analyses a second measure of deprivation is created, contrasting those in the top two quintiles of the Townsend deprivation score (high deprivation coded 1) with those in the lowest three quintiles (low deprivation coded 0). Descriptive trajectories are calculated by comparing high or low deprivation status at each individual's first and last occurrence in the dataset. We compare four categories of trajectories: Low-Low, persistently low deprivation; Low-High, those who experienced downwards mobility to a worse neighbourhood status; High-Low, those who experience upwards mobility in terms of deprivation status; and High-High those who entered the dataset residing in a neighbourhood of high deprivation and who remain in a high deprivation area. These trajectories were only calculated for those respondents with at least two waves of information and allostatic load data (3,095 persons).

Social capital

Participants were asked whether they joined in the activities of any of a list of organisations

on a regular basis, whether or not they were formally a member of those organisations[7]. We use information on this variable from every other wave of the BHPS (from Wave 1 to 17 inclusive) and additionally from Wave 3 of Understanding Society. For each of these 10 timepoints, a summary count measure of the number of organisations respondents identified as regularly active in was calculated, providing a history of structural social capital. The social capital variable ranged between 0 and a maximum of 9.

Covariates

To account for key social and demographic characteristics important to relationships of chronic stress and health, a series of covariates measured contemporaneously with the biomarker data are assessed when predicting allostatic load. Age and sex are included, as well as education, employment status, tenure, marital status and subjective financial situation. Age is a continuous variable, centred around the mean of 51.5 years-old. Education is measured by highest qualification level, grouped into three categories: Higher (Degree or other higher qualification); Middle (A level, GCSE, or equivalent); and Lower (Other or no qualifications). Employment status is categorical, comprising: employed (including self-employed), retired, and those who are unemployed or otherwise inactive. Tenure contrasts those who live in owner-occupied households, socially rented accommodation and privately rented accommodation. Marital status is a binary variable comparing those who are married or in a civil partnership with individuals who are single, separated, divorced or widowed. Participants were asked 'How well would you say you yourself are managing financially these days? Would you say you are…' with the possible responses being: 'living comfortably', 'doing alright', 'just getting by', 'finding it quite difficult' and 'finding it very difficult'. We group the responses into three categories, combining 'living comfortably' and 'doing alright' into the top group, and merging both finding it difficult responses. Summaries of the covariates and allostatic load are presented in Table 6.2.

[7] The list of potential organisations included 16 organisations, such as 'Political party', 'Trade unions', and 'Environmental group'. The full list can be accessed online (www.understandingsociety.ac.uk).

Table 6.2 Summaries of allostatic load and sociodemographic characteristics from the final wave

Factor		Mean (SD)	N
Allostatic load		3.07(2.45)	3210
Age		51.53(17.58)	3210
		%	
Sex	*Female**	54.83	3210
	Male	45.17	
Education level	*Degree**	31.29	3186
	A Level/GCSE	46.39	
	Other/None	22.32	
Employment status	*Employed**	56.07	3210
	Retired	29.16	
	Unemployed/Inactive	14.77	
Tenure	*Owned**	79.25	3206
	Privately rented	8.86	
	Socially rented	11.79	
Marital status	*Married**	69.31	3210
	Single/SDW	30.69	
Subjective financial situation	*Comfortable/Alright**	66.06	3209
	Just getting by	25.62	
	Finding it difficult	8.32	

Notes: * indicates reference category.

IV Methods

This analysis seeks to identify distinct trajectories of social capital and deprivation, and to evaluate how these exposure histories relate to later allostatic load. For the first stage of this process – identifying trajectories of exposure – this analysis uses latent class growth analysis (LCGA). LCGA is a type of growth mixture modelling, a method for modelling the change in a variable allowing for different trajectories across sub-groups of the population (Jung and Wickrama, 2008). These sub-groups are unobserved, capturing inter-individual heterogeneity through latent classes.

To identify distinct exposure histories of social capital and Townsend deprivation scores a set of LCGA models are run, specifying an increasing number of latent groups, building upwards from 2 classes. Each model run is compared using model fit and other indices to determine the most appropriate number of classes. A smaller sample-sized adjusted Bayesian

Information Criteria (SSABIC) suggests a better fitting model. Entropy is a measure of how well separated the classes are from each other; a value closer to 1 is indicative of more clearly defined latent groups (Jung and Wickrama, 2008). A significant Lo, Mendell, and Rubin likelihood ratio test (LMR-LRT) and bootstrap likelihood ratio test (BLRT) also indicate whether the addition of an extra class is an improvement over a model with n-1 classes (Jung and Wickrama, 2008; Lo et al., 2001; McLachlan and Peel, 2000). The count and proportion of individuals classified to each latent group are also examined to ensure a reasonable sample-size, and the identified classes are graphically compared to gauge their conceptual meaningfulness. For Townsend deprivation, the latent classes are defined based on data for 3,095 individuals, for social capital the trajectories are based on 3,096 individuals. Panel membership across the timepoints can vary, resulting in an unbalanced panel which is estimated using full information maximum likelihood[8].

The second stage of the analysis involves investigating how these identified exposure histories relate to allostatic load, the distal outcome. Generally, there are two sets of approaches to examining relationships between latent classes and other variables: one-step and three-step methods. One-step approaches involve the simultaneous estimation of the measurement model (where the latent classes are identified) and the structural model (relating the latent classes to the distal outcome) (Vermunt, 2010). However, the simultaneous estimation of the one-step procedure would mean the distal outcome, here allostatic load, would contribute to the delineation of the latent classes, rather than only the exposure variables of interest (deprivation or social capital) (Dziak et al., 2016). This circularity is undesirable and can also result in a shift in the latent class variables from the specification without the distal outcomes (Asparouhov and Muthén, 2018; Bakk and Vermunt, 2016). In contrast three-step approaches involve: (1) estimation of the latent classes; (2) assignment of individuals to the different classes based on posterior class membership probabilities; and (3) use of latent class memberships as observed variables in predicting the response of interest (Bakk and Vermunt, 2016; Dziak et al., 2016). However, error is introduced through the classification procedure,

[8] For sensitivity analysis of selection bias the analysis was repeated with a fully balanced panel of 1,177 individuals. Results are presented in Supplementary Information.

producing bias in three-step approaches and resulting in attenuation of estimates at the final stage (Bolck et al., 2004; Dziak et al., 2016).

Therefore, to investigate how classes of deprivation and social capital relate to allostatic load at the final wave, an adjusted version of the corrected three-step method proposed by Bolck, Croon and Hagenaars (2004) is used, which we will refer to as the BCH method. The BCH method accounts for classification error in predicting the distal outcome by weighting the assigned class memberships with the inverse of the classification errors. This method avoids shifts in the definition of classes; at the final step the classes are known. The BCH method has been shown to perform well in comparison to one-step, standard three-step and other corrected three-step approaches (Bakk and Vermunt, 2016; Dziak et al., 2016).

A series of models using the BCH method are implemented to assess relationships of deprivation and social capital exposure classes to allostatic load. Firstly, we run a null model where only the latent classes of exposure are used to predict allostatic load. Secondly, a model is run controlling for the key demographic characteristics of age and sex. Finally, a full model containing all socioeconomic covariates is tested to see whether the exposure trajectories influence allostatic load beyond the impact of more proximal, both in scale and temporally, stress-related exposures.

Data preparation and descriptive analysis is carried out in Stata version 15 (StataCorp, 2017). The LCGA and BCH method analysis is conducted using M*plus* version 7 (Asparouhov and Muthén, 2018; Muthén and Muthén, 2015).

V Results

Descriptive analyses using the dichotomised deprivation measure shows that the majority of participants are positioned in the group of consistently low deprivation when comparing their first and last timepoints, around 56% of 3095 individuals. However, the second largest grouping are those classed as exposed to persistently high deprivation (19%), meaning at their first and last occurrences in the dataset they were in neighbourhoods grouped in the top two quintiles of deprivation score. A further 17% experience upwards mobility, either by moving

to a better neighbourhood or residing in an area that improved. Finally, a small group, approximately 8% of individuals, are exposed to a worsening trend in neighbourhood deprivation.

Figure 6.1 presents the mean predicted allostatic load for the descriptive deprivation trajectories, controlling for age and sex as key demographic characteristics. The pattern reflects the theorisation of the stress pathway; belonging to the High-High group results in a higher mean allostatic load score than belonging to the Low-Low grouping, and overall the relationship between the deprivation trajectories and allostatic load is significant.

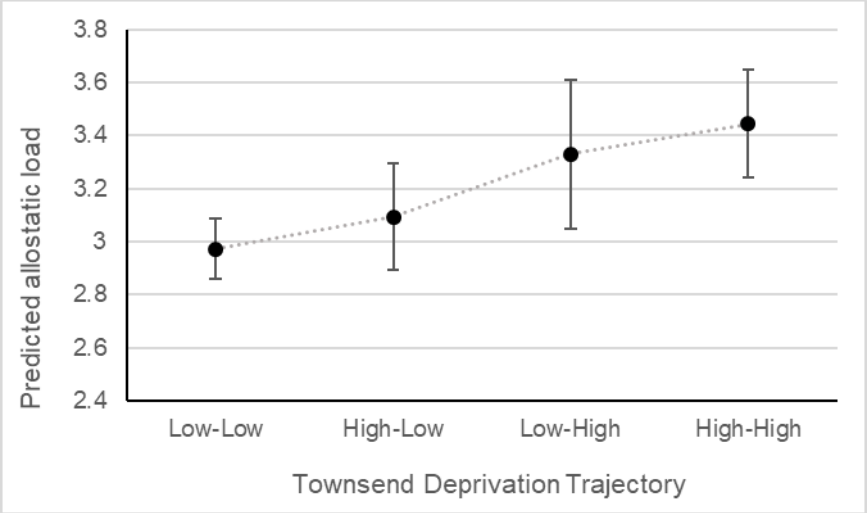

Figure 6.1 Mean predicted allostatic load by descriptive Townsend deprivation trajectory controlling for age and sex

LCGA Exposure histories

The first stage of the main analysis involves identifying an appropriate number of latent classes to summarise the trajectories of neighbourhood deprivation and social capital. Table 6.3 presents the model comparisons for both exposure measures. For social capital a three-class solution is deemed most appropriate as maintaining a larger sample size (>50) for each exposure trajectory is desirable. For deprivation, the four-class solution is chosen: the additional fifth class did not add a substantially different trajectory history, and the LMR-LRT did not return a significant value. The classes for social capital and deprivation are presented

in Figure 6.2. Note that for the Townsend score exposure histories a quadratic growth term is also included as this addition was found to improve model fit over a linear change formulation.

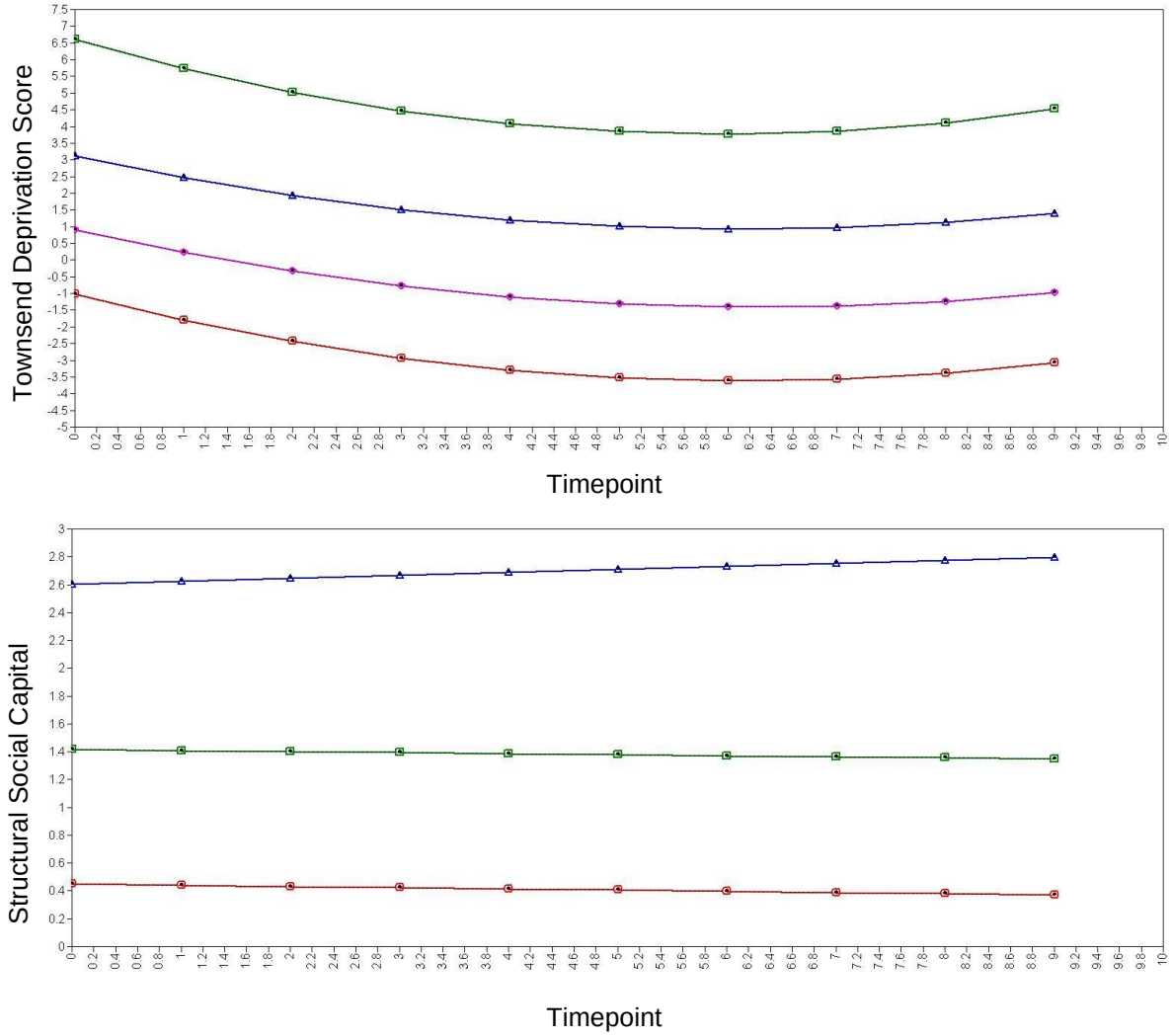

Figure 6.2 Exposure histories for Townsend deprivation score and structural social capital

Table 6.3 LCGA model comparison with different numbers of classes (selected model highlighted in bold)

	Classes	SSABIC	Smallest Class Size		Entropy	LMR-LRT	Bootstrap-LRT
			%	Count			
Townsend deprivation	2	93780.35	0.33	1019	0.907	0.000	0.000
	3	88670.63	0.14	425	0.892	0.000	0.000
	4	**86475.98**	**0.08**	**246**	**0.879**	**0.002**	**0.000**
	5	85530.94	0.05	147	0.844	0.276	0.000
	6	84555.45	0.05	143	0.854	0.129	0.000
Social capital	2	58948.61	0.18	543	0.898	0.000	0.000
	3	**57478.44**	**0.07**	**203**	**0.826**	**0.092**	**0.000**
	4	56809.16	0.02	48	0.808	0.021	0.000
	5	56435.34	0.01	45	0.773	0.099	0.000
	6	56189.13	0.01	46	0.761	0.362	0.000

The second stage of the main analysis concerns the relationship of allostatic load to the long-term exposure histories of disadvantage and social capital. Figure 6.3 presents the mean allostatic load scores for each of the deprivation classes across the series of models. Allostatic load is patterned by neighbourhood deprivation, with histories reflecting greater and more severe exposure to disadvantage associated with higher allostatic load. As expected, the overall difference between the classes decreases as the full range of sociodemographic characteristics are accounted for in Model 3 (see Figure 6.3). Indeed, the exposure histories are significantly related to allostatic load in Models 1 and 2, but the relationship borders on insignificance when more proximal characteristics are controlled for (see Table 6.4).

The results by trajectories of social capital are presented in Figure 6.4. Accounting for the influence of age and sex, and the other socioeconomic characteristics – Models 2 and 3 – revealed those in the high trajectory of social capital exhibited the lowest allostatic load. In Model 2 there is a clear gradient in allostatic load across the social capital histories which is largely in agreement with a stress-buffering hypothesis – that is belonging to more organisations has a beneficial outcome. However, the differences between the social capital classes are not significant at the 95% confidence level in Model 2 and become marginal and highly non-significant when the full range of sociodemographic characteristics are controlled for in Model 3 (see Table 6.5). In terms of the sociodemographic characteristics, for both the

deprivation and social capital models, individuals in more disadvantaged personal circumstances are expected to have higher allostatic load.

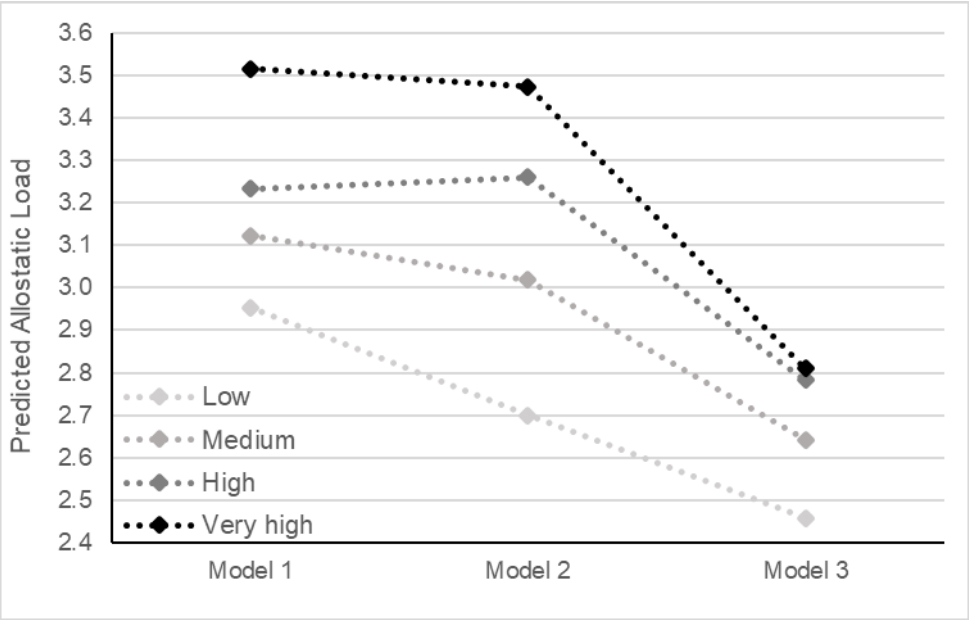

Figure 6.3 Mean predicted allostatic load by deprivation exposure history for each model

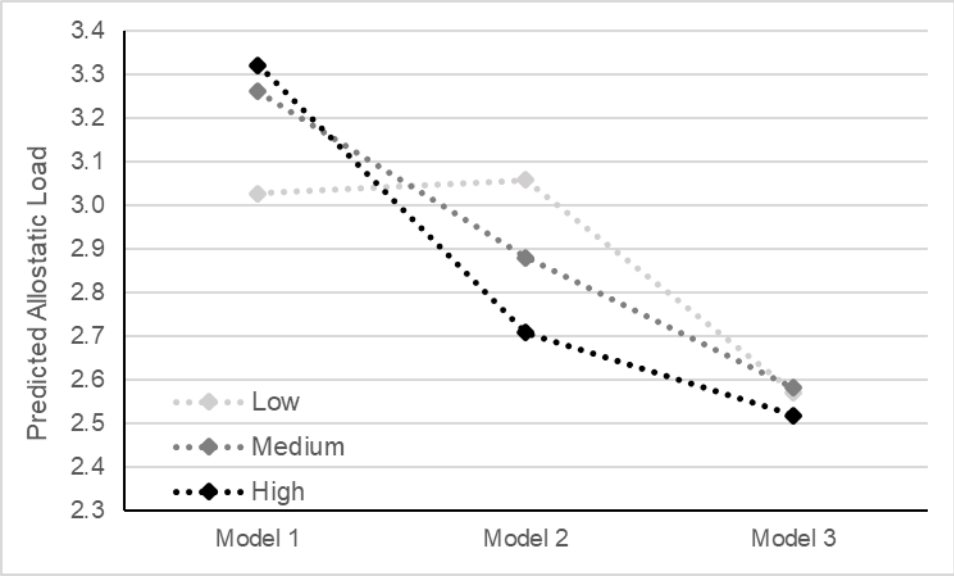

Figure 6.4 Mean predicted allostatic load by social capital exposure history for each model

Table 6.4 Estimated allostatic load means by deprivation exposure histories and covariate coefficients predicting allostatic load

		Model 1: No covariates		Model 2: Age and sex		Model 3: Sociodemographics	
N		3095		3095		3067	
	Allostatic load	Mean	S.E.	Mean	S.E.	Mean	S.E.
Deprivation Exposure History	Low	2.953	0.077	2.700	0.081	2.458	0.108
	Medium	3.123	0.092	3.018	0.092	2.642	0.122
	High	3.234	0.112	3.261	0.108	2.783	0.140
	Very high	3.516	0.187	3.474	0.170	2.810	0.206
	Overall test p-value	0.015		0.000		0.050	
		Beta	S.E.	Beta	S.E.	Beta	S.E.
Age				0.053	0.002	0.052	0.004
Sex	Female*						
	Male			0.292	0.079	0.302	0.080
Education	Degree*						
	A-Level/GCSE					0.238	0.096
	Other/None					0.463	0.123
Employment Status	Employed*						
	Retired					-0.054	0.140
	Unemployed/Inactive					-0.005	0.126
Subjective Financial Situation	Comfortable/Alright*						
	Just getting by					0.268	0.098
	Finding it difficult					0.478	0.170
Tenure	Owned*						
	Privately rented					0.265	0.150
	Socially rented					0.699	0.160
Marital status	Married*						
	Single/SDW					-0.163	0.090

Notes: * indicates reference category. Robust standard errors accounting for the clustering within neighbourhood (LSOA) units are used.

Table 6.5 Estimated allostatic load means by social capital exposure histories and covariate coefficients predicting allostatic load

		Model 1: No covariates		Model 2: Age and sex		Model 3: Sociodemographics	
N		3096		3096		3068	
	Allostatic load	Mean	S.E.	Mean	S.E.	Mean	S.E.
Social Capital Class	Low	3.026	0.060	3.057	0.066	2.571	0.114
	Medium	3.260	0.105	2.880	0.108	2.582	0.121
	High	3.321	0.177	2.708	0.180	2.518	0.189
	Overall test p-value	0.072		0.087		0.950	
		Beta	S.E.	Beta	S.E.	Beta	S.E.
Age				0.053	0.002	0.051	0.004
Sex	Female*						
	Male			0.277	0.079	0.300	0.080
Education	Degree*						
	A-Level/GCSE					0.244	0.100
	Other/None					0.501	0.129
Employment Status	Employed*						
	Retired					-0.051	0.140
	Unemployed/Inactive					-0.003	0.126
Subjective Financial Situation	Comfortable/Alright*						
	Just getting by					0.293	0.098
	Finding it difficult					0.518	0.170
Tenure	Owned*						
	Privately rented					0.280	0.149
	Socially rented					0.803	0.156
Marital status	Married*						
	Single/SDW					-0.143	0.090

Notes: * indicates reference category. Robust standard errors accounting for the clustering within neighbourhood (LSOA) units are used.

VI Discussion

Prior to the main analysis, a descriptive examination of deprivation trajectories revealed that 27% of participants were residing in consistently high deprivation environments or experienced a deterioration in neighbourhood environment when assessed at their first and last occurrences in the dataset. As expected, those with residential histories describing greater disadvantage had higher mean allostatic load in comparison with trajectories reflecting persistently low deprivation or an improvement in deprivation status. This patterning offered initial support for the stress pathway hypothesis. The interest lay in an initial exploration of movement in and out of high deprivation environments, given we expect more severe deprivation to be related to stronger negative effects. Hence the use of a binary high/low definition of the trajectories. Such a non-linear cut-off is also in line with literature suggesting that relationships between neighbourhood deprivation and social outcomes may operate through non-linear or threshold relationships (Galster, 2008, 2014). However, the dichotomised measure is simplistic and it should be noted that the descriptive trajectories use only two-timepoints of information, which may be varyingly spaced for each participant.

The main analysis used the continuous Townsend scores and multiple waves of data between 1991 and 2012, drawing upon a richer history of individual exposure. For deprivation scores we identified a four-class solution reflecting reasonably consistent trajectories, summarising exposure at various degrees of deprivation severity. Each class, with change modelled using a quadratic growth function, also exhibited a small improvement over time, with a slight worsening of scores in the latter years. This could be a reflection of general trends in deprivation nationally. Norman (2015) evaluated changes in Townsend scores in England harmonised between 1971 and 2011, and showed a general improving trend in deprivation, with a small increase to 2011 which they attribute to rising non-home ownership and unemployment.

The identified latent deprivation histories are indicative of relative stability in exposure over time. This stability represents both people remaining in place and individuals who move between neighbourhoods with similar environments. It is beyond the scope of the current analysis to explore these specific movements of people or to say exactly why the exposure

histories appear so stable. However, previous literature on neighbourhood residence and change shows that people are likely to remain in similar places over time (Blair et al., 2015; Van Ham et al., 2014). The social structures of places are often slow to change, with persistent patterning of relatively advantaged and disadvantaged areas over long time periods (Kontopantelis et al., 2018; Meen et al., 2013). In addition, where individuals do make a residential move, this does not usually involve a large differential in the type of place occupied (Clark et al., 2014). We are cautious, however, of overstating any implications of the identified trajectories for questions of social mobility and being 'stuck in place' (Sharkey, 2013), or the 'stickiness' of places and people (Glass and Bilal, 2016). The modelling strategy assumed homogeneity within classes (in other words, internal variance was restricted to zero) which may have limited our ability to delineate more dynamic trajectories which may be important but are less common. This simplified modelling strategy was beneficial to the identification of distinct exposure histories as it was computationally less intensive and more readily achieved model convergence.

The main results offer support for the stress pathway theorisation. Trajectories which represented exposure to higher deprivation over time were associated with worse allostatic load, in comparison with classes which reflected more advantaged histories. This patterning was maintained throughout models controlling for the influence of proximal stressors on allostatic load, though the strength of the relationship was lessened. The findings are in line with cross-sectional studies which have presented graded relationships between multidimensional measures of deprivation and neighbourhood 'riskscapes' with allostatic load (Ribeiro et al., 2018). They also substantiate the results of previous studies which have evidenced cumulative associations of disadvantage with allostatic load (Gruenewald et al., 2012; Gustafsson et al., 2014; Lemelin et al., 2009; Lin et al., 2017). Health inequalities by social status continue to be persistent features of society (Marmot, 2010; Prior and Manley, 2018; Smith et al., 2016). By demonstrating a gradient in allostatic load by exposure histories of deprivation, this analysis supports a biological embedding of disadvantage over time through chronic exposure to stressful environments as an explanation for these health inequalities.

As a further investigation of the stress pathway, this analysis also provided insight into the dynamics of a measure of structural social capital over multiple timepoints. Three classes were identified, capturing groups of individuals that: were active in very few organisations and whose social capital marginally declined over time; maintained a steady level of activity in between 1 and 2 organisations; and that had high levels of social capital and who increased their social participation over time. In the initial null models, the relationship of the latent classes with allostatic load was contrary to expected. The group with a history of low social capital was associated with the lowest allostatic load, opposing the stress-buffering hypothesis as well as theories on the direct negative influence of low social capital on health (Kawachi and Berkman, 2001; Uphoff et al., 2013). However, once age and sex were controlled for, patterning in line with a beneficial impact of social capital was revealed. Those with high structural social capital in the form of activity in organisations are likely to be older, retired persons who have more time to contribute to multiple institutions (The National Council for Voluntary Organisations, 2018). Elderly persons are also more likely to present worse allostatic load due to the general decline in health functioning by age, hence the artificially elevated allostatic load of the high social capital group in the Model 1.

The patterning of the social capital trajectories and allostatic load in Models 2 and 3 was broadly in line with the stress-buffering hypothesis. It follows research which also showed that increased social participation, measured by whether participants became active in any organisations, was associated with improved self-rated health (Giordano and Lindstrom, 2010). However, overall support cannot be provided for the relationship of structural social capital and allostatic load as the differences between the latent classes were not significant. The results instead point towards the apparent impact of structural social capital on allostatic load being largely a manifestation of other individual characteristics that influence stress exposure and health states. Other studies have also shown that structural measures of social capital may be less influential on health than cognitive measures. For example, Yip et al. (2007) demonstrated relationships between cognitive social capital and several health measures, but did not evidence similar associations for structural social capital as captured through organisational membership. Similarly, Fujiwara and Kawachi (2008) did not

demonstrate an association of structural dimensions of social capital with depression at follow-up, whereas they did find relationships for social trust and belonging. It could be that cognitive dimensions of social capital, including aspects such as trust, support, and norms of reciprocity between informal, interpersonal networks (Fone et al., 2007), are more relevant to counteracting stressful circumstances than more formal interactions with organisations. For instance, Riumallo-Herl et al. (2014) found relationships of social support and trust with biomarkers of hypertension consistent with theorisations of social capital as a stress moderator. Research which explores multiple dimensions of social capital and biomarkers is needed to further address their varying contribution to health pathways.

In addition, one limitation of the analysis is that we do not consider interactions between key individual characteristics such as gender and ethnicity and the trajectories, instead capturing heterogeneity through the latent class approach. However, previous research has shown there can be heterogeneity in the relationships of lifecourse models with health across these characteristics. For instance, Ploubidis et al. (2014) found that the association of early life socioeconomic status with physical health in old age was more prominent in women, whereas an indirect effect through later life SEP was indicated for men. Similarly, Walsemann et al. (2016) demonstrated heterogeneity along intersections of race and gender in terms of the significance of different lifecourse models for the relationship of socioeconomic status and biomarkers representing cardiovascular risk. These sorts of interactions may be particularly important to consider in future research on the stress pathway. Intersectionality research suggests the complexities of social power structures and systems of oppression, and thus their impact on outcomes such as stress and health, cannot be understood except through appreciation of the overlapping and intersecting social stratum in which individuals are embedded (Crenshaw, 1989). By not considering such interactions in this analysis we may miss important differences in the relationship between the trajectories of deprivation and social capital and allostatic load.

This study drew upon the framework of the exposome to examine dynamic exposure histories of disadvantage over time, as called for in Chapter 2. By assessing two important social dimensions of disadvantage, deprivation and social capital, this analysis contributes a

valuable insight into the social sphere of the exposome and how it relates to allostatic load. This analysis supported a model of the biological embodiment of disadvantage over time through chronic stress exposure, with persistent experience of highly deprived environments associated with worse allostatic load than exposure to more advantaged histories. In doing so we contribute support for a biosocial explanation for health inequalities. Future research would benefit from further examination of exposure histories and their relation to biomarkers. In particular, there is clear scope to investigate more complex intra- and inter-individual heterogeneity in trajectories and to explore dynamic interactions between different social exposures over time. This would build upon this baseline research of dynamic trajectories to reveal a more nuanced picture of exposure and biosocial health pathways.

VII Supplementary Information

Table 6.S1 Estimated allostatic load means by deprivation exposure histories and covariate coefficients predicting allostatic load for balanced BHPS sample

		Model 1: No covariates		Model 2: Age and sex		Model 3: Sociodemographics	
N		1177		1177		1175	
	Allostatic load	Mean	S.E.	Mean	S.E.	Mean	S.E.
Deprivation Exposure History	Low	3.300	0.102	3.203	0.112	2.741	0.183
	Medium	3.525	0.144	3.482	0.150	2.913	0.228
	High	3.818	0.181	3.793	0.187	3.129	0.261
	Very high	3.678	0.306	3.567	0.305	2.816	0.368
	Overall test p-value	0.067		0.022		0.293	
		Beta	S.E.	Beta	S.E.	Beta	S.E.
Age				0.043	0.005	0.034	0.008
Sex	Female*						
	Male			0.162	0.137	0.226	0.139
Education	Degree*						
	A-Level/GCSE					0.267	0.094
	Other/None					0.254	0.166
Employment Status	Employed*						
	Retired					0.267	0.094
	Unemployed/Inactive					0.219	0.222
Subjective Financial Situation	Comfortable/Alright*						
	Just getting by					0.373	0.303
	Finding it difficult					0.255	0.175
Tenure	Owned*						
	Privately rented					0.554	0.297
	Socially rented					0.191	0.384
Marital status	Married*						
	Single/SDW					0.131	0.156

Notes: * indicates reference category. Robust standard errors accounting for the clustering within neighbourhood (LSOA) units are used.

Table 6.S2 Estimated allostatic load means by social capital exposure histories and covariate coefficients predicting allostatic load for balanced BHPS sample

		Model 1: No covariates		Model 2: Age and sex		Model 3: Sociodemographics	
N		1177		1177		1175	
	Allostatic load	Mean	S.E.	Mean	S.E.	Mean	S.E.
Social Capital Class	Low	3.405	0.099	3.399	0.112	2.641	0.222
	Medium	3.581	0.137	3.464	0.148	2.892	0.194
	High	3.516	0.246	3.230	0.251	2.758	0.282
	Overall test p-value	0.607		0.712		0.397	
		Beta	S.E.	Beta	S.E.	Beta	S.E.
Age				0.042	0.005	0.030	0.008
Sex	Female*						
	Male			0.157	0.138	0.232	0.139
Education	Degree*						
	A-Level/GCSE					0.328	0.099
	Other/None					0.322	0.174
Employment Status	Employed*						
	Retired					0.328	0.099
	Unemployed/Inactive					0.276	0.222
Subjective Financial Situation	Comfortable/Alright*						
	Just getting by					0.389	0.299
	Finding it difficult					0.292	0.171
Tenure	Owned*						
	Privately rented					0.630	0.297
	Socially rented					0.174	0.381
Marital status	Married*						
	Single/SDW					0.194	0.157

Notes: * indicates reference category. Robust standard errors accounting for the clustering within neighbourhood (LSOA) units are used.

Chapter 7. Conclusion

This thesis investigated the stress pathway between places and health, a pathway which offers a biosocial mechanism to explain health inequalities and the embedding of disadvantage in health. The investigation was undertaken through answering four major research questions which developed understandings of: temporal trends in health; neighbourhood deprivation and health relationships over time; the biosocial action of the stress pathway in neighbourhood effects; and the embedding of deprivation histories in allostatic load. To conclude, I first summarise the results for each of the four major research questions, before an account of the overall contribution of this thesis, limitations and a look to future work.

I What is the shape of age and cohort health trajectories over time?

The first empirical chapter – Chapter 3 – explored age and cohort trends in self-rated and mental health, demonstrating a powerful methodology for revealing the underlying shape of these important temporal dimensions in order to provide insight into health development and health inequalities. The multilevel modelling approach treated age, cohort and a combined age*cohort classification as temporal contexts in which observations and individuals were nested in a cross-classified structure. By examining the residuals of these temporal classifications from models predicting self-rated and mental health without covariates, the analysis in Chapter 3 highlighted baseline patterning without the need to impose a parametric structure on the expected relationship between these lifecourse trends and health. Additionally, the analysis provided direct assessment of the relative importance of the different temporal contexts to the two health outcomes, through evaluation of the variance partitioning.

Strong patterning was shown for the underlying trends in both ageing and cohort effects on self-rated health. In line with previous literature suggesting an increasing burden of worse health in old age (Prince et al., 2015) as well as prominent mortality models such as the

Gompertz-Makeham (Greenwood, 1922; Makeham, 1873), self-rated health showed an accelerated decline by age, with older ages demonstrating the highest propensity of being in poor health. In contrast, the patterning of cohorts showed an improving trend over time, with the youngest cohorts demonstrating relatively lower likelihood of being in poor health. Cohort effects were shown to be the stronger temporal influence, explaining a larger proportion of overall variation in self-rated health. These cohort results demonstrate the importance of considering both ageing and cohort influences, and offer a potential positive outlook for societal health in Great Britain, which stands in contrast to concerns over the current state of obesity and related metabolic conditions such as Type 2 diabetes in children (Candler et al., 2018; Lobstein et al., 2015). Given the link between obesity and declining life expectancy (Blüher, 2019; Preston et al., 2018) and the strong association of self-rated health and mortality, it will be important to evaluate the competing dynamics of these health states as the younger generations progress through life.

Cohort effects also emphasise the importance of context and geography in the demography of health. Cohort effects reflect changing social, economic and cultural conditions; that younger generations are reporting better health serves to highlight the significance of developmental context. The better heath of younger generations was further corroborated in an exploration of interactive effects between age and cohorts: the 1990s cohort-years displayed better health than their older cohort counterparts when assessed at the same age in the survey. However, the differences between cohorts lessened and converged for older persons. As the youngest cohorts continue to be followed over time in longitudinal studies such as the UKHLS, it will be vital to explore whether the generational inequalities as identified in this thesis persist, grow or converge in the changing societal conditions of Great Britain. Additionally, given that understandings of what constitutes ‘good’ health inform subjective health assessments, future research would need to consider the degree to which the better health of the 1990s cohort-years represents improving objective measures of health or whether there is a decline in health expectations.

For the mental health response, a different ageing patterning was present when compared to the self-rated health results. The residuals showed declining mental health from early- to

mid-adulthood, followed by improvement through to around the late 60s where mental health declined once more. The results for mental health in part aligned with previous research which suggests that mental ill-health can be expected to increase in old age (Fiske et al., 2003), though they stand in contrast to research which has suggested improving trajectories of wellbeing and aspects of mental health, after a nadir in middle-age (Blanchflower and Oswald, 2008; Jorm, 2000; Steptoe et al., 2015). In contrast to the results for self-rated health, the patterning by cohort was much less clear, with small variations in the mental health residuals, though with a slight indication of worsening mental health for the younger cohorts. The suggestion of a cohort effect for mental health, albeit quite insubstantial, contributes to widening public awareness of a potential youth mental health crisis (Schraer, 2019; Siddique, 2018) and the debate over whether this reflects a generational inequality or improving identification and diagnosis of conditions.

The analysis was deliberately exploratory in nature in order to demonstrate the utility of the multilevel modelling approach to the initial identification of trends. Without control for covariates, it was noted that there may be changes in the validity of the measures as representations of health states at different ages, for instance due to the somatization of depressive symptoms in older age where there is not adjustment for physical health. Moreover, separate analyses for males and females were explored to preliminarily assess sex differences in the age and cohort trajectories, finding similar patterning as to the full sample, but potential heterogeneity by other population characteristics was not investigated. It may be that individuals belonging to more advantaged societal groups would see more consistently positive health over time, whereas those in vulnerable populations might exhibit accelerated declines. For instance, telomere length, a biomarker of biological ageing has been shown to vary by social status and ethnic groups (Geronimus et al., 2015). A further limitation is the potential role of attrition and non-response in producing bias in the results.

However, the aim of Chapter 3 was to highlight the baseline age and cohort trends in self-rated and mental health, serving as a crucial first step in investigating further health relationships over time. Overall, the temporal trends for mental health were smaller and accounted for less of the total variation than they did for self-rated health. For this reason,

Chapter 4 continued the investigation of the stress pathway and health over time with the self-rated health response. The exploration of interactive effects between ageing and cohort trends also revealed potential health inequalities, with the emerging better self-rated health, but also conversely the indication of worsening mental health, for the youngest cohorts. Overall, Chapter 3 contributes to the health and lifecourse literature by contributing knowledge on current and potential health inequalities, on how health could be expected to change over time, and through demonstration of a useful technique for exploring temporal contexts.

II Is heightened exposure to deprivation over time associated with worse general health and how does neighbourhood deprivation interact with social capital and individual-level disadvantage?

Chapter 4 investigated associations of neighbourhood deprivation with self-rated health. The objective of this chapter was to examine the overarching relationship of the stress pathway: that residence in deprived neighbourhoods would be associated with worse health than living in relatively less deprived circumstances. It capitalised on the rich longitudinal data of the BHPS and UKHLS to investigate interactions of neighbourhood deprivation with individual-level financial status, social capital and age, and to explore variability in health trends between neighbourhoods. This analysis, therefore, contributed a study which appreciates some of the heterogeneity and nuance of health relationships to the neighbourhood effects and health and place literatures.

The first research hypothesis of Chapter 4 – whether higher exposure to deprivation was related to worse health – was supported. A clear gradient was present across the neighbourhood deprivation profile (measured using Townsend deprivation scores). Crucially, a significant association remained after controlling for compositional characteristics, suggested that there is a robust effect of the neighbourhood environment on health, a 'black-box' that can potentially be explained through biosocial processes. Individual-level variables of socioeconomic status also showed graded relationships with self-rated health, which

aligned with the proposition of the stress pathway. Through the addition of cross-level interactions between neighbourhood deprivation and age, as well as a random slope term for age at the neighbourhood level, Chapter 4 also demonstrated the variability in the relationship of deprivation to health trajectories and heterogeneity in lifecourse trends between neighbourhoods. It was shown that neighbourhood deprivation made less difference for younger persons, with more severe gradients by Townsend score present for the more elderly participants. This was posited to be a potential signal of a mobility differential; elderly persons are likely to be less mobile, spending more time in their residential area and to be more reliant on local amenities and services. Additionally, there was small but significant variation in the effect of age between neighbourhoods. Variation in self-rated health was higher between neighbourhoods for older ages, suggesting that the health state of elderly persons is less similar across different neighbourhoods than the health state of individuals in young-middle age. Again, this points towards the varying importance of neighbourhoods throughout the lifecourse, with old age appearing to be a pertinent time for the impact of neighbourhood exposure. This result potentially reflects the changing geographical and social scope of neighbourhood and different contexts across the lifecourse. Variation between neighbourhoods in terms of self-rated health was lowest between the ages of 30 and 50 approximately; other contexts such as work-life or family conditions are likely to be the more powerful controls on health at this life stage. Lifecourse research has also shown that the conditions of earlier life contexts impact on the type of areas individuals reside in later in life (Van Ham et al., 2014); the lifetime impact of these exposures could be amplified and have more chance to manifest in combination with the neighbourhood environments of old age. Finding a varying neighbourhood effect is particularly relevant in view of the demographic shifts in the UK towards an ageing population (Office for National Statistics, 2017a) and indicates the potential widening of areal health inequalities as people age.

Chapter 4 further explored variability in deprivation-health relationship by investigating two research hypotheses: whether social capital operated through a main effect on health or buffered the negative impact of neighbourhood deprivation; and whether individual-level and neighbourhood-level deprivation interacted to form a ‘double jeopardy’ on health. Social

capital was assessed through a structural measure, representative of social participation. A beneficial main effect of this feature of social capital on self-rated health was demonstrated, with individuals who were a member of, or active in, more organisations exhibiting a decreased probability of being in worse health that those who were not active or members. However, there was no evidence of a significant stress-buffering effect which was in line with previous theorisations suggesting dimensions of support are more valid for mitigating stress (Cohen and Wills, 1985).

Meanwhile, there was a small but significant interaction between neighbourhood deprivation and subjective financial situation – that is how individuals considered they were managing financially day-to-day. However, this did not operate in the manner expected for a 'double jeopardy' hypothesis; we did not observe an exacerbated impact of higher neighbourhood deprivation for those who are personally disadvantaged. Rather, the difference between levels of subjective financial status was larger in less deprived areas than more deprived areas. This suggests support for a relative deprivation hypothesis, whereby it is worse for your health to be markedly different from the general status of the area (Stafford and Marmot, 2003). Usually, evidence for the relative deprivation hypothesis is presented as a consequence of poor persons living in wealthier areas, where adverse status comparisons can induce stress and other negative psychosocial outcomes (Wilkinson and Pickett, 2007). Here the cross-level interaction results presented a different story in that the slope of the neighbourhood deprivation effect was steeper for those who were not struggling financially and shallower for those individuals who were finding it difficult to cope. This indicates that the adverse consequences of poor personal circumstance, such as chronic stress, may 'overpower' the potential influence of neighbourhood exposures, resulting in the worst health across the profile of neighbourhood deprivation. For those who are not struggling personally, stressors from the neighbourhood environment are instead able to manifest more readily in the varying health states of individuals. The size of the interaction was small, however, with all categories of subjective financial status showing similar trends of worsening self-rated health with higher deprivation environments. The findings of Chapter 4 are an important contribution to the health and place literature in highlighting both the persistence but also variability of

neighbourhood health inequalities. All together they corroborate the initial assessment of the overarching premise of the stress pathway.

III Are relationships of deprivation and health mediated by allostatic load as a measure of cumulative biological weathering in response to stress?

As with much of the previous neighbourhood health work, Chapter 4 demonstrated clear neighbourhood deprivation and health associations. Yet less is known about how these aspects of health and place link together – that is what the processes are through which neighbourhood exposures become manifest and embodied in health outcomes. This is despite a history of neighbourhood research commentary which has emphasised the need to investigate the mechanisms of place (Galster, 2012). One plausible explanation for the neighbourhood deprivation-health relationships is the biosocial mechanism of the stress pathway, where exposure to chronic stress imparts a weathering on biological function and adversely impacts health over time. Chapter 5 brought forward the central biosocial aspect of this thesis and explored a biological marker of weathering due to chronic stress exposure (allostatic load) as a mediator in neighbourhood deprivation and health relationships. This analysis provided a novel and innovative demonstration of the biosocial action of the stress pathway in health and place associations, and as such is an important contribution to an emerging biosocial health geography as highlighted in Chapter 2.

To connect neighbourhood context to individual health, a biosocial multilevel mediation analysis was developed, assessing whether allostatic load acted to explain the associations between neighbourhood deprivation, here measured by the Index of Multiple Deprivation, and summaries of physical and mental health. As part of the investigation it was hypothesised that: higher deprivation would relate to worse allostatic load; heightened allostatic load would be associated with worse physical and mental health; and that higher deprivation would relate to worse health. Support was shown for all three pathways, corroborating the mechanism of the stress pathway and substantiating the benefit of biosocial analysis in uncovering the embedding of exposures in bodies.

Furthermore, this chapter extended the contribution to knowledge on health inequalities by presenting clear and consistent gradients, with quintiles representing the most deprived areas in Great Britain related to the worse health outcomes and to the highest allostatic load. The mediating effects of allostatic load were also stronger – that is explained more of the deprivation-health association – in more deprived relative to less deprived areas. For physical health, an interaction effect was additionally identified: the impact of allostatic load on physical health was strengthened in neighbourhoods characterised by higher deprivation. This further validates the stress pathway theorisation and the embodiment of context through exposure to heightened and chronic stress.

Mediation effects were shown for both physical and mental health, although support was stronger in relation to physical health than mental health. The associations between mental health and allostatic load were smaller than for physical health, and measures of the mediation effect size also showed the expected decline in mental health through action of the allostatic stress pathway was very marginal in comparison to the total variation in mental score. By exposing heterogeneity in the action of the stress pathway between physical and mental health, the analysis in Chapter 5 points towards further avenues for exploring different biosocial processes.

IV How are different exposure profiles of deprivation and social capital related to later allostatic load?

Having tested the action of allostatic load within the deprivation and health relationships in Chapter 5, the final empirical chapter extended the investigation of the stress pathway by exploring how histories of exposure over two decades related to later allostatic load. It identified distinct trajectories of deprivation and structural social capital, within which groups of the population tracked over time. In doing so, it exposed how the dynamics or stability of exposure relate to the biological imprint of disadvantage in allostatic load, serving as an explanation for social health inequalities.

Chapter 6 employed latent class growth analysis to identify subgroups of exposure trajectories, exploring heterogeneity in disadvantage histories by allowing each latent subgroup to have its own intercept and slope parameter. Through comparison of a series of models with varying numbers of latent classes, a four-class solution was chosen for neighbourhood deprivation and three classes were identified for trajectories of structural social capital (activity in organisations). The neighbourhood deprivation exposure classes represented tracking through time in either low, average, high or very high deprived neighbourhoods, with all four showing slight improvement over time. The social capital classes reflected activity in very few organisations, being active in between 1 and 2 organisations over the 20-year period, and showing high and marginally increasing social participation over time.

Allostatic load derived from the UKHLS nurse health assessment was regressed on these classes of exposure history. Support for an association of historical social capital with allostatic load was not found. Whilst those in the class reflecting high social participation in organisations exhibited the lowest allostatic load, in line with the idea of a stress-buffering effect, the differences between the social capital classes was not significant. This aligns with results from Chapter 4 where the measures of structural social capital were not found to have a stress-buffering interaction effect on the neighbourhood deprivation and self-rated health relationship. In Chapter 6, it is suggested that the lack of association could be due to structural dimensions of social capital being less powerful at counteracting stressful experiences and circumstances than more informal, cognitive dimensions of social capital. In both Chapters 4 and 6, the analysis is limited by the available social capital measures which are present at multiple waves across the whole survey timeline.

However, the association of allostatic load at the final timepoint with classes of deprivation exposure history did offer support for the stress pathway of neighbourhoods and health. Trajectories representing higher cumulative exposure to neighbourhood deprivation over time were related to worse allostatic load. This association was robust even when controlling for the influence of socioeconomic and demographic characteristics measured contemporaneously with the allostatic load biomarkers. This is an important result in this

thesis and for the wider biosocial health literature; it shows that the trace of long-term historical exposure to neighbourhood deprivation can be identified in allostatic load over and above the impact of more spatially and temporally proximate factors. Thus, there is a lasting biological imprint of place. Therefore, Chapter 5 provided understanding of trajectories of deprivation exposure over a long time frame, adding knowledge on the relationship of dynamic exposure with later health biomarkers. By demonstrating a gradient in allostatic load by exposure histories of neighbourhood deprivation, this analysis substantiated the biological embedding of disadvantage through chronic stress exposure as an explanation for health inequalities.

V Overall summary

As with all studies, there are limitations to what is achieved by this thesis. For instance, throughout the analysis 'neighbourhood' was represented by Lower Layer Super Output Area (LSOA) or the equivalent Scottish Data Zone (DZ). As highlighted in the review of health literatures in Chapter 2, static and bounded measures of neighbourhood have been heavily critiqued for their deficiencies in capturing the exposure of highly mobile persons (Kwan, 2009; Montello, 2001; Perchoux et al., 2013). However, LSOAs and DZs are sized in reasonable correspondence to colloquial understandings of the neighbourhood environment and were at least partially designed to reflect this in the administrative purpose of reporting neighbourhood statistics. It should also be noted that whilst the term 'neighbourhood' traditionally connotates the urban setting in particular, the LSOAs and DZs cover the whole of Great Britain and therefore reflect a range of rural and urban localities. The statistical geographical units employed throughout this thesis are also useful for linking neighbourhood information resources, being a unit at which Census data and the Index of Multiple Deprivation are readily available. Moreover, as the analysis in Chapter 4 highlighted in particular, the neighbourhood unit as operationalised in this thesis does remain an important source of variation in health. Neighbourhoods still accounted for 7% of total variation when considering multiple decades of health data, the dependency within individuals over time and the differences between individuals – all potent sources of health variation. Chapter 4

additionally demonstrated that the LSOA or DZ neighbourhood operationalisation was able to pick up notable health variations for older persons whose activity space and mobility may be more restricted than that of younger individuals.

Future work could look to integrate developments in the operationalisations of neighbourhood and other areal units in order to create more realistic portrayals of exposure contexts. Investigations could attend to exploring the phenomenon scale (Montello, 2001; Petrović et al., 2018) for instance by using multiscalar approaches such as that developed in Petrović et al. (2018). An important step would be to additionally explore other geographical, social and familial contexts. A key omission in this thesis is the role of the household environment in health. The household and family environment are likely to be potent sources of stressors and also of salubrious exposures and support (Feng et al., 2013). It is also an environment with shifting patterns and importance throughout the lifecourse, through changing patterns of control between a childhood home and an adult household, for instance. In this thesis, the exploration of household dynamics over time was complicated by longitudinal household codes not being available in the BHPS and UKHLS. The decision was made to focus on the neighbourhood in order to explicate the benefit of biosocial theorisations in the well-established health and place literatures.

Another major limitation of the research contained within this thesis is the possibility for the identified neighbourhood associations to be the result of selection effects, or otherwise different processes from the social causation or stress pathway model theorised. For example, previous research has questioned the validity of a social causation model of neighbourhood deprivation and health: Jokela (2014, 2015) showed within individual changes in neighbourhood deprivation accounted for little of associations between deprivation and health outcomes, with relationships instead due to between-person differences. For the analytical chapters where relationships of deprivation and health were assessed over time (Chapters 4 and 6), the main analysis was repeated with fully-balanced panels – that is with those individuals present at all possible waves. Through comparison of the main analyses with these sensitivity tests, it was possible to test the impact of selection effects, and particularly selection out of the study, to some extent.

The supplementary information of Chapter 4 shows that the overall conclusions regarding the deprivation and health relationships remained the same using a balanced sample, giving some confidence in the results presented regarding the stress pathway hypothesis. For Chapter 6, for a balanced BHPS sample we were able to identify very similar classes of deprivation and social capital trajectories as to the main analysis. The association of the deprivation histories with allostatic load was broadly similar for the balanced sample; histories reflecting higher total exposure to disadvantage were related to worse allostatic load than for less severe exposure trajectories. However, the allostatic load of the very high deprivation exposure trajectory was not the highest as expected and as portrayed in the main Chapter 6 analysis. This class was the smallest in size, with 72 individuals classified as tracking in very high deprivation neighbourhoods, which would have contributed to imprecise estimates. Additionally, these supplementary results do point towards some attrition bias; those in the most disadvantaged circumstances and worst health were likely selected out of the study.

Relatedly, it is important to consider the potential impact of differential non-response. The datasets employed are household surveys and Lynn et al. (2012) indicate response rates were slightly lower in areas with high proportions of full-time employment or single person households. At the within household level, there is also evidence of differential non-response, and for differences in follow-up. For instance, younger individuals had lower rates of response and for re-interview at Wave 2 of Understanding Society (Lynn et al., 2012). Importantly for this thesis, re-interview at Wave 2 was found to have little association with health status, though interview rates of continuing BHPS participants into the UKHLS at Wave 2 were lower for those in poor health (Lynn et al., 2012). Therefore, the results, particularly from the longitudinal analyses, where both the BHPS and UKHLS datasets are employed, may be subject to bias.

In addition, the results of the analysis in this thesis are limited through application to only the BHPS and associated UKHLS datasets. Whilst these large-scale surveys offer a valuable tool in the breadth and depth of their social and health content, as well as through their geographical linkage, cross-validation in other populations is needed. It would be particularly relevant to examine these hypotheses in non-Western societies whose cultural and economic pressures

are likely to be distinct from that studied here, and thus would help further expose the heterogeneous processes of the biosocial health geography of the stress pathway.

There remain a number of questions to be answered regarding health and place relationships and their biosocial mechanisms. Throughout the analytical chapters, heterogeneity was identified in the interaction of exposures with different health measures. Stronger and more consistent evidence was provided for relationships with physical and general health outcomes than for mental health, such as in the mediating role of allostatic load in deprivation-health associations. Similarly, less consistent evidence was presented for the biosocial health associations of structural social capital. Further theoretical work and biosocial research is needed to delve into the biosocial pathways of mental health outcomes and to explore a wider range of social capital and support mechanisms. Additionally, this thesis has shown that it is possible to identify the lasting signature of disadvantage in the biological functioning of individuals, giving a picture of the persistence of health inequalities over time. It would be beneficial in future research to explore the potential for resilience in deprivation and health relationships. For example, whether when tracked further through time there are individuals who do not develop poor health, despite disadvantaged exposure histories. Similarly, further analysis of the dynamics of ageing and cohort trends will inform on the development of inequalities and how the health of the youngest cohorts evolves in interplay with uncertain societal and economic conditions in Great Britain and the UK.

Overall, the major contribution of this thesis lies in bringing together developments in health geography, epidemiology and quantitative social science to develop and empirically demonstrate a new schema of biosocial health geography that can provide knowledge on the *how* and *when* of health and place relationships. Chapter 2 offered an important theoretical contribution to the literature with potential benefits across disciplines through provision of a focal framework in which diverse contributions can talk to each other. Chapter 2 additionally highlighted the relevant existing toolkit of quantitative approaches that could be utilised to implement the study of exposomic geographies of health and place. The empirical chapters of this thesis explored different aspects of health inequalities and the stress pathway. By capitalising on the rich longitudinal social data of the BHPS and UKHLS studies, this thesis was

able to interrogate the shape of health trajectories over time, building on the long history of research into the development of health states through demonstration of a powerful exploratory technique not tied to parametric models. In doing so, possible new health inequalities were revealed that inform on the current and developing health state of the younger generations growing up in times of societal and technology change. Chapter 3 also makes a methodological contribution in highlighting the potential use of multilevel models in the exploratory analysis of temporal contexts. Additionally, this thesis highlighted the heterogeneous relationships of neighbourhood deprivation with self-rated health, using multilevel modelling to expose ageing trends varied between neighbourhoods. In Chapter 4, emphasising the importance of neighbourhood environments to older persons also helps expose the complex configurations of social, cultural and biological phenomena that must be taken into account when investigating the lifecourse relationships of health and place. The potential vulnerability of older persons to the conditions of their local environment additionally raises questions about marginalisation and the neighbourhood and social assemblages that could insight positive health benefits.

Additionally, through exploitation of the biomarker data collected in the UKHLS, this thesis brought biosocial perspectives on the stress pathway to the fore in health geography. In overview of the health and place literatures, Chapter 2 highlighted that exploration of the processes which link neighbourhood or place exposures with health outcomes has long been an aim of health geography (Diez Roux and Mair, 2010; Galster, 2012; Rosenberg, 2016b). The critique is that researchers still need to attend to the theoretical underpinnings of health and place associations and to be explicit in investigating biologically plausible mechanisms for how environments are embodied in health. Without this attention to biosocial process there remains a 'black-box' in our knowledge of neighbourhoods and health. This thesis focused on the stress pathway as a common theory drawn upon to link neighbourhood exposures and health, and as a conceptualisation that brings together social and biological elements. As such, the stress pathway is a mechanism which notably benefits from quantitative biosocial research as conducted in this thesis. A novel exploration of allostatic load as a mediator in neighbourhood deprivation and health relationships, and the empirical demonstration of the

biosocial action of the stress pathway, was a key contribution to the literature, as well as an investigation which demonstrated the value of biosocial theorisations as possible explanations for the cumulative impact of neighbourhood disadvantage over time and the lifecourse. Chapter 6 also highlighted the exposome as a framework for research that aims to reveal the dynamics of social exposure over time, an area currently underappreciated in work on the exposome. In evidencing an imprint of contextual exposure in the health of individuals later in life, Chapter 6 showed the lasting importance of place in health relationships and the need for long-term perspectives when assessing health inequalities.

Ultimately, this thesis aimed to foreground a new biosocial health geography, where the focus is on exploring and explicating the mechanisms linking exposures and health over the lifecourse and in doing so inform on health inequalities. As explicated in Chapter 2, biosocial health geography forefronts the activity and dynamism of bodies and environments, positioning the relationality of exposure and response as vital to our understandings of the impact and emergence of disadvantage in health inequalities. This thesis has highlighted that through the integration of biodata with large scale longitudinal surveys, quantitative research has a valuable toolkit of methods that can be used to access and gain insight into exposure-health relationships. Such a biosocial health geography can help to move beyond the standard cross-sectional, associational research which has dominated the neighbourhood effects literature and inform on the exposome in improving knowledge on the relative circumstances and timing under which place mechanisms are of most importance. Throughout this thesis, the importance of context and the neighbourhood environment has been upfront, and whilst heterogeneous and variable, the signature of place exposures can be found in health and biological weathering.

Chapter 8. Bibliography

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