Understanding variance in health outcomes in England, a study of deprivation and health inequality.

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Preface

When the training and preliminary work for this doctoral thesis commenced in 2018, I could never have predicted how a global turn of events would so affect the course that this work would take.

In March 2020, when the pandemic was declared and the first UK lock down put into place, as a parent to two children of school age, I was immediately thrust into home schooling with myself, my partner and our boys sharing devices and desk space in a way we had never envisaged. As the weeks of lock down extended to months, the pandemic impacted in many ways upon my work as a researcher.

I had at that time been developing ideas for my second and third papers. The availability and accessibility of suitable data sources was limited by resource (we did not have the research budget to fund paid-for datasets) and legality - sources which we had almost agreed, were pulled as organisations realised that they either did not indeed own the data to which they were offering access or could not grant the access they had anticipated. I had experienced multiple cycles of meetings resulting in the realisation that data could not be shared. I wanted to investigate inequity in health outcomes by levels of deprivation, but finding novel sources of data with sufficiently granular individual level variables and gaining permission for its use was proving difficult. I had worked on a measure of access and considered this in the context of deprivation (Jennifer Murphy et al. 2021) but needed further data resources to answer emerging research questions and avenues of enquiry as I developed the work of the thesis.

The advent of the pandemic both opened and closed data doors. I had several open lines of data enquiry and data requests for developed ideas were in progress at the hands of local hospital teams when the health crisis began to unfold. Understandably these fell to the bottom of the priority list and became forgotten as local management information teams became overwhelmed with operational needs and many moved to remote working - often in the same situation as my own with children at home. Emails went unanswered and the memory of meetings and verbal data sharing commitments faded.

At the same time, health providers and policy makers were in desperate need of quality timely quantitative analysis and understanding of what was happening in hospitals and in the wider community. The academic world was swamped with thousands of papers on pre-print servers, arriving in a deluge of information without peer review. Health providers made available datasets which would previously have been heavily restricted, calling for operational help from academics across multiple institutions. The pandemic had not just altered all of our daily lives, but had also radically altered the data landscape with unprecedented data sharing and open access becoming more possible.

Where government needed accurate reliable timely information, there was significant noise. Clearly the emerging health situation was of huge interest from both an academic and moral perspective - as a 'non-keyworker' instructed to stay at home, the need and desire to contribute in some way was overwhelming. Specifically, how the pandemic would affect the worst off in society was of interest to me and my work and so when I was offered the opportunity to join Manchester's contribution to the Rapid Assistance in Modelling the Pandemic call for teams of quantitative researchers, I was keen to be involved.

I worked on one published paper (provided as an appendix here) as part of a wider departmental interdisciplinary team within the university and contributed to briefing papers which were taken to SPI-M (the scientific modelling panel feeding into government policy). My contribution included data wrangling and manipulation, advice and assistance on imputation of geographical variables onto administrative datasets, imput into discussions around data provenance and reading and commenting on substantive work. After several weeks of effort, it became apparent that I needed to prioritise my youngest child who was still at home due to school closures. At just the time when data access was the most relaxed and available, my time was simultaneously at its most restricted as I struggled to balance the needs of my family, and in particular the education and care of my two children, with my own work and health. I should have liked to work on further papers with the team, and given more imput to work which was conducted in tandem with my own, but as such I am proud of my small contribution to the pandemic modelling effort.

It is fair to say that at this point (Autumn 2020) I had all but given up hope of completing the research needed for the doctorate. Delays to progress prior to the pandemic that were within the normal range of tolerance for a doctorate dependent on external sources of sensitive data felt insurmountable. I had been unable to progress independent research on ideas I had developed prior to the pandemic, and the impact of the lock downs had ground my capacity to work to a halt.

With so many leads having fallen away, when I resumed work in September 2020 as the schools reopened, I needed to rethink my approach to the thesis and overarching questions about inequality such that I could complete the work needed within the time available. I had originally planned to use administrative data throughout however the pandemic yielded a different opportunity through the rapid response of the *Understanding Society* team at the University of Essex. At the start of the lock downs, the team had quickly produced from previously tested survey questions, a bolt-on COVID-19 module to the main survey which was collected monthly and it was here that I was able to develop a new idea for investigating the impact of deprivation on health outcomes, through a self-reported measure of wellbeing. Unfortunately, just as this work started to yield interesting results, and only a few months before my vaccination was due, I contracted COVID-19. This resulted in a loss of almost three months working time as I struggled to recuperate from moderate illness and whilst schools were closed for a second time. Researching the impact on well-being of the first UK pandemic lock downs, whilst recovering from the illness during the second UK pandemic lock down provided a unique experience. As I recovered I did manage to finish the research and the resulting paper is now published (Murphy and Elliot 2022). The inclusion of survey related work in this thesis was unexpected, but has, I think provided a more rounded body of research, considering the impact of deprivation across the pandemic from a truly lived personal perspective, rather than through the statistics and figures of operational data.

As cases reduced and the burden on hospital staff receded, the evolving operational needs and altered attitude to data-sharing eventually resulted in me gaining access to a deep and rich data source relating to hospitalisations across the Greater Manchester area. Somewhat ironically, this very same dataset had been locked to my access for an alternative project earlier in my studies, but the need for information about how this global health event has proceeded at a local level has now tipped the data sharing risk and reward scales in favour of access and so I have been able in my final year, to conduct useful and important research into the impact of deprivation on health outcomes.

Although the pandemic has significantly interrupted and disrupted my work, the changing data landscape has provided an opportunity to complete a cycle of work which although separate, is in fact interconnected with themes of access to health care, wellbeing and clinical outcomes. It is this which I present here as my contribution to the field of health inequalities research.

Abstract

In this thesis, I present a body of quantitative empirical work on the theme of deprivation and health, linking administrative and survey datasets to publicly available census data to provide insight into the factors affecting a range of health related outcomes. In the first paper, I investigate the impact of distance and deprivation on the uptake of extended hours services in Primary Care and conclude that there is evidence of geographical inequity in the service but that deprivation was not directly associated with rates of use. In the second paper, I analyse the trajectory of well-being over the course of the first wave of the COVID-19 pandemic, and found that wellbeing decreased but bounced back in a similar way across all deciles of deprivation. In the third paper, I analyse the outcomes for hospitalised COVID patients in Greater Manchester during 2020 and conclude that there was a deprivation effect in risk of death but that the length of stay in hospital for any given patient was not associated with their level of deprivation.

The work highlights that investigating health outcomes and inequalities therein is a complex and difficult task, and at the heart of this must be an understanding of what the researcher seeks to measure and how this relates to the lived experience of the study population.

Declaration

I declare that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

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Dedication

To Olly and Ted,

To learn is simply the best thing you can do. Never stop learning, and always remember it is never too late to try something new.

Love Mum x

Acknowledgements

I would like to acknowledge the ESRC and the Centre for Data Analytics and Society for providing the funding and opportunity to complete this doctoral research.

I am indebted to my supervisors Professor Mark Elliot, Dr. William Whittaker and Dr. Rathi Ravindrarajah for their support, guidance, patience and kindness. To Mark, thank you for not once, not twice but indeed three times refusing to accept my ‘resignation’ and for displaying exemplary professionalism in the face of my many PhD related flounces. I have always valued your opinion and I enjoy working with you. To Will, thank you for stepping in with an excellent idea for my first paper and for always delivering your thoughtful and thorough feedback with kindness and consideration, I knew when I saw the lego model in your office we were going to get on. To Rathi, thank you for understanding the pressures that combining study with parenthood can bring, and for always making the time to offer coffee and a catch up.

Thank you to my fellow Manchester Data Analytics and Society students, Ollie, Noelyn and Chris and everyone in the Social Stats PhD office. You have provided a constant source of cheerful code-block busting cat meme filled banter and this would have been much less fun without you.

I am fortunate to have many friends who have continued to take an interest in my work, always being kind enough to remember to ask about it (and on the bad days, to remember not to.) There have only been a *few* instances of “Are you *still* doing that PhD?” I thank them all for the tea and solidarity. Not one of them has ever believed me when I have said I should give up.

To my parents and parents in-law, thank you for your support, I shall have a copy of this weighty tome bound for you and you can pretend to read it and then use it as a coaster, and I promise not to take offence.

To Olly and Ted, you have done a lot of your growing up during a very difficult time with a mummy who always has half an eye on her PhD. Thank you for being your brilliant selves, you are my most favourite people.

Finally, I say thank you to Peter. My husband and best friend. I don’t think I would have started, continued or indeed finished this without you.

List of publications and other outputs during the thesis period

Peer reviewed publications in press

1. **Murphy, J.**, Elliot, M., Whittaker, W. and Ravindrarajah, R. (2021) *Investigating the impact of distance on the use of primary care extended hours.* International Journal of Population Data Science. 6(1). doi: 10.23889/ijpds.v6i1.1401.

2. Shryane, N., Pampaka, M., Aparicio Castro, A. L., Ahmad, S., Elliot, M., Kim, J. H., **Murphy, J.**, Olsen, W., Perez Ruiz, D. A. and Wiśniowski, A. (2021) *Length of Stay in ICU of COVID-19 Patients in England, March - May 2020.* International Journal of Population Data Science. 5(4). doi: 10.23889/ijpds.v5i4.1411.

3. **Murphy, J.**, Elliot, M. (2022) *An analysis of changes in well-being during the COVID-19 pandemic in the UK.* Discov Soc Sci Health.

2(6). doi: 10.1007/s44155-022-00009-x

In (1) and (3) the majority of work was conducted by the first author including all results, the majority of text, and all figures. All co-authors provided comments and were contributing editors to the drafts for each publication. William Whittaker had a leading supervisory role on *Investigating the impact of distance on the use of primary care extended hours*. Mark Elliot led the supervision of *An analysis of changes in well-being during the COVID-19 pandemic in the UK.*

Length of Stay in ICU of COVID-19 patients in England, March to May 2020(2) was produced as a response to the Royal Society's call for Rapid Access to Modelling in the Pandemic (RAMP). My contribution included data wrangling and manipulation, advice and assistance on imputation of geographical variables onto administrative datasets, input into discussions around data provenance and reading and commenting on substantive work.

Publications in submission

Murphy, J., Elliot, M., Ravindrarajah, R. and Whittaker, W. (2022) *Deprivation effects on length of stay and survival of hospitalised COVID-19 patients in Greater Manchester.*

The majority of work for this paper was conducted by the first author. Mark Elliot led the supervision of this work and ran an additional version of the models when investigating weighting. Jamie Stooke of the Greater Manchester Health and Social Care Partnership assisted with running data queries using Structured Query Language (SQL). This paper is currently undergoing peer review prior to publication.

Working Papers

Tranmer, M., **Murphy, J.**, Elliot, M., and Pampaka, M.(2020) *Multiple Linear Regression (2nd Edition).* Cathie Marsh Institute Working Paper 2020-01. https://hummedia.manchester.ac.uk/institutes/cmist/archive-publications/working-papers/2020/2020-1-multiple-linear-regression.pdf

I authored the re-write of this paper, originally co-authored by Mark Tranmer and Mark Elliot. Co-authors contributed comments and revisions during the redrafting phase.

Conference Presentations

1. 4th International Conference on Administrative Data Research (2019)

   Murphy, J., Whittaker, W., Elliot, M. and Ravindrarajah, R. (2019). *Geographical factors in access: investigating the impact of distance on the use of primary care extended hours, an administrative data study.* International Journal of Population Data Science, 4(3). doi: 10.23889/ijpds.v4i3.1245.

2. UK Data Service, Health Studies User Conference (2021)

Murphy, J. Elliot, M. (2021). *Wellbeing during the COVID-19 pandemic in the UK: a secondary data analysis.*

Conference presentations were prepared and delivered by the lead author, based on work which was further developed and ultimately published in peer reviewed journals as listed above.

Chapter 1

Introduction

There is extensive research in the field of inequalities which demonstrates clear relationships between social disadvantage and poorer health outcomes. Health inequalities are observed within and between countries across the world – even in developed economies with sophisticated health infrastructure such as the UK (Mackenbach 2012; Balaj et al. 2017; Hu et al. 2016; WHO 2010; Black 1980; Acheson and Britain 1998; Marmot 2005; Marmot 2010; M. Marmot et al. 2020).

But why do we care about health inequalities and why is this an area for academic enquiry? Whilst inequalities have widened, health has improved for most, and on average health has improved (Black 1980; Acheson and Britain 1998; Marmot 2005; Marmot 2010; M. Marmot et al. 2020) and so does it matter that there are inequalities if the overall trajectory is upwards?

Throughout this thesis I refer to inequalities and inequities of health. A health inequality arises when there are different outcomes between members of a population. It is a difference in a measurable health quantity. An inequality is however different to an inequity. A health inequity can be considered to occur when an inequality occurs unfairly or as a result of some injustice and thus although inequalities are inevitable (some of us may get cancer or any other disease, some may not), inequities can be considered to be avoidable. Many forms of health inequality are rooted in inequity and the separation of the concepts is nuanced; we all experience subtly different health outcomes and measurable health is a complex concept, impacted by multiple, interacting factors. Inequities are thus an issue of social justice, and are a political concept which is distinct from inequality (Kawachi, Subramanian, and Almeida-Filho 2002).

Poverty and deprivation are associated with poorer health outcomes. Absolute poverty has been defined as a household income of less than 60% of the median net income of 2010-11, uprated by inflation (Limb 2022). This means that over time, if income increases outstrips the rate of inflation, the level of absolute poverty reduces within the population. Relative poverty is arguably a more meaningful measure, and is measured as falling below 60% of the contemporary median income. Both absolute and relative poverty can be calculated before or after housing costs. Deprivation is defined within the Cambridge Dictionary as ‘an absence or too little of something important’. One could therefore construct many different types of highly context dependent deprivation. Typically poverty and deprivation are linked, however it is in theory possible to meet the definition of absolute or relative poverty whilst not actually experiencing deprivation, and likewise be above the relative or absolute income needed to not meet the definition of being in poverty, but still be deprived. In this work, I use deprivation as measured by the English

Indices of Multiple Deprivation (McLennan et al. 2019) which is an area level metric, rather than the personalised measure of poverty which is measured as the household position within the income distribution.

Deprivation is a readily available metric and one which can be used to assess the manifestation of different inequalities. Considering financial inequality, wealth and income are becoming more concentrated with the gap between the ultra rich and the poor increasing. It might be assumed that as long as the situations of the poorest were on an improving trajectory, then the gap between the top and the bottom of the society in wealth terms should not matter. However, as Kawachi and Kennedy (1997) report there is increasing evidence that it is not just the absolute standard of living of those with the lowest means that is important but also the distribution of wealth. The authors argue that income inequality leads to residential segregation and deeper pockets of poverty and affluence. The resulting disintegration of social cohesion can then be attributed to higher rates of mortality with spillover effects on society, including poorer productivity and economic growth, and higher rates of crime. The premise - that inequality is in fact bad for all of us - is the central tenant of Pickett and Wilkinson (2010)'s 'The Spirit Level', a book which brings together multiple research papers evidencing the costs of inequality to society and argues that the way to improve the quality of life for the largest proportion of the population is to reduce inequality. The authors write that socially integrated people experience better wellbeing and live longer and that wide income disparities result in a breakdown in social cohesion, undermining democracy and shifting funding from public schools and health care systems. The resulting disintegration of society increases stress and frustration across the range of income brackets and leads to a declining quality of life for all.

The social health gradient is well established within the literature and is observed in all countries; increased deprivation is typically associated with poorer health outcomes (WHO 2008; Kawachi and Kennedy 1997; Mitchell, D. Dorling, and Shaw 2000; Pickett and Wilkinson 2010; Ritsatakis 2009). We might think that adverse health outcomes for the poor to be an isolated issue for the groups affected by deprivation and this is easy to conceptualise if we are fortunate enough to be comfortable; we see the conditions and experience of those in poverty and can recognise that this may well result in adverse outcomes. However even within richer groups for whom all material needs are met and exceeded, the social gradient of health persists. Those at the bottom of a richer grouping will experience different outcomes compared with those at the top, related to their socio-economic position. The gradient manifests its effects throughout society and it is not just those below the absolute poverty line for whom it is relevant.

Considering that we know there are deprivation effects in health outcomes, that health and wealth are inextricably linked, that wealth inequality is growing and that the gradient for wealth is reflecting in that of health at all levels, it is then clear that this is and should be an area of great interest. Understanding the link between deprivation and health equality can inform policy and should therefore be used as a tool to improve outcomes for all.

In the UK the past 40 years have seen regular publishing of reports into health inequality. Ever since Booth's 1896 survey of inner London (Booth 1889; Booth 1902b; Booth 1902a), statisticians, health economists, medics and policy makers have sought to understand the geography of inequality and its resultant health impacts. Black (1980) reported that mortality rates across social groups were different and that lower social groups suffered excess mortality and inequalities in access to health services, specifically preventative health care and that the lowest uptake was amongst the working classes. The report recommended that intervention by the state be increased with more spending on health but also increased spending on benefits designed to alleviate deprivation for example child benefit, housing conditions and employment conditions recognising that the health of the population is not only determined by the state of the health service, although these recommendations were never implemented.

Acheson and Britain (1998) confirmed the persistence of a social gradient in health and made wide ranging recommendations for organisational change within the National Health Service and also more radically, a wholesale redistribution of wealth, recognising again that health cannot be improved without addressing underlying income and wealth deprivation and inequality.

Marmot (2010) conducted a strategic review into the health inequalities in England and wrote that the social gradient in health continued to persist and that people in the least wealthy areas on average had a healthy life expectancy (considered to be the proportion of life lived without disability) some seventeen years below their rich counterparts. The author argued that these health inequalities were not inevitable and could be tackled, but that this would require concerted policy action across all social determinants of health. Marmot also presented economic benefits in reducing inequalities and distributing health and wellbeing more evenly across the population.

Since the original Marmot Review, progress in addressing health inequalities in England has been limited. The Institute of Health Equity's 2020 review of the priorities identified by Marmot brings understanding of English health inequalities up to date and showed both that improvements in life expectancy have stalled and that the social gradient of health has become steeper. Decreases in life expectancy in the past decade have been in the most deprived areas, with a spatial element highlighting that deprived communities in the North have suffered disproportionately compared with wealthy areas of London. The gradient in *healthy* life expectancy has also worsened, with the most deprived areas experiencing more of their already shorter lives living with ill health (M. Marmot et al. 2020). It is in fact the case that despite the creation of the National Health Service and many improvements to living standards in the past 100 years, Booth's poverty map of London can still be used to predict younger and older age mortality as a function of deprivation, mapping areas of entrenched health inequality today, back to the areas of entrenched poverty in the 19th Century (Dorling et al. 2000). Those who reside in poorer communities, continue to experience worse outcomes.

Marmot and Allen (2021) posit that this lack of progress was a fundamental contributing factor to the poor state of health of the population of England immediately prior to the declaration of the global pandemic in March 2020. With the advent of a disease for which risk factors for severity and death such as lung dysfunction, obesity and heart disease are so highly correlated with poverty, it is easy to conclude that the widening gap in health equality seen over the past forty years, and the failing of policy to address the social gradient of health which persists in the UK, can be considered to have caused at least some of the COVID-19 deaths of the past two years.

M. Marmot et al. (2020) identified regional differences in life expectancy improvement, but these national trends are also observed within the regions. In a city region, population health may be considered at a useful scale, but with a local focus that is absent from the national view. Taking the case of Greater Manchester; the metropolitan area has the fastest growing economy in the UK but life expectancy lower than other parts of England (GMHSCP 2015a). The data show that there is a geographical element to the health inequality observed in the city region (Purdam 2017). Deprivation is associated with poorer life expectancy with significant spatial differences across the city. For men, the difference in life expectancy between the most and least affluent wards is 18 years, and for women 13 years. In many ways, the city region of Greater Manchester can be considered microcosm of the UK reflecting the same underlying economic, social and cultural influences as the national picture.

In 2016, Greater Manchester became the first city region in the UK to sign a devolution deal and since 2017 has taken control of a £6bn health and social care budget. A core aim of politicians and policy makers in the devolved body is to address health inequalities experienced by the residents of the city (GMHSCP 2015a). There is therefore a need for continued research into the social and demographic factors affecting the health outcomes of the local population so that care commissioners can understand if services are improving and meeting the needs of residents and act on emerging inequities.

This research should inform policy and invite action to close gaps in health attainment not just for moral reasons of social justice but that so that we can all enjoy the benefits of a more equal society.

This thesis is a contribution to the field of health inequalities research, presented as a series of interdisciplinary papers spanning the specialisms of health economics, health services research, social statistics, survey research and population data science. The nature of health inequality and the social determinants of health are such that the topic can be approached in a multitude of ways.

1.1 Aims and Objectives

The aim of my work is to research health inequality. In this thesis I seek to exploit administrative data to answer the broad research question 'What is the impact of deprivation on health?' in each paper focusing on a different aspect as identified by the reviews of inequality in the UK, and the specific case of my local area, Greater Manchester.

Inequality is expressed in terms of access to health services, in general wellbeing and in clinical outcomes. Through this work, I explore each of these specific concerns in turn, looking to uncover the relationships present and explore whether deprivation measured at an area level is in fact associated with the outcome variables selected. The work thus forms a trio examining inequalities in access to services, inequalities when services are unavailable to all and inequalities as they present within health care settings. These pieces of work contribute to the research needed by policy makers to take action on the social determinants of health and to move towards a more egalitarian model of health in the population.

The objectives for each empirical piece of work within this thesis are listed below:

Investigating the impact of distance on the use of primary care extended hours

- to determine the impact of distance on the uptake of extended hours GP services in a hub practice model
- to determine the impact of deprivation on the uptake of extended hours GP services in a hub practice model

An analysis of changes in wellbeing during the COVID-19 pandemic

- to investigate the trajectory of wellbeing over the course of the first pandemic lockdown
- to specifically consider ore-existing medical conditions, social isolation and financial stress as predictors for any change in wellbeing.

Deprivation effects on length of stay and survival or hospitalised COVID-19 patients in Greater Manchester

- to investiate the impact of deprivation on outcomes for hospitalised COVID-19 patients in Greater Manchester during the first wave of the pandemic in the UK, controlling for proven risk factors from elsewhere in the literature.

1.2 The structure of this thesis

In Chapter 2 I present a brief review of the literature in the field of health inequality. This review considers how we define inequality, its relationship to inequity and the vocabulary and concepts required for considering specifically health inequality in a UK context. Firstly I consider theories of access, focusing on access as a multi-dimensional concept, which can present inequalities across multiple domains. I then focus further on the specific issue of extended hours services in primary care as a way of considering deprivation and distance factors in access equality and thus access equity. Next I extend my review to the components of health resilience in the context of a global health crisis. I consider how wellbeing is impacted by the removal of services, how individuals co-construct their care when faced with long term illness and how the pandemic impacted on individuals, considering specifically the impact of deprivation on outcomes. Finally I consider clinical outcomes in the first wave of the COVID-19 pandemic and how these are related to deprivation and place. I discuss recent research into risk factors for severe disease and studies of length of stay as a way to understand how different communities may have been affected by the disease and how outcomes may be associated with underlying social economic determinants of health.

In Chapter 3 I discuss potential ways to measure inequalities, the data and methodological approaches used to address my research questions. The thesis contains work which utilises both administrative and survey data. Administrative data as a potentially N= all dataset is fundamentally different to survey data and this is discussed as part of my reflection on appropriate methodology and the extent to which any uncovered associations can be considered representative or indeed causal. Statistical methods for modelling time series data, the nuances of count data and conducting regression analyses of complex datasets are discussed further as I explore appropriate methodologies for addressing the questions of health inequality. Throughout the work I consider the impact of location and how we capture this important variable in inequalities research.

I then present three pieces of empirical work. Paper 1 is a published paper investigating the impact of distance on the use of primary care extended hours. In this paper I use an administrative dataset to analyse access to services as a function of deprivation and distance, measuring utilisation as a proxy for access. Paper 2 is a published secondary data analysis of survey data considering non-COVID related well-being during the COVID-19 pandemic considering how inequalities expressed themselves in measures of subjective wellbeing. The paper uses survey responses collected as part of the long running Understanding Society household panel survey during the first lock down in 2020. Paper 3 investigates deprivation and location effects in clinical outcomes for hospitalised patients with COVID-19 in 2020 in the Greater Manchester city region. In this paper I analyse hospital episode data obtained directly from the Greater Manchester Health and Social Care Partnership to look for associations between deprivation and place and clinical outcomes for admitted patients. The work has a geographical focus on the Manchester city area as policy makers and health care providers seek to understand the difference in experience and outcomes for patients of Greater Manchester hospitals admitted with confirmed or suspected COVID-19 infections in 2020. This paper has been recieved by the COVID-19 cell of the health partnership and is in the process of undergoing peer review for publication.

In Chapter 7 I draw these empirical pieces of work together and discuss my findings, hypothesising potential policy implications, suggest future directions for research and consider the wider context of growing inequality in the UK.

Chapter 2

Literature Review

In this review of literature, I consider and discuss research from multiple disciplines that is relevant to the study of health inequalities. In the first section, I provide a synthesis of the major issues in health inequalities research and why this is an important topic, worthy of attention, also including a discussion of how we might define health and inequality and how inequality and inequity are nuanced concepts which must be understood before embarking upon work in this area. I then consider access to health care and specifically focus on the domains of access and how they relate to primary care.

In the next section I review the research on resilience and health inequalities, and how community can be a form of health care. The global COVID-19 pandemic has tested community and health care structures as the UK has undergone repeated lock downs and closure of services. Previous literature from the field of resilience, and the literature emerging from research conducted over the course of the pandemic, provides a rich background to the work on wellbeing presented in paper 2.

Finally, I review research into clinical health outcomes during the pandemic and how these are related to social inequality as context for my third paper where I analyse hospital data for a cohort of hospitalised patients and how their social context and demographic groups may have manifested differential and inequitable health outcomes.

2.1 Health inequalities

There is an extensive body of research into health inequalities and researchers in the field have consistently demonstrated a link between health and the social gradient. This link is not limited to any geographic or development grouping, in fact health inequalities can be observed within and between countries across the world – even in developed economies with sophisticated health infrastructure such as the UK (Mackenbach 2012; Balaj et al. 2017; Hu et al. 2016; WHO 2010; Black 1980).

Kawachi, Subramanian, and Almeida-Filho (2002) develop a glossary of health inequalities, relevant to the contemporary study of inequalities in health. The authors define health inequality as the difference in the equivalent health outcomes of individuals and populations. Thinking about the example of a randomly distributed disease to illustrate this concept; if the incidence in two groups of the same size is the same, there is no inequality. If however, group A and group B have different incidence of the disease there is a health inequality present and therefore a variation which is worth investigation. If we think of an inequality as a difference in a measurable quantity, then a health inequality is therefore a difference in a measurable health quantity. Such health inequality can arise through personal choice/behaviour; for example a pair of identical twins where one sibling chooses to smoke, are unlikely to experience equal health. On the other hand, it may occur through random circumstance, for example a person may live in an area with an infectious disease outbreak and so experience unequal health relative to someone living in a location without this particular disease. However, health inequalities also occur unfairly or as a result of some injustice. When this happens, there is not just inequality but also *inequity* and the differences in mensurable health that arise are - theoretically at least - avoidable. Many forms of health inequality are rooted in inequity and the separation of the concepts is nuanced; we all experience subtly different health outcomes and measurable health is a complex concept, impacted by multiple, interacting factors. To give an example, two patients with the same health complaint will experience different outcomes if one chooses to refuse treatment. Their access to health care here would seem to be equal, but the outcome is not - they have unequal outcomes but a theoretically equal access to care and opportunity to be well. The situation is more complex that it seems, each patient is subject to different factors contributing to their decision to take or refuse treatment, and these may be resulting from a complex unrelated inequity and so even in this seemingly equal situation, there may be inequity. The complexity is further increased when we consider individual agency, for example when a child is not of an age or understanding to make their own health decisions, or when a person lacks capacity and so we must consider health inequity as being something which arises through the circumstances in which people grow, live and age and the systems which are put in place to deal with illness when it occurs. Inequities are thus an issue of social justice, and are a political concept which is distinct from inequality (Kawachi, Subramanian, and Almeida-Filho 2002).

Within the field, there are two distinct and complementary measurement approaches. We can measure the distribution of a measurable health outcome of individuals in a population but this carries the risk of grouping individuals by health profile, with scant regard for their social context. Alternatively, we can measure the outcome of groups, using some a priori system of grouping based on particular characteristics such as ethnicity, sex, or socio-economic factors, amongst others. However, when social groups are defined and the differences between them measured, the social groups chosen by the researcher will use an ontology which in turn will tend to operationalise pre-existing theories about socially significant characteristics including their impact on the distribution of resources within society. This theory may have embedded within it, normative assumptions about the health of groups divided by characteristics such as class, or ethnicity bringing bias into the study design. Given that neither of these measurement approaches is ideal, it is important to consider both. The researcher must be congniscent of these drawbacks, recognise the limitations of any approach, acknowledge inbuilt bias and carefully define research questions such that variables are selected to identify health determinants, and categorisation is only applied where it is informative and useful to explain variation (Murray, Gakidou, and Frenk 1999; Braveman, Krieger, and Lynch 2000).

Populations are easily divided and characterised by wealth. We can group individuals, drawing on not just specific income variables, but also on other measures of relative comfort such as housing quality to provide a more rounded understanding of an individual's absolute wealth and also of their relative wealth within society. The World Health Organisation reports that in all countries health follows a 'social gradient' (WHO 2008). This social gradient means that those who are below the absolute poverty line suffer multiple severe deprivation and experience worse health outcomes than their wealthier peers. However it not just those in abject poverty who experience differential health. One might suppose that once material needs are met and existence is no longer a struggle to survive with limited means, that the gradient might disappear but this is not the case and everyone is affected by the same phenomenon, dictated by their socioeconomic position. Even within more advantaged groups of wealthy individuals, a gradient exists, with outcomes improving with increasing wealth across the social spectrum, even past the point at which a person's means are more than adequately meeting their basic needs (ibid.).

Successive reviews of health inequality in the UK over the past forty years have revealed a widening gap in health outcomes between the rich and the poor (Black 1980; Acheson and Britain 1998; Marmot 2010; M. Marmot et al. 2020). Increasing deprivation is typically associated with poorer health outcomes (Kawachi and Kennedy 1997; Mitchell, D. Dorling, and Shaw 2000; Pickett and Wilkinson 2010; Ritsatakis 2009). This overarching thesis was examined and confirmed by the Marmot strategic review of Health Inequalities in England, conducted in 2010. The review concluded that the social gradient in health identified first by Black (1980), and subsequently by Acheson and Britain (1998), persists in the UK and that reducing health inequalities is a matter of fairness and social justice. The authors wrote that people in the poorest areas of the UK had on average a life expectancy seven years below those living in the richest areas and when considering healthy life expectancy, that is to say the proportion of life lived without disability, the gap was even wider, at some seventeen years.

Since this original Marmot Review, progress in addressing health inequalities in England has been poor. The Institute of Health Equity's 2020 review of the priorities identified by Marmot showed both that improvement in life expectancy has stalled and that the social gradient of health has become steeper. For England's residents, the largest decreases in life expectancy in the past decade have been in the most deprived areas, with a spatial element highlighting that deprived communities in the North have suffered disproportionately compared with wealthy areas of London (M. Marmot et al. 2020). The authors showed that the gradient in healthy life expectancy has also worsened, with the most deprived areas experiencing more of their (already shorter) lives living with ill health (ibid.). Marmot and Allen (2021) write that the lack of progress in reducing health inequalities is a fundamental contributing factor to the poor state of health of the population of England.

Population health is defined as, "the health outcomes of a group of individuals, including the distribution of such outcomes within the group" (Kindig and Stoddart 2003). Multiple factors affect population health; McGinnis et al brought together research on the impact of behaviour on health outcomes with evidence for the influence of social circumstances on health to define a framework of health. Taking a holistic view, the authors argue that health is determined by individuals characteristics and circumstances in five domains; genetics and gestation, social circumstance, the living environment, behaviour, and medical care (McGinnis, Williams-Russo, and Knickman 2002). Their framework proposes that personal physiological health factors determined by our genetics and antenatal development, lie at the bottom of a pyramid of other determinants which are societally determined and can be influenced by policy. Inequalities are present in all of these domains, and can interact to cause unequal health outcomes, mediated by inequitable underlying processes. For example, an inequality arising in access to health care, impacts on the medical care domain of health. This access inequality may affect people who have particular behavioural characteristics in different ways and so the interaction of the domains is complex. An area may have a lack green space and be characterised by inadequate housing - for example older high density tower-block style accommodation tends to be co-present with other forms of material deprivation. This means that the health of residents in these areas has the potential to be adversely impacted by not only their social circumstances, but also their living environment. These multiple factors and their interaction are hard to capture and to measure but by reviewing population based evidence, the authors estimated that the contribution of each domain is such that personal factors contribute only 30% to an overall measure of health, and that health care systems contribute only 10%. This suggests that, at the time of writing - in the evidence reviewed, 60% of measurable variance in health outcomes was determined by factors which can be influenced by policy, but that the health care systems proportion of this would account for only a small part of the variance in morbidity and mortality (that is to say the excess illness experienced, and the years of life lost). The health economy from which these statistics were drawn (in the US) is radically different to that experienced in the UK, however, the breakdown of health determinants into five domains is a useful framework to consider in the context of UK health inequality and the estimates of different contributions to health care show that policy and thus research into policy is critical for addressing health inequities.

2.2 Access to Health care

Although as discussed above, the provision of health care accounts for only a small proportion of the variation in early mortality at a population level, the provision of health care has received the greatest attention and is seen as a key tool to redress inequalities. Most developed economies have some kind of public or state intervention in the health care market designed to address previously inequitable access and open up services to all. The UK's National Health Service arose from the politicisation of health inequalities after publication of the Beveridge report of 1942. Beveridge showed that many of the poor in the UK were unable to obtain medical care and so in 1946, the NHS was devised to deliver care from a single provider, publicly managed, free at the point of access to all those who need it. This was the first time that many of the lowest income individuals in the UK had been able to access medical care (Heys 2012). At it's inception, there were no governing rules on allocation of services within the new NHS and so although there was now some provision for lower income patients, the existing unequal resource allocation was perpetuated. Tudor Hart (1971) described the emergence of an

’inverse care law’ whereby richer geographical areas with lower need for health care, were benefiting from the NHS more than those poorer areas despite their greater need as privately practicing clinicians set up NHS surgeries in their pre-existing customer bases. The Black report in 1980 identified that as the NHS had grown organically, areas in the south and south east experienced greater provision whereas areas in the north still had unmet need leading to a widening geographical inequality of health (Black 1980). This continued inequality has been the subject of policy and strategy in the intervening years, with the aim to reduce these health inequalities but although overall health has improved, inequality has increased as the wealthiest have benefited from greater health improvements than those suffering deprivation (Asaria 2017).

The intention of the NHS to be an equal service for all is embedded in the constitution which stipulates that access should not depend on the ability to pay, and is determined by need. The NHS constitution is bound by the Equalities Act (2010) and has a public sector equality duty to work to advance equality of opportunity between groups. However, the extent to which the NHS can adapt to address all inequities, as they present themselves, can be limited and it requires not just additional resource but also a deep understanding of the multi-faceted nature of health inequity and how it arises to design and provide services which result in equal care for equal need.

Health inequities are by definition, unjust. However, it is not simply morally the right thing to do to seek to right these injustices, but reducing inequality and addressing inequity benefits everyone along the social gradient – including those who are the most privileged (Marmot 2010; Pickett and Wilkinson 2010). We all benefit when inequality is reduced. Good access to the right health service systems for dealing with illness when they are needed is one way of addressing inequitable health and, as such, is a priority for global health policy makers. In recognition of this, member countries of the World Health Organisation are committed to developing health financing systems that enable all people to have access to health services, known as 'universal coverage' (WHO 2010) demonstrating that access to health care is an internationally recognised issue.

Health care is recognised as a key policy area and so understanding the extent to which health care services are needed is an important step in determining policy. A. Culyer, van Doorslaer, and Wagstaff (1992) define need in terms of being able to benefit and so a need for care, is the capacity to benefit from that care. In the context of health inequalities, different needs for care are experienced along the social gradient - and these differences in need must be addressed appropriately to ensure that inequities are minimised. Inequities arise when a capacity to benefit from care, i.e. a need, is not adequately met for one person, when it might for another and this difference has arisen for some reason of social injustice and the cause of that difference is a systemic but rectifiable social, economic, political or cultural process. The authors propose a clear distinction between a need for care and a need for health. We all need health but we do not all need care - for example, person who is ill, but for whose illness there is no technology or treatment available that can improve the illness, prevent deterioration, or improve quality of life has no capacity to benefit from care. The patient needs health, but because they have no capacity to benefit from it, they do not need health care. Culyer and Wagstaff (1993) argue that if we are seeking to rectify health inequalities, we should be aiming for care to be distributed such that the distribution of health is equal in a population. To achieve this, the distribution of care in the population may not itself be equal, as those suffering health inequities and other forms of disadvantage may require more or different provision to their more privileged peers, in order to attain an equality of health.

2.2.1 Access as a multi-dimensional concept

Access is a complicated and multi-dimensional concept. Unless the population whom care provision is designed to serve are able to access the care on offer, then its design, nature and location is irrelevant and so in this section, I consider the literature that conceptualises access and how this is relevant to the question of health inequality.

Many different definitions and conceptualisations of access exist and access is often conflated with utilisation; that is to say that the presumption is, if a health care service has been used, it has been accessed. Mooney (1983) observes that there is a lack of agreement in what is meant by equity in the provision of health services, and that multiple definitions exist and so the field seeks to build a conceptual understanding of access so that research questions can be constructed to investigate how access impacts upon health. Considering access and utilisation specifically, the author describes utilisation using the economic concepts of supply and demand and propose that access is a supply side variable and that for equity, supply and demand must be balanced (ibid.). This purely economic standpoint overlooks whether or not the capacity to benefit from care has been maximised in any given health care interaction. Just because a patient has attended an appointment, does not necessarily mean that the patient has indeed benefited from care, had their needs met and thus have truly accessed the service in question. Studies based on the use of care, which fail to consider this more complex dynamic, are not as informative when considering equality of access, and equity of provision.

Mcintyre, Thiede, and Birch (2009) present a conceptual framework of access in which access is viewed as concept with three domains; availability, affordability and acceptability. The authors define access to health care in terms of the extent to which an individual is empowered to use the systems in place when needed. This means that where policy makers are seeking to increase access, this must be through a dialogue between providers, decision makers and users at all levels such that being empowered to use services is the key driver for provision, rather than merely service capacity. Sufficient capacity is not enough; in order for there to be good access, the health care system needs to interact favourably with those needing to use it so that there is a good fit between the needs of users and the care provided. The three domains of availability, affordability and acceptability proposed by Mcintyre, Thiede, and Birch (ibid.) are the precursors for such favourable interactions. In the following paragraphs, I discuss these three domains further to provide a better understanding of the conceptual framework that is the basis for the work in my first paper.

Availability of health care describes whether or not the needs of the population are met through there being sufficient appropriate health care services in the right place, at the time of need. Systemic and individual factors interact to create the availability domain. Within the domain, geographical location is important as in order for the service to be available, it must be co-located with the individuals who need to use it. A doctors' surgery located miles from the nearest habitation, in an area with no public transport and poor roads, is not easily available for the population it is intended to serve. Furthermore, the opening hours for receiving care must fit with the times at which users prefer to use the service. For an emergency care scenario, opening hours must facilitate availability of services at the time of need and when considering an appointments based service, there must be sufficient appointments at busy times, such that users can see a provider when they need to.

The cost to the individual of using a health care service is defined as its affordability. Affordability does not simply refer to the financial cost of the service itself, but also includes indirect costs such as travel, childcare, loss of income, and time. In the UK, our NHS is free at the point of access but this does not automatically make it affordable in this sense. Depending on the resources available to the user, the same service may be affordable to some, but not to others. Reducing inequity in access here, requires the affordability to be equal; if one individual's food budget is compromised by the cost of using a service whereas another is able to pay from purely disposable income, the service is not equitably financially affordable. The opportunity cost to the family of using resources to access the health care service, for example time off work and the sacrifice of leisure time must also be considered as part of the affordability equation.

Care services also need to be acceptable (in the domains model of access).

There are educational and communication elements to this acceptability and the attitudes and expectations of a user and provider influence the patient's ability to receive and benefit from care. A user may have an expectation that the service they access will 'solve' their health issue, without any pro-activity from their side (for example exercises, lifestyle change and so on), and conversely users may opt not to try to access care because they perceive there will be limited benefit. This mismatch of expectation may work against optimising health benefits. The match between what the service can provide, and what the patient expects it to provide, is described as the acceptability of the service. In order for the benefit to be optimised the user must perceive the service offered to be acceptable – this will include that they are heard, treated respectfully and have trust in the methods and professional ability of their care provider. A provider with embedded attitudes towards a user based on life style, ethnicity, gender or other characteristics, may compromise the care provided, and likewise the user may reduce their capacity to benefit from care through their attitudes towards and expectations of the care giver. An example of these issues can be found in the study of sex workers by Mastrocola, Taylor, and Chew-Graham (2015) who found significant unmet need for primary health care related to long term conditions and co-morbidity in a group of women working in street prostitution. This barrier to access was largely attributed to the domain of acceptability. General practitioners were reported not to meet the expectations of these users, and interactions impacted on future care seeking behaviour, resulting in additional use of emergency services, rather than (more appropriate) primary care. The compromise in acceptability led to disempowerment of the women in the study, and thus limited their ability to access the care they needed (relating to the the acceptability domain of access). In this example, this compromise in access is to an extent structural, as these women are already marginalised through societal attitudes to their work and criminalisation of their income stream. This has a significant impact on their ability to both integrate fully with society and lead a health promoting lifestyle and is an example of how, if a system is managed top-down rather than through participatory mechanisms, users may be systematically and structurally disempowered and there may be sufficient appointments, in convenient locations at suitable times, but the users still cannot have their needs met.

Mcintyre, Thiede, and Birch (2009)'s three access domains interact, and this in turn impacts on equity of access. Considering the three domains together, it follows that a lack of availability, may compromise affordability and acceptability. A doctor's appointment that can only be made during your hours of work, with a male doctor, for a woman's health issue, might be unaffordable - the patient cannot have the time away from their job, or unacceptable - the patient may not wish to see a doctor of a different sex for this health issue, and these compromises in affordability and acceptability are rooted in the lack of availability. Poor communication can further exacerbate such access issues leading to a perception of deficiency in one or more domains that then restricts a patient's access to care. If a patient does not know that they could book an appointment outside of work hours, with a preferred clinician, then despite there being a well designed service in place to meet need, access is still restricted. Communication difficulties within a population may therefore introduce another level of inequity, requiring that service providers work to provide not just appropriate and adequate services, but also appropriate and adequate information about those services (in all relevant languages), so that access is not compromised.

2.2.2 Access to Primary Care

The nature of a socially determined health gradient has the consequence that groups within society experience different health problems, priorities and needs. It follows from this that if health care services are organised in a way that aims for an equal distribution of health, then services must be adapted to need and these needs are different for different groups and in different locations (Gulliford, Figueroa-Munoz, et al. 2002). In order for services to be adapted to localised needs, providers need to understand how an individual's context impacts on their capacity to receive care. This in turn implies that providers need to evaluate the nature of the use of their services and seek to understand whether or not differing contexts means that groups within a population remain marginalised and excluded. Moreover, there are sectors of the population for whom relative disadvantage causes a greater need for health care, but the very reasons for the need also contribute to the barriers to access (Gulliford and Morgan 2013). To counteract these barriers, systems need to facilitate access such that individuals can command the care they need to halt deterioration in, or improve their health. This is referred to as a vertical dimension of equitable health care which requires people who are unequal, to be treated unequally, in order to strive for equal outcomes.

There are also other ways in which the healthcare system can be or should be organised. Other possible maximands might include the maximisation of efficiency within healthcare - perhaps using a measure of health benefit per unit spend. The system could likewise be organised to maximise equality of treatment, using perhaps a measure of spend per capita. Whilst these other maximands may be important, they are not relevant to the focus of this thesis and so they are not discussed further.

In the UK there has, in recent years, been a specific policy and innovation focus on access to primary care. Primary care is generally not an all-hours service and many countries with developed health care systems report limited access to primary care outside of core hours (Monday-Friday, 9-5pm) (Schoen et al. 2007). A further issue in the UK is a national shortage of General Practitioners, which restricts capacity both within and outside of core hours. The King's Fund reported that the NHS is struggling to recruit and retain a sufficient number of general practitioners (GPs) to work in primary care (The King's Fund 2016) and Majeed (2017) writes that 'GP's are a scare resource' and that the NHS continues to underestimate the shortage given the rising complexity of the role and the increase in patient need. This chronic workforce shortage has wide ranging impacts on access to primary care as those GPs who remain within the service are spread thinner.

2.2.3 Extended hours services in primary care; the case of Greater Manchester

Since 2014, Greater Manchester has piloted and subsequently rolled out an extended hours service in general practice. The service forms part of the region's devolution and health and social care strategy, a central tenant of which is to address the health inequities experienced by residents of the city region (GMHSCP 2015a). The extended access service includes appointments that are offered in addition to the usual non-core hours services (out of hours GP appointments, walk-in centres, accident and emergency departments and NHS 111). The appointments are delivered in person by general practitioners and practice nurses at 'hubs' which are distributed across the main population centres within CCG areas. The extent to which same-day and/or pre-bookable appointments are available, the time of the appointments and the availability of different medical disciplines is locally determined.

Motivated by the perception that excess emergency department attendance is being driven by poor access to primary care, and a patient perception of decreasing access to primary care services, extended hours schemes have been piloted since 2013 and form a key component of the NHS strategy for primary care by 2020/21. All Clinical Commissioning Groups (CCGs – an administrative body responsible for planning and commissioning local area health services) are expected to provide extended access in the evenings and weekends in line with local demand from 2020 (England 2016).

In the decade between 2003-4 and 2013-14, the number of Accident and Emergency department attendances in England rose sharply from 16.5 million to 21.8 million (32%)(NHS England 2015). Whittaker, Anselmi, Kristensen, et al. (2016) studied primary care practices in Greater Manchester, using a differences in differences technique to compare those which offered extended access seven days a week, with those offering only routine core provision (defined as Monday-Friday 9-5pm). Analysing the associated hospital administrative records demonstrated that populations registered with practices which offered extended hours, recorded 26.4% fewer visits to the emergency departments for “minor” problems, when compared with matched populations at practices with only core hours provision. This resulted in a cost reduction for emergency settings of £768,000 . These findings are confirmed by Lippi Bruni, Mammi, and Ugolini (2016) who used administrative data to demonstrate a reduction of over 10% in the rate of “unnecessary” emergency attendance when primary care providers increased their hours to 12 hours a day.

When emergency settings are used to meet health care needs which would be more effectively and efficiently met through primary care, for example in the management of long term conditions, it indicates that there is some compromise in the access to primary care and so extending the hours of primary care health settings has the potential to not only reduce pressure on emergency care services reporting to be stretched by excess demand, but also to improve access.

Cowling et al. (2013) used data from a national survey of patients registered with General Practices in England (GP Patient Survey) to show that 10% of patients were not able to get an appointment when they wanted, representing 33.8 million unsuccessful attempts to access care per year. Scores for availability of appointments and the perception of the ease of seeing a specific GP fell across the board compared with prior years. It is clear from the research that patient access is being compromised

While the evidence suggests extended access is likely to reduce A&E pressures, little is known with regards to the impacts the services have on patient perceptions of access. Studies have so far only assessed uptake and use of extended access to understand which patients are being directly impacted. For example, Whittaker, Anselmi, Nelson, et al. (2019) analysed the use of extended hours appointments in five CCGs within Greater Manchester. Using figures from the General Practice Patient Survey they showed that users of the extended hours service were typically younger than those using primary care services in core hours before the scheme was launched. Female patients were more likely to book appointments outside of core hours than males. Their study revealed significant spare capacity within the service and questioned whether this was the result of the way the service is delivered or due to a lack of demand for the service. This research however only records who is using the appointments, and does not consider whether patients are truly accessing care and whether or not they perceive there to be acceptable and affordable services on offer.

If a service is designed to improve access in order to reduce health inequity, then any evaluation of these goals needs to consider the barriers to the domains of access which might exist. For good access there must be sufficient appointments such that there is availability. The patient needs to be aware that the appointments exist and attending an appointment must be affordable – not just financially but also in terms of the opportunity cost of time spent travelling and attending the service; clearly deprivation is an obvious factor affecting this affordability domain. Patients experiencing work insecurity, and with low income, may be much less able to take time to attend an appointment, particularly if it is not geographically nearby and requires the time and financial resource of a public or private transit. Finally the service needs to be acceptable – patients need to be prepared to visit a practice or doctor who is not their regular GP, and GP practitioners themselves need to agree that primary care can be delivered in this model such that it is promoted in their surgeries. Deprivation may again play a part here, the complex nature of experiencing low income and insufficient means, may impact on mental health, self esteem and basic skills which compromise this domain of acceptability, and thus increases the barrier to access.

Haynes et al. (1999) found that distance is a factor in attendance rates at both primary and acute care sites. Controlling for the needs of the local population and the existing health provision, distance from an emergency care provider had a marked impact on the rate of episodes, with the greatest reduction being seen in psychiatric cases (37% over the five distance quintiles within the study). Likewise, distance from a GP surgery had a similar effect, reducing elective acute episodes by up to 15%. Further investigating the phenomenon of distance related attendance, The National Audit Office conducted a multilevel regression analysis of GP practice level rates of attendance at accident and emergency departments. They found that out of hours, patients from practices located nearer to accident and emergency attended more than those who were further away and in fact the rate of attendance was some 2% lower for every additional kilometre that the practice was further away (National Audit Office 2015). Considering out of hours services, it has been found that distance matters again. When a patient needs an appointment, the out of hours service is often accessed by first making a telephone call, and then attending a hub service. These hubs are often located in emergency care settings such as at a local hospital. A study of telephone data from the Devon out of hours service showed that call rates to the out of hours service varied with the straight line distance from the caller to the centre. Furthermore, those living in deprived areas called the out of hours service more often, however, the further away the caller was from the emergency care setting where an appointment would be taken, the lower the rates of calls (Turnbull et al. 2008). This was confirmed to hold for many developed countries in work by Berchet and Nader (2016) who observed geographical factors in accessing out of hours care in an international study of OECD countries, reporting a similar distance effect.

Calls to out of hours providers are dependent on distance from a service - O'Reilly et al. (2001) examined the effect of distance and deprivation on use of an out of hours GP cooperative in Northern Ireland with four centres and found that calls to the service were proportional to proximity to the centres with those living further away, representing fewer calls even after controlling for confounding factors. Raknes, Hansen, and Hunskaar (2013) examined the utilisation of out of hours health services by municipality in Norway, calculating distances from population centroids to service providers. The study concluded that distance was important in service uptake, even in acute cases and as such, extreme distances could impact patient outcomes. Smits et al. (2015) examined a small sample (N=20) of general practices in the Netherlands, related to five cooperatives classifying use as 'high' and 'low' for out of hours care. Greater distance from the out of hours provider was associated with lower use at a practice level. All three of these studies confirm the same finding; when accessing primary care, distance matters.

Distance is a significant driver for health care use, and so geographical location as a facet of equitable access must be considered when commissioning services. In a city like Greater Manchester, where deprivation driven health inequity has a proven spatial element (Purdam 2017), distance is a barrier to access, compromising the availability and indirectly affordability and acceptability domains, may serve to exacerbate health inequity.

The supply of primary care practitioners impacts how patients access care to meet their needs. Patients registered at larger GP practices attend accident and emergency departments less often with research showing that for every additional GP, the rate of attendance for a practice reduces by 4% (National Audit Office 2015). When there are more GPs, there is greater provision of core hours services and this means that fewer patients need to attend accident and emergency. The level of provision of core hours services is likely to affect the extent of extended hours service use in a similar way. It follows therefore that where GP time is scarce, the use of an out of hours or extended hours services may therefore increase.

There has been a longstanding inequality in the supply of primary care with deprived areas likely to have fewer clincians per head of population than wealthier areas. Asaria et al. (2016) showed that the inequality gap in the supply of primary care was reducing, but had not been eliminated (by public policy) however, more recently, Bostock (2018) found that the primary care workforce in deprived areas is reducing at a faster rate than more affluent areas. It follows therefore that the number of GPs serving a community and the deprivation of the patients within that cohort are likely to be correlated and both may in turn be associated with the rate of use of an extended hours service. Patients in deprived areas, experiencing care needs, may not have equitable access to primary carers because of this shortage of GP availability.

As patients, we prefer to have a medical “home”, that is to say a place where we *normally* access services for our primary care needs. Schoen et al. (2007) confirmed that the concept of such a “home” was associated with better outcomes for patients. Patients place a lot of importance on familiarity of surroundings; Rubin et al. (2006) conducted a discrete choice experiment investigating the preferences of adults registered at six general practice surgeries in England. The study showed that for working age patients, a choice of GP was six times more important than a shorter waiting time. Patients with chronic illnesses valued seeing a GP of their choice seven times as much as having a shorter wait time. A sex effect was also observed with women being prepared to wait longer than men indicating that the medical home was even more important for women taking part in the study. The research concluded that speed of access for many patients is less important than GP choice or timing convenience (ibid.). The preferences observed in this study, help to illustrate how patients choose to construct their own access - picking between a known GP or a faster appointment depends on each patient’s own personal circumstances, whether they work, whether they are making an appointment for a dependent child, and the presence of any pre-existing medical conditions. Continuity of care is important and valuable to patients for psychological and quality of provision reasons. It therefore follows that it matters who we see as patients because of the acceptability domain of access, for many care needs, the person providing the care affects our ability to meet our needs. Where distance, practice resourcing or other factors limit the availability of a preferred medical practitioner, then the potential for further inequity arises.

The extended hours service within Greater Manchester provides an opportunity to investigate how distance, deprivation and familiarity determine the use of the service, and therefore whether or not extending the hours of primary care appointments, improves access to health care for the Greater Manchester population.

Paper one investigates the impact of these three factors on the uptake of extended hours appointments in primary care. The study considers all extended hours appointments in 2016 from four CCGs within the Greater Manchester area. We hypothesise that practices which are located further away from a hub account for fewer uses per capita of the extended hours service, than those which are located nearer and that therefore distance is an impediment to access. If distance is a barrier then it may mean that this service does not improve access for all and that this geographical inequality has the potential to widen underlying socio-economic inequity in access.

2.3 Health Resilience

Within the context of reducing health inequalities as a key strategic priority (WHO 2008; WHO 2010; GMHSCP 2015b; M. Marmot et al. 2020), building resilience has been presented as an individually focused phenomenon, placing the responsibility for health inequalities on citizens, rather than systems, through lifestyle choice and personal capacity (Public Health England 2014). This is exemplified by the extensive pressure on individuals to reduce their alcohol consumption, despite increasingly relaxed legislating around alcohol sales for example extended hours and low retail pricing (UK Government 2010). The system expects citizens to act in the interests of their own health, in line with public health messaging, and yet permits a regulatory framework and retail environment which is directly contradicts this messaging.

When faced with a challenge, the extent to which we are able to recover quickly is a measure of our resilience. Challenges may come in different forms during the life course for example redundancy, the loss of a loved one, a period of ill health or, in the case of 2020, a global pandemic. Health is subject to social determinants, and so a challenge in our social lives to which we are not resilient may indirectly and directly impact on our physical and mental health.

The way in which we react to life challenges and our ability to withstand forms of adversity, can be described as resilience. Resilience is an evolving concept, that encompasses not just individual characteristics but also the broader interactions of an individual with their environment. Resilience as a personalised concept is criticised for holding individuals solely accountable for outcomes, as opposed to recognising the inherent inequalities in society, which might impact their ability to withstand adversity (Hart et al. 2016). Masten (2007) describes the concept of resilience in developmental science, as "positive adaptation during or following exposure to adversities that have the potential to harm". The author discusses the four waves of resilience research and how these have moved from a individualised approach, to one which considers environments and systems surrounding the individual. There are correlates of resilience which reveal risk and protective factors, and the concept must be understood and investigated as a rich, dynamic contextual phenomenon. (Hart et al. 2016) argue that researchers and policy makers should recognise the potential for marginalised groups to alter and transform their own adversity, but should not place upon them the responsibility for any barriers which may impact their ability to do so. Research into this area should therefore be embedded with a 'social justice approach', so we consider not just the individuals but also the system in which they operate.

An alternative to the individualistic view of resilience, is to place responsibility with policy makers. If wider socio-economic conditions within a society are determined by those at the top, they too are responsible for an individual's ability to respond and adapt in the face of adversity. Health inequity is a systemic issue, and a political choice (Marmot 2010; M. Marmot et al. 2020) and the extent to which an individual is resilient to the health challenges they face, is influenced by the policies and systems prevailing over their time of distress. It has been proposed that upstream structural population wide strategies are more likely to reduce health inequality than downstream strategies targeting behavioural change (Asaria 2017; Theis and White 2021) and so to help those who have less 'health resilience' there should be state led intervention at the population level to provide services to support healthier outcomes, rather than a shift of responsibility and potentially blame onto the individual.

The World Health Organisation defines health as a state of physical, mental and social wellbeing (WHO 1948). Extending this concept to include resilience, a community's health resilience should therefore be thought of as it's capacity to maintain individuals who are physically, socially and mentally well, in the face of adversity or change. Wulff, Donato, and Lurie (2015) argue that community resilience in the face of a crisis, is important for limiting and rectifying damage and for thriving at both an individual and a community level. Considering two large disasters, the authors explored how a consideration of community resilience might serve policy makers in their efforts to organise public health systems, particularly in respect of medical preparedness. They conclude that promoting robust every day systems, prioritising community resilience and meeting the needs of marginalised groups, could then address underlying health inequalities, i.e. the social determinants of health. Both Hurricane Katrina (2005) and the attack on the World Trade Centre (2001), are studied in this work, and both resulted in renewed efforts in the USA to rebuild the capability to respond to public health emergencies. The authors argue that investment is necessary not only to provide capability when responding to a major disaster as an acute event, but also to withstand known threats as more chronic conditions and thus thrive on an ongoing basis. Investment in preparedness and building the resilience of systems and communities, can therefore be considered to be a method of tackling health inequalities.

Morton and Lurie (2013) present several domains of community resilience. The authors discus physical resilience - that is the built environment and infrastructure; the resilience of individuals; and the resilience of organisations, meaning governance, public and private sector entities. Physically and mentally well individuals are more resilient, with better underlying population health contributing to their individual resilience. Conversely individuals with poorer underlying health, or with under-treated chronic conditions, find it more difficult to re-establish a health promoting way of life in the aftermath of adversity. Psychological resilience allows individuals to adopt positive adaptations despite external stress factors. This mental resilience can be impaired by changes to the normal social life of an individual, for example through disruption of social networks leading to reduced population health. Organisations upon which communities depend, must also be resilient, for communities to be resilient. A resilient organisation can adapt and improvise when required, such that they do not fail when faced with challenges.

These individual, community and organisational factors combine and provide an overall level of resilience which can have unexpected impacts. For example, the negative association of deprivation and health does not always hold and there are examples within the literature of deprived communities which exhibit health resilience resulting in outcomes which are significantly improved compared with expectations. These results can be counter intuitive and several investigations have shown that communities can record better health outcomes than might be predicted, based on socio- demographic factors. These communities can be said to display 'health resilience' that is to say, they outperform expectations on certain measures.

Doran, Drever, and Whitehead (2006) used simple and multiple regression models to analyse data from the UK census in 1991 and mortality statistics from 2000-2, using life expectancy as a measure of resilience. They found that some areas of higher deprivation, had higher than expected life expectancies, despite the typically observed negative association between deprivation and life expectancy - that is to say that people from more deprived communities, experience shorted life expectancy. Furthermore, the authors describe associations with areas which 'over perform' for life expectancy, with certain shared socio demographic factors. A regional analysis showed that life expectancies were lower than predicted in the Northwest of England, but higher in London and the south. Tunstall et al. (2007) considered mortality as a measure of health resilience and showed eighteen areas with reduced mortality, despite long term economic disadvantage. The authors proposed that particular socio-cultural features of the areas may be protective against the adverse effects on mortality of deprivation and thus suggest that there are resilience factors which are important in health outcomes.

Cairns, Curtis, and Bambra (2012) consider morbidity and mortality as a multidimensional concept of 'health resilience'. Their study identified four parliamentary constituencies which appeared to be 'resilient' in this respect, despite high levels of deprivation. The authors identified factors which may make a population more health resilient including greater availability of social housing, higher density of ethnic minorities, and employment in higher occupational grades. The authors also found that areas where there was greater health resilience, appeared also to be subject to more 'population churning' that is to say greater levels of migration, and also a higher level of social fragmentation. They proposed that this may be due to initiatives to regenerate areas with entrenched inequality.

2.3.1 Community Stress Events; the case of COVID-19

An understanding of resilience as an individual, community and organisational concept, bridging physical, mental, financial, and social wellbeing, is a useful framing of the response to the COVID-19 pandemic. We can consider the extent to which individuals, communities and organisations were able to adapt, and retain healthy function in the face of unprecedented strain as a reflection of their resilience.

In early 2020, reports of a novel respiratory virus with a high mortality rate began to emerge from China. The virus had started in the province of Wuhan and rapidly spread causing significant strain on the critical care facilities of health systems across the world. The World Health Organisation declared a global pandemic on 11th March 2020 (WHO 2020). In response to the rising cases of the disease in the UK, the government declared a 'lock down' on 23rd March 2020 where citizens were requested and required to stay at home, unless for a very limited number of sanctioned reasons (UK Government 2020b). Mass gatherings were banned, travel was restricted. Leaving the home was reserved for those working in so-called 'key-worker' roles such as health care, education and the food system. Non key-workers were permitted to exercise alone outside of the home once daily, and to make trips for essential supplies. All non-essential services were closed including shops and leisure facilities. Non-emergency care was seriously compromised with many routine care services stopping for several months including cancer diagnostics, chemotherapy, surgery and outpatient clinics. The exceptional circumstances of this global world health event, presented a challenge to resilience at the individual, community and organisational level.

The pandemic has caused significant suffering with large numbers of fatalities. There have also been fatalities as a result of the precautions put in place to control and restrict the transmission of COVID-19. Kontopantelis et al. (2020) examined excess mortality during the first wave of the virus and reported that between 7 March and 8 May 2020 there were nearly 10,000 excess deaths in England and Wales, unrelated to COVID-19. These excess deaths showed geographical and social patterns with excess mortality varying from 1 per 100,000 in Wales, to 26 per 100,000 in the West Midlands, showing that the pandemic has had a measurably different effect on different regions. These excess non COVID-19 deaths are *indirect* impacts of the pandemic. These indirect effects, are likely to be pervasive and have long lasting psychological and social impacts and the extent to which these are adverse, will be a test of resilience across the whole framework proposed above. In the early stages of the pandemic, there was a lack of information and understanding about how these non-COVID but COVID related issues might be playing out within the community, communities responded in different ways, some coming together and providing relief aid for those in need, and others potentially becoming more fragmented. (E. A. Holmes et al. 2020) called for resources to be deployed to understand the varied effects, collecting data and conducting multidisciplinary research to ensure efficient targeting of policy mitigations. The authors specifically reference mental health, and the growing threat of virus mitigation measures, alongside the potential physiological effects of contracting the virus on brain function and mental health in patients testing positive with COVID-19. At the individual level, psychological resilience to extended uncertainty and circumstance changes, as well as physical resilience to the health impacts of the crisis have been, and continue to be important in influencing direct and indirect outcomes of the pandemic for all.

The pandemic also threatened to widen existing health inequalities, as the socio-economic implications of the economic contraction and closure of the education system have fallen unequally and the social gradient has thus steepened. Controlling the spread of COVID-19 has been a priority to protect the ability of the health care system to provide care for those who need it, and to reduce the excess deaths attributable to the disease. The measures taken have impacted incomes, social contact and job security and to cope with such adversity, there is a need to be able to adapt, and display resilience. These factors all contribute to an individual's ability to live a healthy life and there should therefore be expected to be a significant impact on long term health (Nicola et al. 2020). Sadly, the burden of these long term health impacts are unluckily to fall evenly. The Trussell Trust reported a rise of 122% in emergency food parcels for children during March 2020, compared with the prior year (Trust 2020). Those on a low wage, in particular the young, and women, were seven times more likely to work in sector forced to close by the COVID-19 restrictions with a third of employees in the bottom decile of the income distribution working in a closed sector, compared with only 5% of those in the top decile (Institute for Fiscal Studies 2020). Given these statistics, arguably the young and women may have needed to adapt more than older male counterparts, and may have been more reliant on the organisations and systems around them continuing to function. The pandemic restrictions led to an expected additional 3.5 million claims for universal credit from the UK welfare system (Telegraph 2020). Pre-existing inequalities cause uneven impacts of the virus, and it follows that complex patterns of health inequity will result (The Health Foundation 2020b). Considering the resilience framework, the wellbeing of people affected by closures and shrinking financial means, will certainly be impacted on how they, and the organisations on which they depend, are able to adapt. Many businesses were able to carry on trading in the lock downs by adapting their business models, offering different services or products thus retaining critical employment opportunities for staff. Lots of communities adapted with relief efforts reported across the country. However, even in the context of a strong community and adaptable critical organisations such as the welfare state and local health care services, low personal resilience may still lead to poorer outcomes in the event of a significant stress event.

Schools were closed and these closures affected not just the educational outcomes of young people, but are likely to have disproportionately affected lower income families for a wider range of reasons. For these families, child care was abruptly removed, alongside easy access to services such as free school meals (Douglas et al. 2020) causing a strain on income. Their ability to work was reduced by a contracting economy and childcare needs, simultaneously to the removal of services such as meals at school. This represented a step change in how families lived, impacting work, home dynamics and financial means. Where resilient schools were able to put in place strong home provision and act as a safety net, especially for those whose main meal was abruptly removed, families may have been in a better position to cope with the changes.

Incomes during the crisis were for some families put under severe strain and we know that income influences health. Families need enough money to meet their material needs and to participate and engage in health promoting activities, such as having sufficient non working time to take exercise, or being able to afford fresh goods and the time to prepare meals using them. Having insufficient money is stressful, and living with disadvantage can make a person more likely to engage in unhealthy behaviours. The effect that money has on health, can impede people's education and employment causing an ill-health income feedback loop (Benzeval et al. 2014). It is clear that for many people in the UK, the pandemic restrictions have either reduced their income, or increased the threat of financial stress in the future through the prospect of unemployment or furlough. This may last for some time, a recession is underway with large scale unemployment predicted to last for several years. There is evidence that unemployment can be linked to excess mortality and so a lack of work caused by the pandemic may also contribute to pandemic related non-COVID-19 deaths and outcomes. Roelfs et al. (2011) conducted a systematic review and meta analysis of 42 studies looking at unemployment. These data covered 20 million people (within the US) and demonstrated that the risk of death for someone out of work was 63% higher than for those in employment and that effects persisted in the longer term studies reviewed indicating that unemployment has a long term impact on mortality. Financial resilience (the ability to withstand life events that impact income or assets) is critical here, those with savings and secure housing will have experienced a much smaller burden than those on a low income, even with the moratorium on evictions. The lack of financial resilience of those on lower incomes and how this might make adaptation to COVID-19 more difficult was in fact recognised by the government with a temporary uplift to basic benefit payments.

The impact of social isolation and social distancing on the population was measured as a snapshot through a survey conducted by Ipsos Mori, looking at the situation for people already suffering from mental illness as at March 2020. This study showed participants concern about the impact of social isolation and social distancing, part of the UK's response to controlling the spread of the virus, on wellbeing. This included an increase in depression and anxiety, elevated stress levels and practical concerns about other issues related to the COVID-19 related restrictions, such as financial insecurity. Participants were less concerned about falling ill with COVID-19 itself, than with the indirect impact of the restrictions in their everyday lives. The study focused on people with an identified mental health issue. These patients registered concern around a worsening of their existing conditions and difficulty in in accessing support and services under the COVID-19 restrictions (E. A. Holmes et al. 2020). There may have been some people who were mentally resilient to the impact of the pandemic and those who did not have the capacity to cope with the restrictions, and that those with pre-existing mental health illness may have been worse affected and more concerned about the impact of social isolation. The resilience of organisations to which these patients normally turn for support may also have been important here - where support for those with pre-existing mental health diagnoses was maintained, then the extent of adaptation needed to cope with the pandemic may have been reduced.

Sadly, the restrictions associated with COVID-19 are expected to have a measureable effect on the risk of anxiety, depression, self-harm and suicide. The unprecedented circumstances of the pandemic, could reasonably be expected to increase stress, however the associated economic downturn is also likely to affect patients, and those who are carers. In 2003, there was a global pandemic of a novel respiratory virus referred to as Severe Acute Respiratory Syndrome 'SARS', in considering the impact of COVID-19 in the UK, studies from the countries worst affected by SARS provide a useful parallel. A study of older adults in Hong Kong showed that during the outbreak, suicides in the age 65+ age group increased by 30%. This increase was attributed to fears of being a 'burden' to family during the outbreak, but also social disengagement, mental stress and anxiety (Yip et al. 2010). Nickell et al. (2004) showed that health care workers in a Canadian hospital setting during the same outbreak had a significant increase in emotional distress, as measured by a general health questionnaire, affecting their families and their lifestyle. Further research from Hong Kong showed that a significant proportion of patients infected with SARs who recovered, suffered from increased anxiety on recovery, lasting beyond the period of the viral outbreak (Tsang, Scudds, and Chan 2004).

An analysis of Google Trends data by Brodeur et al. (2021) provides further evidence that wellbeing was negatively impacted by the pandemic and by the lock down regulations. Using a difference in differences approach, the authors showed that for countries with a full lock down during the study period (9 Western European states), there was an increase in search terms for boredom, loneliness, worry and sadness (ibid.). The impact of the pandemic was not restricted to the UK and indeed Europe, a study of 6,142 adults from 18 countries within the Middle East and North Africa in May and June 2020 concluded that the pandemic was associated with a mild psychological impact. Half of the sample in this study reported feelings of horrified, helpless or apprehensive (Dhaheri et al. 2021). It is clear therefore that the negative impact on wellbeing observed in earlier pandemics, was also observed by researchers analysing wellbeing in 2020.

For patients living with a long term condition, the impact of the social isolation and shut down of informal health care services such as support groups may impact on self management. Reeves et al. (2014) studied 300 patients with diabetes or chronic heart disease living in deprived areas of the North West of England. The authors found that self management, and physical and mental health were supported by social involvement with a variety of groups and people. Patients increased their use of their social networks as their care needs increased, showing a dynamic effect that was reflected in financial savings to the care providers. Social networks act for these people as a support to and a substitute for more formalised health care services, and increase the ability of actors to adapt, forming a core part of the resilience mechanism.

This social network effect may have been significantly disrupted by the COVID-19 pandemic. At a time when care services were stretched by patients requiring care for COVID-19, patients living with a long term care need may have needed to draw more on this social network for their own self-management as access to formalised health care settings became restricted. Availability was reduced with many non-COVID-19 related services cancelled, and many users may not have found the services on offer to be acceptable, expressing fear of contracting the virus given the risk of disease transmission in any setting with social contact (Thornton 2020). Access to groups, socialising and networks was at the same time restricted for all, and particularly for those living with significant co-morbidities who were at the time instructed to 'shield' for a period of three months (UK Government 2020a). Support for self-management of long term conditions is a networked and collaborative construct, as opposed to merely based on the action of individuals and so a time of significant social isolation may well have caused a break down in self-management of health and wellbeing for those with longer term care needs (Von Korff et al. 1997; Vassilev et al. 2013; Mossabir et al. 2015).

The highly infectious nature of the COVID-19 virus necessitated significant organisational changes for health care services on a global scale. In a multinational survey, resource reallocation from chronic disease to COVID-19 disrupted the continuity and the quality of care across all countries, with specific impact on diabetes, chronic obstructive pulmonary disease and hypertension (Chudasama et al. 2020). Elective surgeries and outpatient clinics were cancelled with many care appointments postponed most care moving to remote provision by teleconsulting (Spinelli and Pellino 2020). In the early stages of the first wave, evidence of risk factors for infection and mortality had not yet emerged and a crisis in demand for respiratory care de-prioritised other areas of the health care system. Health care service overcrowding affected the resourcing and facilitation of ongoing treatment and palliative care for conditions such as cancer (Spicer, Chamberlain, and Papa 2020). Diagnoses were reported to be delayed as services for screening and testing were suspended and many patients were reticent to engage with health care services for fear of contracting the virus in a hospital or other setting (Richards et al. 2020). Maringe et al. (2020) modelled the impact on cancer deaths as a result of delays to diagnostic and treatment services, and predict over 3,000 excess deaths over the next five years, in a sample of 93,607 patients suffering from one of four specific tumour types. In the case of diabetes care, the strain on emergency health care services required many medical staff to be seconded to alternative roles, further compromising the availability of specialist services. Nagi et al. (2020) report a reduction in acute admissions for diabetes and related endocrine disorders and a reduction in investigations. Standard outpatient clinics were closed and cancellation of face to face clinics alongside a reduction in availability of services, caused the care to be delivered to be sub standard in addition to there being concerns of ”important unmet clinical need”. Paper 2 considers the impact that restrictions designed to limit the spread of COVID-19 have had on non-COVID-19 related health. By challenging individuals, our communities and the systems upon which we rely, the pandemic lock down posed a risk to health against which, resilience at individual, community and organisational levels may have been protective, and a lack of resilience and resources of adaptation may have led to worse outcomes. The study uses questionnaire responses from the COVID-19 modules of Understanding Society to examine the change in wellbeing for respondents during the lock down period associated with the UK's 'first wave' of COVID-19 infections, in the first half of 2020.

I hypothesise that as a result of the pandemic and the accompanying lock down, wellbeing has been impacted and that there are likely to be widespread indirect effects important to policymakers and health professionals as the population recovers. Studies using the UK Household Longitudinal Study show that there has been a deterioration in the average mental health of respondents when comparing data waves before and early in the pandemic. Proto and Quintana-Domeque (2021) report that the extent of the deterioration varies by ethnicity and by gender. Pierce et al. (2021) explored the trend in UK mental health, demonstrating that there had been a deterioration compared with pre-COVID-19 trends, highlighting greater increases for younger adults, women, and people living with young children. As the pandemic continues there is a need for further research into the extent of this deterioration and also how people responded to the ongoing crisis. Understanding the extent and nature of any decline and recover, and whether any adaptation was impacted by other social factors, is important for policy makers looking to implement any further restrictions in this or future such events, when deciding and designing which areas of society to restrict in order to reduce disease transmission.

The aim of the study is to uncover differences in the extent of the decline in wellbeing and subsequent recovery. I predict that there is an association between deprivation and decline in wellbeing, reflecting lower levels of resilience in deprived populations where there may be fewer resources, personal, communal and organisational, to call upon in the face of a crisis. Services and support networks were not resilient to the initial lock downs and almost all services ground to a halt and this is expected to cause a greater decline in wellbeing and reduced ability to recover for those with long term health conditions. I also consider effects attributable to ethnicity and sex as important social determinants of health.

2.4 Outcomes in a health crisis

When the COVID-19 pandemic was declared in March 2020, health inequality and wider resilience of the population were tested.

As discussed above, progress in addressing health inequalities between government commissioned reviews has been slow. Improvements in life expectancy have stalled and that the social gradient of health has become even steeper (M. Marmot et al. 2020). In Greater Manchester, Michael Marmot et al. (2021) reported a stronger association between deprivation and mortality in than other areas in England, when measured at an aggregate level. COVID-19 related mortality was 25% higher in the city region than the mortality for England as a whole and this additional mortality burden compounds the already lower life expectancy in the city region compared with other parts of England (GMHSCP 2015a). In a blog for the British Medical Journal, Marmot and Allen (2021) write that the persistent inaction on social determinants of health over decades, highlighted by successive reports, contributed to a nationwide poor state of health present before the arrival of COVID-19 and that the poor state of health of the nation, can in part be linked to the high levels of mortality experienced by the population during the course of the pandemic.

Evidence has emerged that there are a number of risk factors for severe and fatal COVID-19 infection. Older age groups are more at risk of hospitalisation and death, and men are more likely to be at an increased risk of severe infection (Wu and McGoogan 2020; Jordan, Adab, and Cheng 2020).

Drefahl et al. (2020) linked recorded COVID-19 deaths (in Sweden) up to May 2020 to high quality personal records. Using individual level survival analysis the authors showed that being male, having lower income and lower education levels all independently predict higher risk of death from COVID-19. They conclude that the virus was, at that time, exerting an unequal burden on the most disadvantaged, observing at an individual level, the same deprivation link as reported in the UK. It appears therefore that the risk factors for severe COVID-19 disease, are the very same health markers that indicate poorer national health - in particular comorbidities and obesity (noting that many comorbidities are indeed related to or worsened by carrying excess weight).

The correlation of social phenomenon with physiological attributes makes distinction between physical and social risk factors difficult to determine. Age and sex are known risk factors for the disease; these are physiological characteristics but are socially relevant, for example women are more likely to be in lower waged work and experience poverty than men in the UK (Collingworth 2018). Comorbidities may also be considered physiological however the prevalence of many of the pre-existing conditions which are known risk factors may follow a social gradient; heart disease and excess weight are correlated with deprivation and so it is then difficult to determine if the disease burden is related to the specific physiological risk factors, or if there is a wider social effect at work.

Williamson et al. (2020) conducted a large cohort study of COVID-19 related deaths in England using primary care data (N = 17,278,392). The authors found male sex, greater age and deprivation to be associated with increased death risk. Underlying health conditions (diabetes, asthma and others) were linked with increased mortality as was ethnicity, with black and South Asian people more likely to die. The study used only records from one particular provider of general practice electronic health record software and was conducted early in the pandemic. Period effects were not examined and there was a high level of missingness in the ethnicity characteristics of patients included (26%).

Air pollution and COVID-19 have been linked in England at the regional level (Travaglio et al. 2021). Controlling for age, population density and income, the authors showed positive association between the concentration of air pollutants (specifically nitrous oxides) and COVID-19 mortality. The study also demonstrated that $PM_{2.5}$ particulates were linked with increased case numbers in areas of higher concentrations. Becchetti et al. (2021) reviewed literature pertaining to air quality and covid outcomes. The authors found robust, strong evidence that there is a link between air pollution and COVID-19 outcomes, and that this included both the hypothesis that long term exposure to air pollutants has a measurable impact on patient trajectories, and also that there are shorter term consequences of exposure which are relevant. For this reason, I included a measure of pollutant levels both at home (to approximate long term exposure) and in hospital (to approximate short term exposure) within the analysis.

Shryane et al. (2020) investigated the length of stay of patients admitted to intensive care (ICU) between March and May 2020 using data from the COVID hospital surveillance system (CHESS) in England. Changes in admission policy were found to be confounders of clinical knowledge of the disease in this early stage of the pandemic and earliest admitted patients spent significantly longer in ICU than those admitted after April. Sex and ethnicity were not found to be related to the length of stay. Age was not monotonic in this study, which was most likely because it included the length of stay for individuals who did not survive the disease.

Vekaria et al. (2021) used four variables to predict length of stay for hospital admissions in a hospital in Manchester using different methods to model pathways to outcomes (discharge/death). In addition to sex and age (categorised), the authors found that the stage of the pandemic was predictive of the total length of stay, and that patients admitted to ICU who survive, have longer hospital stays.

Female sex, and kidney or liver disease were associated with longer lengths of stay in a retrospective cohort analysis of patients with COVID-19 in Hefei, China, in the earlier stage of the pandemic, excluding patients who died (Guo et al. 2021).

Given the extensive literature linking deprivation with poorer health outcomes, and the established excess mortality experienced by the population of Greater Manchester (GM), there is therefore a need for further research to uncover localised effects and to explore how the social gradient is acting upon people's health outcomes with respect to COVID-19 in this particular geographical area and whether the nationally researched picture for determinants of COVID-19 outcomes are relevant in the GM city region context.

In paper 3, I use NHS administrative data to study the effects of risk factors on the outcomes of hospitalised COVID-19 patients in Greater Manchester. I investigate severity of disease and death as health outcomes for patients hospitalised with COVID-19 hypothesising that patients from more deprived areas who survived hospitalisation were more likely to spend longer time in hospital, and that the risk of death is associated with deprivation and other demographic factors.

This third paper completes a triptych of research papers in the area of health inequality. Although the nature of the papers has largely been defined by the epoch, the trajectory of research is a coherent addition to the literature. At first I consider the ability of a population to access care for their needs and how the structure of service provision can embed or disrupt place and person based deprivation effects. In the second paper I investigate how self reported wellbeing is impacted when care structures are compromised in both the health services and community spheres. The third paper is the only part of the work to analyse actual health outcomes, investigating whether once a patient is within the care of the National Health Service, deprivation and place effects persist for patients admitted with COVID-19. In my work I assess the relationship between deprivation and space and three aspects of inequalities; inequalities in access, inequalities in wellbeing, and inequalities in outcomes. This is a topical assessment conducted on recent and emerging policy approaches and thus adds to the literature concerning ways to reduce inequalities and ensure equitable health for all.

Chapter 3

Methodology and Data

The *data universe*, that is to say the sum of all data collected and stored, is only partially accessible to any given agent. The available data universe can be considered to be that part of the data universe which we can see and use. When designing data science research, the available data universe drives the methodology, and to an extent the range of questions which can be addressed (Stahl and Staab 2018). This might be constrained by knowledge (we might not know that a specific data record exists), ownership (we might not own the data or have permission to access the data and thus not be able to use it) and capability (we may not have the tools or resources to explore the data to which we have access).

This thesis presents three pieces of empirical work, however the simplicity of the journal format for the finished published research hides an important part of the methodology underlying my work. Throughout my doctoral studies I have undertaken a complex and multi-layered data discovery process which has been critical to developing the understanding needed to complete my research and has been a core part of the development of the studies. The research therefore can be considered to have been a fusion of the deductive and inductive. I both sought data which could help answer questions about health inequality, and also examined the data I found to understand what questions it could answer and whether these lines of enquiry could shed light on the overall topic.

The work here has to an extent been determined by the availability and capability of data within the accessible data universe. It is also however useful to consider the presentation of these studies as a quasi-facet approach (Mason 2011). In facet methodology, a small number of investigations are strategically designed and selected to highlight specific 'facets' of a topic or subject area. The topic of health inequality is large, complex, and indeed multifaceted. The researcher therefore has different ways to approach the task of increasing knowledge in the field, and drawing useful conclusions which advance our understanding and make a positive contribution not just to the research domain, but also to the policy arena. A researcher could choose to select a narrow and defined aspect, designing a series of incremental related research tasks, presenting these at intervals as an in-depth but linear increase in understanding. Alternatively, the researcher can investigate the topic by designing related questions and puzzles which consider the topic from different angles and - potentially - using very different methods. The findings of these enquiries can then be considered as a collection of rich and rounded outcomes, which as standalone pieces provide insight to a particular aspect of concern, but which when considered together, provide a broader understanding and insight into the whole.

In the studies presented here, I consider complicated and unpredictable social systems. Complex non-linear interactions are likely to be behind many of the emerging regularities and there will exist multiple feedback loops. Developing the work into a more deductive phase, I seek to discuss these unseen mechanisms and ask why the outcomes arise. In doing this I propose, or reference hypothetical models which may be at work.

Each study is designed to highlight a particular aspect of the greater topic of health inequality, each looking at a different angle. Health inequality is a wide field and so I have sought to conduct enquiries such that I am able to present a rounded collection of findings which as individual pieces of work give a detailed and specific understanding of a singular narrow aspect, but which together shed different lights on the topic as a whole. The benefit of this approach is that it is compatible with the data driven strategy of the thesis, and that it has allowed my pathway to adapt to the challenges presented by at first, difficulty accessing data, and latterly the global COVID-19 pandemic. Consequently, the three papers presented here, address distinct research questions. For each question, different methodological challenges and considerations arise, and for each an approach is determined which is robust, capable of answering the question posed, and compatible with the available data.

3.1 The Field of Population Data Science

The field of population data science is defined by McGrail et al. (2018) as “the science of data about people”. The increasing size and complexity of digital datasets presents an opportunity to introduce linkage such that data science methods can be used to respond to issues facing human populations. The authors of this position paper define four ‘characteristics’ of data science about people. These are: (i) that work in this field seeks to use data for positive impact on social systems, (ii) draws data from multiple sources (linking as appropriate to give greater insight), (iii) uncovers insights at a population level, and (iv) establishes a research ecosystem which is respectful and protective of privacy, and operates ethically. The field is inherently interdisciplinary and this is certainly the case for the research presented here. During the work on this thesis I have drawn from the spheres of health economics, medicine, population health, human geography, mathematics, computer science, sociology, and social statistics. My reading and knowledge gathering has stretched from the highly specialised and largely mathematical field of digital privacy to the practical research of hospital based clinical trials. It is clear then that work within the field of population data science can be considered an umbrella term under which fall topics which include health and social science investigated using novel data science techniques where appropriate and using data drawn and linked from multiple sources, much of which is not gathered for the primary purpose of research, but is instead, gathered through the functioning of the system serving the population to be investigated.

McGrail et al. (2018) credit the exponential increase in the availability of digital storage with the development of this field. As the cost of storing data has decreased and the technology for sorting ever larger quantities of digital information has increased, human systems have created and recorded vast swathes of information about our lives. The implementation of digital solutions within the health care service have translated to a huge opportunity to access information about our health and interactions with health care, possibly in real time, covering the breadth of human experience.

Methodologically my work falls within the field of Population Data Science, as applied to the topic of health inequalities. Health data science is the application of data science techniques to health and medical data taking observed health outcomes and using medical and health data to investigate these and thus learn about improving human health. This might use medical records, tracking technology and other sources. Social data science uses data science to explore social phenomena, how humans behave in society using big data sources such as social media, tracking technology, survey and census data amongst others. The work here combines elements of these into a super-field of social health data science whereby discussion of the social is combined and explored with the medical, to understand how the social system impacts health.

The field comes with many challenges, not least the need for a researcher to be conversant in many different skills which stretch across disciplines. Foremost of these challenges - when using administrative data and/or seeking to link multiple datasets - is the question of privacy which must be considered in balance with research for public good. For many population data scientists, this is complicated by research across legal jurisdictions; however in this work, I constrain my research to the single legal and regulatory territory of England using as my primary source of guidance on matters of privacy and anonymisation, Mark Elliot et al. (2016) and training provided as part of the

Office of National Statistics Safe Researcher program, under which I have gained accreditation as part of my doctoral studies.

3.2 How do we measure health equality?

Although the field and topic are defined, the concept of health equality and how one might go about measuring this complex concept is less clear. It requires a considered methodology which can capture the distribution of health in a population, rather than the average level of health. This means research needs to be designed such that it is capable of analysing differences in health and the reasons for these differences across a sample, rather than simply the health of a population which might mask groupings of poorer or indeed better outcomes.

Similarly, the direct measurement of what we conceive as 'health' is not a straightforward question to address. We can take biological measurements - sampling blood, measuring body mass, testing lung function, but there is no simple way to combine these factors and assign a value that could for certain be a clear measurement of 'health', and simple assessments of this type would neglect other aspects of healthy living such as mental wellbeing or the ability to access employment or a social life. The measurement of the difference in health between two individuals is thus complex to measure and this further complicates the determination of any inequities which might be arising within a population. We must therefore think creatively and critically when designing projects to answer research questions in this field and draw from the huge literature in this area to select an appropriate measure and method for any given question.

There are also economic approaches to measuring inequalities. The slope index of inequality measures the difference in average life expectancy and healthy life expectancy between most groups based on deprivation. Such is the close link between life expectancy (using the slope index) and income quintile, Khang et al. (2019) propose that this should in fact be substituted for measures of health when communicating results and findings in a public forum.

If there is no health inequity and unlimited resources, then all individuals in the system should attain their maximum possible health. This means that a person should be able to live their best possible healthy life, given their lifestyle choices and genetic pre-disposition. Health care services should attend to their every need as it arises, and there should be no difference between groups of users, all of whom will display a range of outcomes, but the variance in these outcomes will be attributable to factors other than the health care services available or a person's social and economic grouping. In this scenario, there would be no expected difference in life expectancy and healthy life expectancy across different social and economic groupings, other than those which arise through underlying biological factors or through life choices - for example occupation or health related behaviours such as smoking. In disease populations, outcomes would be equally distributed, albeit differently to populations without the underlying disease burden. However, as previously discussed, there are multiple social determinants of health, of which the access to health care is one. We can consider the health of an individual to be comprised of different components which determine the health outcome; genetics, lifestyle, social determinants and so on and conceptualise this as a mathematical function which compiles these. One part of this 'health function' is health care. This is the portion of maximum attainable health that is attributable to health care. If all need for health care is met, there are no barriers to access, and no resource constraints, then the portion of the health function attributable to health care for the population should be maximised. Measuring this is more complex, as the health of the population is determined only partly by access to health care and is impacted by the other parts of the health function. Measuring adequate access to health care via objective health is therefore non-trivial, not least because of the significant privacy barriers to a researcher using person level objective health outcomes as a means to measure adequate access. A study would require the explicit permission of participants, and for additional data capture in order to secure a minimum dataset for the analysis. The data access agreement in and of itself, along side the need to be subject to further data collections, may in fact exclude certain groups, and by definition, any use of health care records would mean that those not accessing health care at all, would be excluded by their absence.

The concept of access to health care is likewise complicated and identical services cannot be assumed to mean equal treatment by the health care system. If as a researcher we decide to focus on the health care services portion of the health function, then need, demand and utilisation must be differentiated, to understand the cause of inequities, and to measure one, is not to measure the others (Culyer and Wagstaff 1993; Ozegowski and Sundmacher 2014). A need for health care arises when a service is capable of increasing a person's health, but this is not quite the same as the demand for health care. Need may arise, which does not give rise to demand for reasons associated with barriers to access as discussed in Chapter 2. Utilisation may in fact be to a large extent unrelated to need or demand, depending on the structure of the provision, again impacted by complex domains of access and barriers to health care participation. Therefore, any measurement of a health care service, designed to investigate inequity, needs to bear this complex system in mind and remember that to measure any form of access even with an understanding of the barriers in place and the economics of utilisation is not the same as measuring equal treatment for equal need for care, nor does it consider equality of health outcome (A. Culyer, van Doorslaer, and Wagstaff 1992).

3.3 Location in inequalities research

Macintyre, Maciver, and Sooman (1993) described a long tradition of research into the relationship between place and health. Mostly this research uses place based statistics derived from census or other data and assigns them to individuals based on their residence within a particular geographical unit. Less focus is placed on the characteristics of places that might promote or restrict people's ability to adopt health promoting activities.

Booth (1889) first demonstrated spatial patterning of poverty. In the intervening century, research has consistently shown that inequality has a spatial element, for example Dorling et al. (2000) showed that in fact the spatial inequalities demonstrated by Booth have persisted and can still predict contemporary all-cause mortality in London. This demonstrates how the local environment can be a driver for inequalities and as such space, location and environment are determinants of health. So, when investigating inequalities, including variables related to geographical location can be informative. In the research presented in this thesis, I use geographical markers to impute relevant variables and enrich data to provide a greater depth of analysis.

Linking variables assigned to geographical units between datasets is a straight forward procedure, however the level at which the geography is determined, and how this relates to the individual or populations within the sample, must be understood to avoid drawing incorrect conclusions and falling into the trap of an ecological or atomistic fallacy[1].

In census statistics, postcodes are used to build “Output Areas” (OA), the lowest unit for which census data is routinely available. These output areas are then amalgamated to form “Lower Super Output Areas” (LSOA) for statistical and census purposes. Each LSOA will contain between 1,000 and 3,000 people. Although postcodes may fall neatly within an OA, where the threshold limits for size are breached, the postcode may be broken down and the households within, split into two OAs, possibly then falling into different LSOAs. Throughout this thesis, where a postcode is used to determine geography, the “best fit” LSOA has been used, as per the 2011 UK census (ONS 2011).

The LSOA code can then be used to link the records to other publicly

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[1] An ecological fallacy is an error in methodology where inferences about individuals are deduced from inferences about the group to which they belong. An atomistic fallacy refers to the inverse error - that is to say when an inference at a group level is made using information from an individual (or lower level group).

available data such as the index of multiple deprivation (IMD) for that particular area (McLennan et al. 2019). In this thesis, I use the 2019 edition of the index. The index of multiple deprivation is made up of 39 separate indicators, which are organised into seven different domains of deprivation, each weighted to calculate the index. The domains and weightings are listed below.

- Income (22.5%)
- Employment (22.5%)
- Health Deprivation and Disability (13.5%)
- Education, Skills, Training (13.5%)
- Crime (9.3%)
- Barriers to Housing and Services (9.3%)
- Living Environment (9.3%)

The index provides an overall measure of deprivation experienced by people living in an area. All neighbourhoods are ranked, and deciles are then calculated and assigned. There is no threshold for what is considered to be 'deprived' or indeed 'not deprived' and as such the index measures relative deprivation.

Within the barriers to Housing and Services domain, the road distance to the GP surgery is included. This may be considered a barrier to access measure. This value is one of 4 items which are standardised to form a subdomain of Geographical Barriers which is equally weighted with another subdomain of Wider Barriers to form the domain score, which itself is then weighted at 9.3% of the whole index. The GP distance therefore contributes only 1.2% of the index value.

Some researchers may choose to use selected domains from within the index to avoid introducing multiple measures of the same phenomena into statistical models, however in this work I opted to use the index in it's full form, conducting tests for correlation and multi-colinearity at all stages.

As these are area level measures, it is important to exercise caution as there is a risk of misclassification at the individual level, something which is an aggregated area statistic. This may cause the index measure in the model to under perform as a predictor and this under-performance can be explained in some circumstances by the modifiable area unit problem. Furthermore, such an index contains both compositional and contextual factors, with contextual factors set at an area level and thus not open to misclassification for individuals (for example green space, transport availability) and compositional factors representing a sum of parts (for example mean income) which may grossly misrepresent any given individual within the catchment.

The modifiable area unit problem (MAUP) arises when a point based measure is aggregated to a larger area. The same basic data may give different results when aggregated in different ways, that is to say that the location of boundaries in a space may have an important effect in the value of an area (Gehlke and Biehl 1934). There are two core issues to consider; the scale effect and the aggregation effect. The aggregation effect shows major differences depending on how the space is divided, even at scale. The scale effect refers to differences dependent on the size of units used, with bigger units causing greater differences. Schuurman et al. (2007) demonstrated that the use of area based deprivation indices such as the English Indices of Multiple Deprivation as a proxy for individual socioeconomic status is impacted by the scale and aggregation effect and as so throughout this thesis I consider the impact of the aggregation for area based measures on the validity of results (ibid.).

3.4 Administrative data

In the digital age, whenever an individual interacts with a system, data are created. Every encounter with the health care system therefore generates a data trail collected for administrative or financial reasons or which is used to support clinical care.

Administrative data can be considered to be those data collected for ancillary purposes. For example a database of appointments is necessary for the delivery of care, but is an incidental data source to the medical record for each individual using each appointment. The size and complexity of these data offers an opportunity for researchers to exploit this resource to study health care and possibly to explore aspects of the systems which might not be immediately apparent within a person centred record.

In a traditional data collection exercise, researchers must recruit and retain subjects, seek permissions for data use and design the nature of the data collection. With administrative studies, the retrospective data set is potentially an N=All and possibly a so-called 'big data' sample and so the sample is not designed but rather arises through opportunity. Although all cases may be included, and the dataset may contain the whole population, this is not necessarily the case and an understanding of why cases may *not* appear in an administrative dataset is important for study design and for subsequent inference from any analysis. A benefit of this type of data source is that a researcher does not need to design and carry out a data collection exercise, or recruit to the study, however a deeper understanding of the nature of the data and how this might impact understanding of any conclusions to analyses is imperative. For any given variable, I have needed to consider how and why these data are captured and whether the nature of the collection has impacted upon the data quality, or if there are any time based data improvement/refinement processes in operation. With NHS hospital data, the quality typically improves over time as records are corrected and audited. There are however fields which might be omitted because the information is not critical for the purpose of the data collection - for example an ethnicity field will not be of primary relevance to the payment of a tariff within the NHS accounting system for a particular medical procedure. It is important to a researcher investigating equality, but it is not needed for the primary use of the data, (albeit that it may be important within the care organisations for management information and monitoring).

There are also very specific ethical considerations which must be considered when using these data. The participants in a study may not have consented to the use of the information for research, as the data collection was not originally intended to be for research purposes. In the case of NHS data, this presents a very particular issue around privacy, particularly when linking data using location stamps to other datasets which give a richer source for research, but also increase the re-identification risk. Sometimes who owns a data set is not abundantly clear, and even if it is, it is not always straight forward for the data owner to grant access. A substantial proportion of my studies have been spent understanding the data ownership landscape and many avenues of inquiry proved to be fruitless precisely because of this data ownership opacity and and the structuring of the health system with separate owners of data between acute care, primary care, Care Commissioning Groups, and in my case, the Greater Manchester Health and Social Care Partnership.

All forms of data require cleaning and manipulation prior to analysis, however this is particularly the case for administrative data which has not been specifically designed for the use of researchers. In all of my work, I spent the greater proportion of my time manipulating and investigating the data and variables prior to cleaning, re coding and linking to external data sources. It is easy to forget, once in the throes of analysis and substantive interpretation, that this is in fact a large part of the research process. Understanding the data allows the researcher to seek to avoid (or at least to understand) bias and understand the limitations of my research. It is also vital that researchers talk to those responsible for maintaining and/or creating the data sets. The process of creation, and the human or machine interaction which creates the original flow of information is critical to understanding the data and a product of my research process has been a much deeper understanding of the nature and capabilities of NHS administrative data and in particular, the processes within the health care system that create the resources used for my research. Throughout the work I have used Python as my primary modelling environment making use of the many packages specifically designed for data analytics. Wrangling was conducted using Pandas (McKinney 2010), variable transformation using NumPy, visualisation in Seaborn (Waskom et al. 2014), statistical modelling using StatsModels (Seabold and Perktold 2010) and Scikit-learn (Pedregosa et al. 2011).

3.5 Paper 1

In paper 1, I investigate distance and deprivation factors in access to primary care appointments. The paper considers health equity in terms of an equity of access to primary care appointments, specifically those scheduled outside of normal working hours. Paper 1 uses a count of appointment utilisation by practices to investigate whether there are practice level effects in the uptake of extended hours services, and whether therefore there may still persist underlying inequity, despite spare system capacity. In an analysis of utilisation, it is expected that there may be higher utilisation in more deprived areas as there is greater need associated with deprivation, and this might indicate that needs are being met. However, we should not see an association between distance and use rate if distance is not providing a barrier to access. There are limitations to using utilisation as a measure of access and these are further discussed here, within the paper, and as part of the discussion.

In the work, I analyse an administrative dataset of appointments at an aggregate level to determine the use rate of out of hours services by patients at different practices within a "hub and spoke" model for delivering care. This proxy measure may also bear a complex relationship with the underlying question of whether needs are met. The extent to which spare capacity exists in a system, could be interpreted to mean that all needs have been met, however this is not necessarily the case. Considering the example of primary care, a practice with spare capacity during normal opening hours, but no extended hours service, may not be meeting the need for those whose working or caring responsibilities preclude them from attending an appointment during normal hours. Likewise, spare capacity in extended hours, may still mean that other barriers to access have not been addressed, for example those living in area where services are not geographically co-located, may still struggle to attend even with an extended choice of appointment times for reasons of mobility or transport. The paper includes a discussion of these issues and proposes several frameworks by which service design may shift usage but not necessarily increase access. As discussed above, I took the complexities of measuring health and health care access into account when designing, conducting and reporting on this research.

3.5.1 Data

The data for paper 1 were released to the university for research as part of an ongoing evaluation of the performance of the extended hours primary care service within Greater Manchester commissioned by GMHSCP, undertaken as an academic research partnership between the NHS and Manchester University (Whittaker, Anselmi, Nelson, et al. 2019). These data were pseudonymised in that most patient characteristics were removed leaving only sex, age in years and practice data available.

Each line within the dataset represents an appointment and only service provider codes, along with age and sex of the user remain. For every appointment within the service, the record shows the sex and age in years of the user, along with the code for their home registered GP surgery, and the code for the surgery providing the extended hours appointment.

This coding allowed me to link all practices in the dataset to an NHS provider address database, and subsequently using the government GIS portal, to a postcode centroid and a census lower super output area code. This provided some information about the location of service users albeit flawed in that it relates to the location of their service use, rather than to their home.

This initial linking of location to usage data did incrementally increase the reidentification risk of these data, however the data were sufficiently devoid of characteristics such as to be very low risk and the location data restricted to the practice level rather than the individual level. Nonetheless, work was conducted and stored on a secure University server within the Population Health department.

The data were further manipulated to provide an aggregate annualised count of uses per 1000 registered patients by practice. Practice level characteristics from publicly available data such as the number of full time equivalent GPs per practice, the registrations segregated by sex[2] and the age profile

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[2] Sex is treated as binary for simplicity and to reflect the recording system employed in most administrative data systems. The different experience of non-binary people is not captured, nor is the difference in experience of cis- and trans- gendered people.

of patients at each practice were then added to the data to enrich the analysis. Questions from the GP patient survey provided additional enrichment based on patient responses. In this way we attempted to adjust for aspcts of need, once controlled for, we should not see differences in the use of extended access services.

Distance and location in paper 1

In paper 1, each line in the dataset is an appointment. The base dataset includes some person specific information (age and sex) but not a person specific geography. The person specific geography is limited to the unique practice code for the practice where the extended hours appointment was taken, and the patient's home practice. For the research, I amalgamated the appointment dataset at a practice level to see the number of appointments used by patients at each practice. Using the postcode of the practice, I used a best-fit LSOA, to impute the IMD for the area in which the practice resides, assuming that practices are co-located with registered patients. This is a simplification, but GP surgeries in England do have geographical catchments albeit that these may overlap with other nearby practices and so it is a reasonable approach, with recognised limitations. The level of deprivation may be an over or under estimate for any given individual in the practice; e.g. if the surgery happens to be located in the most deprived area of its catchment, or indeed the least.

The lack of person specific geography in the data also poses a problem for assessing the impact of distance from services on utilisation. Here again, I used the practice level geography. Taking the practice postcode, I imputed the eastings and northings based on the postcode centroid. This was then used to calculate the minimum straight line distance to a hub practice within the same CCG for every practice (again using the eastings and northings of the postcode centroid). For every practice within the study, there were a number of available hubs, and patients are free to choose which to use. I deemed the minimum distance to the nearest hub to be the relevant distance for determining distance based barriers to utilisation. Notwithstanding issues of public transport, parking, and avoidance of particular areas to name just some of the other factors in play, I assert that if distance is a barrier to utilisation, and thus access, it seems that the minimum distance needed to travel, will be a reasonable approximation and more specifically will be monotonic with the distance considered by the patient in determining whether or not the service is used.

An alternative method would be to calculate a travel time or a network distance for each hub-practice pairing. Travel times are difficult to estimate as they are time and mode dependent, a more complex gravity model can be employed to encompass all modes of transportation however the data for this type of distance measure has not been readily available for this work. Network distances are a reasonable alternative to the Euclidian straight line distance used and have in some instances been demonstrated to be a more relevant measure - for example where a physical barrier such as a coastline exists within the straight line space (Schuurman et al. 2007). Network distances can now be obtained via multiple calls to one of many online mapping sites. Boscoe, Henry, and Zdeb (2012) analysed travel paths and straight lines in a nationwide sample of the United States. Ordinary least squares regression analysis estimated the detour index[3] to be approximately 1.4 for all but a few extreme areas, which accounted for only 10% of the population and were exclusively related to large physical geographical features such as extensive wilderness, large uncrossable lakes or coastline. The straight line distances and network distances were highly correlated and so for analytical purposes, the substitution of straight lines should not, in the absence of very large physical geographical barriers, have noticeable consequences for the results. In my work, I tested model sensitivity to network or straightline distances. I found distances to be largely very similar and there to be no modelling effects and so in paper 1, distances have therefore been taken as straight lines from postcode centroids for ease and speed of computation.

Using practice geography rather than patient geography will tend to misclassify the relevant distance for each individual in the system as actors do not all exist at the point location of the home practice at all times. Even to use home geography may also result in misclassification as individuals may use services based on an alternative more convenient location such as childcare or work. The aggregation of the use rates to a practice level in paper 1 mitigates this effect, although it is still a limitation. The impact of the use of practice code is to re-scale the distances and the effect is deemed to be random and as such does not introduce bias into the results.

Variables in the analysis

The final variables in the analysis are given in table 3.1

The number of hubs, practices and patients are given in table 3.2.

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[3] The ratio of the network distance to the straight line distance.

Variable in the analysis	Values
use_rate	Number of service uses per 1000 registered patients, by registered practice. Any use of the extended hours service, regardless of location is assigned to the registered practice of the patient.
mean_age	Mean age of patients at the practice
female_proportion	Proportion of patients registered as female
min_dist	Distance to nearest hub in miles to one decimal place. For hub practices, this distance is zero.
hubs	Hub = 1, Non-hub = 0
imd_decile	Decile of Indices of Multiple Deprivation (IMD) score for the LSOA in which the home registered practice is located. Decile 1 relates to the least deprived areas, decile 10 to the most deprived. This refers to the overall IMD score, including all domains.
GP_per_1000	Number of full time equivalent GPs (doctors) per 1,000 registered patients
supply_measure	Percentage of respondents who could not get an appointment the last time they called their surgery, because of the time, the data or the unavailability of their preferred GP. Weighted Responses taken from the GPPS survey, 2015
CCG(1,2,3)	Dummy variable to indicate the CCG of the practice

Table 3.1: Variables in the analysis (Paper 1)

CCG	Number of hubs	Number of practices	Registered population
1	4	37	227,267
2	2	35	238,924
3	2	41	243,828
4	6	45	247,842

Table 3.2: Hubs, practices, and registered populations within the four CCGs included in the final dataset (Paper1)

3.5.2 Statistical modelling

In paper 1, the number of uses of the extended hours service was calculated for each GP practice within the dataset. GP practices have differing registrations and so an adjustment for exposure is required. The number of uses were equivalised by the number of registered patients at each practice, transforming the count from a discrete to a continuous value; a number of uses, to a rate of use per 1,000 patients. An NB2 Negative Binomial model using the Cameron and Trivedi (2013) estimation method for α gave the most coherent and robust estimations of model parameters.

Count data refers to observations which are non-negative integer values, in the range zero to some maximum (theoretically ∞). In a statistical model, the response or dependent variable is a random variable, where observations are independent of each other. For an ordinary least squares regression model, it is assumed that the dependent variable for which we seek to estimate the underlying probability distribution function, is normally distributed. As count data are bounded at zero, the assumption of a normally distributed dependent variable is likely to be violated and so the Poisson and negative binomial distributions are instead used as as the foundation for modelling.

It may seem that these data violate a required assumption of Poisson modelling that the outcome is a count, that is to say an integer. In this paper, the rate is a value which cannot be negative and has the fundamental properties of a count, that is to say that it relates to a number of instances over a defined period of time. The practice list size has been applied to construct a proportional intensity model as a weighting here and this weighting is an adjustment for exposure. No further adjustment is required because all practices in the analysis operated the extended hours service for the full calendar year.

Ordinary Least Squares (taking the natural log of the response variable), Poisson and Negative Binomial models (adjusted for exposure) were estimated early in the data analysis. The Negative Binomial model parameter α was estimated both by experimentation and the method described in Cameron and Trivedi. Once the Negative Binomial method was selected as the most appropriate, the AIC statistic, alongside contextual assessment of the model results was then used to determine the most appropriate model.

In the Ordinary Least Squares regression, values identified as of interest, using Cooks distance were removed and the analysis repeated, however this did not yield any improvements. Substantively, it does not make sense to remove the outlier cases as although they contribute to a large skew in the data, they are all valid observations which are of interest. A Poisson model showed unacceptable levels of dispersion. This dispersion is not relevant within the NB2 modelling framework as it is accounted for through the inclusion of the α term.

3.6 Paper 2

In paper 2 I looked for differences in the extent to which people experienced a decline in their wellbeing, and the trajectory of this subjective health measure as the first lock down of 2020 progressed. I looked specifically at the association between deprivation and changes in wellbeing and considered how the removal of services and support networks for those with long term health conditions impacted the decline in wellbeing and affected the ability of patients to recover. I also considered effects attributable to ethnicity and sex.

This work fell during the advent of the global pandemic and this timing was a significant driver of the data methodology and the focus on COVID-19 as a specific area of investigation. The data for this work are freely available through the UK Data Service.

3.6.1 Survey data in health and inequalities research

It may be difficult to directly sample a population for the purposes of addressing a specific research question. The cost and logistical considerations may be prohibitive, and to collect data directly in response to a rapid change in circumstances, such as those seen in 2020 with the COVID-19 pandemic, is difficult to achieve without access to infrastructure and a large workforce. In these circumstances a researcher can look to existing incidental sources of data, such as administrative datasets or personal records, or turn to a number of long standing surveys which contain large numbers of variables at the individual level.

Considering the question of non-COVID related health outcomes during the the COVID-19 pandemic, the shut down of medical services has necessarily resulted in non-recording of outcomes at an individual level within the medical records system. Likewise, the administrative data for this period may show an absence of contacts at an aggregate level, observed as lower appointment numbers, but no details of individuals' lack of interaction with the health care system, and the nature of their health outcomes at a time when services prioritised COVID-19 disease burden, and it appears that many people opted out of health care access through concern about contracting the virus. Statistics are emerging about adverse outcomes in heart disease and other illnesses, thought to be attributable to the pandemic lock down however these are at an aggregate level, seen through excess deaths or missing referrals. Survey data collected during the pandemic time frame therefore offers an opportunity to investigate impacts at an individual level, often with a reference baseline for variables which pre-dates the pandemic. For my purposes, the existence of survey data in this period allowed me to continue my research when otherwise the data sources I sought were unavailable and the completion of work was seriously threatened by personal circumstances and the pandemic crisis.

Understanding Society - a Longitudinal Panel Dataset

Understanding Society is a large longitudinal study designed to be representative of the UK population (University of Essex, Institute for Social and Economic Research 2020). Understanding Society started in 2009 and builds on the British Household Panel Survey (BHPS) which ran from 1991 to 2009 and included 10,000 households. In the first year, Understanding Society interviewed a total of 40,000 households, including 80% of the original BHPS. The study covers all ages and information is collected from every member of the household. The study is multi topic and also includes bio marker and genetic data. The sample is sufficiently large that there are approximately 10,000 people for each birth cohort per decade from the 1940s onward. Participants cannot volunteer for the study unless they move into a household which is already a participant, or are born into the study (currently there are 17,000 children to whom this applies.) Under normal circumstances, data collection is annual providing a source of continuous data which can be used to understand short and longer term changes in people's lives. A core set of questions are asked annually, with further topics asked less frequently in line with the long term content plan which forms part of the survey metadata.

In response to the COVID-19 pandemic, additional monthly questionnaires were launched in 2020 using tried and tested modules from other parts of the survey or previous waves. All households were asked to take part and were incentivised by voucher payments to complete either online or telephone surveys. The main survey is also conducted as a face to face data collection exercise however due to pandemic restrictions, this was not possible for the COVID modules. Questions were designed to gather critical information for researchers and policy makers on the changes affecting the lives of people living in the UK so that we can understand and explore the impact of the pandemic on communities, families and individuals. Data collection took place monthly in April, May, June and July, spanning the time of the first major lock down restrictions. Further waves were collected in September as schools and colleges returned, and again in November, during a further lock down (albeit less restrictive than previously experienced). Further waves of data collected in 2021 fell outside the scope of my work. All members of the household are asked to complete the questionnaires, and for participants who do not use the internet, a telephone survey was conducted in some months (University of Essex, Institute for Social and Economic Research 2020).

The core modules of the COVID-19 dataset, included questions on subjective wellbeing, the management of long term health conditions and loneliness. The questionnaire also included intermittent questions on finance, and changing financial situation (Table 3.3).

Module	May Wave 1	April Wave 2	June Wave 3	July Wave 4	Sept Wave 5	Nov Wave 6
Long term health conditions	✓	✓	✓	✓	✓	✓
General Health Questionnaire (GHQ)	✓	✓	✓	✓	✓	✓
Loneliness	✓	✓	✓	✓	✓	✓
Finance	✓	✓		✓		
Financial Security	✓	✓		✓		
Social contact			✓			✓
Neighbourhood cohesion			✓			✓

Table 3.3: COVID-19 Data Collection Study Content

General Health Questionnaire: Self reported health as a measure of objective health

The General Health Questionnaire (GHQ) is a series of questions designed to quickly diagnose mild psychiatric illness. GHQ-12 is a short form of the questions (a longer GHQ also exists) where each question is rated on a 1-4 likert scale. Questions and likert responses are phrased such that responses 3 and 4 indicate a worsening outcome for each question. In the GHQ likert variable, the scores are summed over the 12 questions. The maximum score for a complete questionnaire is 48 and the minimum is 12. The measure has been validated and shown to perform well in longitudinal studies and is robust to any retest phenomena (Pevalin 2000). Within the covid modules of the survey this variable was retested with every wave and so forms a valuable source of information about the trajectory of the participants experience during the period.

The caseness variable is computed by recoding all responses to a binary 1/0 value. Responses of 0 and 1 are recoded to 0, indicating no change from usual, whereas 3 and 4 and recoded to 1. Summing over the 12 questions gives the caseness score. A caseness score of 1-2 is considered to indicate mild psychiatric illness although Hardy et al. (1999) showed that a threshold of 3-4 gave the best conservative estimate of minor psychiatric illness.

Self reported health is widely used as a measure of objective health, but this measure is not without bias. Health inequalities by education level were masked by bias in self reporting in a study of older Europeans (Bago d'Uva, O'Donnell, and Doorslaer 2008). Dowd and Todd (2011) studied self reported health as a means of measuring health inequality in the United States and found age, sex, education status and ethnicity bias in self reported health score, indicating that when used to assess inequalities of health based on these groupings, the inequity might tend to be underestimated, and hence an adjustment for reporting bias could be needed. Self rated health can therefore be conceptualised as two factors; the latent health of the respondent, and their reporting behaviour (Layes, Asada, and Kephart 2012).

3.6.2 Modelling time series data

In paper 2, I consider the trajectory of wellbeing during the first wave of the COVID-19 pandemic using English respondents in the Understanding

Society Covid Survey. The trajectory was resolved into two phases to enable the use of ordinary least squares regression modelling to examine the associations between wellbeing trajectories, deprivation, pre-existing conditions and socio-demographic factors.

The longitudinal nature of the Understanding Society survey allows individuals in the panel to be linked across data waves. This means that for the purposes of studying the impact of the pandemic, we can compare responses directly with those collected prior to 2020 from the same individual. Using the most recent full data release (Wave 9, released November 2019) we can see how responses to the wellbeing module changed from a pre-pandemic data collection to April when the first of the special COVID-19 survey datasets were collected. Following these individuals through the subsequent monthly data collections allows a trajectory of scores to be plotted, forming a five point time series dataset of wellbeing for all respondents. Longitudinal datasets allow us to estimate associations between features and the inter-person variance of an intra-person change over time, using grow curve or other forms of modelling.

The time series are parabolic. The mean GHQ-12 scores start at the baseline and rise to a peak at the beginning of the pandemic, after which a steady decline in the scores is seen until the July data collection, scores having returned almost back to the baseline level. These time series are thus non-linear when considered as a whole.

The shape of these data mirrors the unfolding of the pandemic in the UK. The emergence of COVID-19 as a serious threat in the UK was reported not long before the country entered into a lock down. We were as citizens thrust very suddenly into the unknown, with rapidly rising illness and death rates around us. The daily death toll peaked in early April 2020, at around 1,000 deaths a day. The situation improved and the restrictions on our freedoms reduced gradually until July.

In paper two, I model wellbeing as two phase phenomenon in the first wave of the pandemic. A decline, measured as the change in the caseness score from the baseline to the April measurement, and a recovery, measured as the change in the caseness score from April to July. Resolving the time series into two phases allows the initial impact of the emerging pandemic to be modelled separately to the ongoing longer term change in wellbeing.

The wellbeing trajectory could also have been analysed by fitting a polynomial growth curve model to these data. Such a model might be at risk of masking two distinct processes and so it was felt to be more parsimonious and empirically valid to model the two phases of the lock down independently - the implementation and its easing using an ordinary least squares regression. Resolving these time series data into two phases has a number of advantages as a method. It allows the initial impact of the emerging pandemic to be modelled separately to the ongoing change in wellbeing and it also allows the different phases of the lock down to be more clearly seen, particularly as this research found that baseline and final scores were very similar. The resolution of the data into two phases also allows a simpler and straightforward modelling approach as each phase can be analysed using an ordinary least squares multiple linear regression model, significantly simplifying the interpretation of results. Survey weights contained within the main dataset were applied within this analysis and R^2 used to compare model fit (University of Essex, Institute for Social and Economic Research 2020). Multiple linear regression is a widely used method within social sciences research and practice.

Location

The LSOA unit was available for all records within the data and so a person level geography was available for analysis in this work. This is an improvement on the catchment geography used in paper 1, although it is still a compromise and it may not give a more accurate result. I used the person level LSOA to link to the English Index of Multiple Deprivation for each individual (McLennan et al. 2019). This again is susceptible to the modifiable area unit problem and could significantly misclassify deprivation experienced by an individual within the LSOA. The use of a geographical index to describe deprivation also necessitated the restriction of the analysis to English cases only. Wales, Scotland and Northern Ireland compute separate indices and publish country specific rankings and so the deprivation deciles do not map between the home nations.

I also considered a community level factor in my analysis, inspired by the work of Macintyre, Maciver, and Sooman (1993) and seeking to include place based features which might impact on the outcome variable. I produced an index for community cohesion, based on answers to the survey module on neighbourhoods, which sought to measure subjectively, the extent to which the place in which a survey participant lives can be considered to be a cohesive community. I hypothesised that a more cohesive community might be protective against poorer wellbeing during a time of crisis. This type of subjective measure is useful as the perception of one's environment is important here. If people feel that they can ask a neighbour for a favour, or people in their area are friendly, then this may well be a very important contributor to wellbeing, regardless of any objective measure of a neighbourhood such as crime rates, noting that in these data, the community variable is set as a person specific experience of community, rather than a more generalisable feature of a specific neighbourhood. Limited location information for cases in the study again limited the work here. At the LSOA level, it is possible to impute deprivation, and with the neighbourhood module, I could include a measure of community, but without an address, details of place are absent.

Measures of income

Assessing the change in income for a household over the period was important for understanding how respondents' financial situations had changed during the lock down. The variable *income_decrease* is derived from the household composition and household earnings amounts. The household makeup was summed using variables[4] which correspond to the number of adults residing in the household and those[5] which correspond to the number of children within the household. This was then equivalised to account for the differing costs of adult and child residents using the formula given by the OECD as an appropriate method for equivalence: OECD n.d.: $household\_equivalence = 1 + 0.5(adults) + 0.3(children)$.

The income change was computed using the baseline and third wave

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[4] *cc_hhcompc*, *cc_hhcompd* and *cc_hhcompe*

[5] *cc_hhcompa* and *cc_hhcompb*

household income values, equivalised to an annual figure. [6]

The economic impact of the income decrease was calculated by scaling the change in income between the baseline and wave 3, by the equivalised household size and then recoding this variable to show whether or not income had decreased during the period of the lock down.

Financial crisis was determined by recent foodbank use.

Variables in the analysis

The variables used in the analysis are described in Table 3.4.[7]

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[6] using the variables *cc_hhearn_period, cc_blhhearn_period, cc_hhearn_amount and cc_blhhearn_amount.* The *_period* variables give information on whether the figures given for household income are weekly, fortnightly, monthly or annual.

[7] The variables are a mixture of derived, re-coded, calculated, imputed and original variables.

Variable Name	**Description**
wellbeing_decline	Change in GHQ-12 caseness score from wave 9 of the main survey ({i_scghq2_dv}) to wave 1 of the COVID-19 survey {ca_scghq2_dv}).
baseline_wellbeing	GHQ-12 caseness score from wave 9 of the main survey ({i_scghq2_dv}).
wellbeing_recovery	Change in GHQ-12 caseness score from wave 1 ({ca_scghq2_dv}) to wave 4 ({ca_scghq2_dv}) of the COVID-19 survey. Positive values indicate a reduction in the score, an improvement in wellbeing.
age	Age in years, calculated from birth year (renamed from survey variable: {ca_age}).
sex	Sex, binary. 1 = Female, 0 = Male. (recoded from survey variable: {sex_dv}).
community_cohesion	Variable (derived from questions on neighbourhoods: {scopngbhh, nbrcoh3, nbrcoh2 and nbrcoh4}).
imd_decile_2019	English Indices of Multiple Deprivation decile for the respondent's LSOA as at wave 1 data collection [imputed from McLennan et al. 2019.]
eth_minority	Binary variable to indicate white and non white ethnicities. 0 = White 1 = Black, Asian and Minority Ethnic (derived from the survey variable {race_dv}).
health_condition	Binary variable to indicate underlying health conditions. 0 = no health condition, 1 = health condition. Taken at July data collection as those diagnosed during the COVID-19 survey period are likely to have been living with symptoms and accessing care for an undiagnosed condition during the period. (derivation of the survey variable: {cd_ff_hcondhas}).
lonely	Binary variable to indicate experience of loneliness in the 4 weeks prior to the wave 1 data collection. 0 = has not experienced loneliness, 1 = experienced loneliness some times or often. (derived from the survey variable {ca_sc_lonely_cv}).
always_lonely	Sum of binary variables over waves 1 to 4 to give a score for persistent loneliness. Max = 4, min = 0. (calculated from derivations of four survey variables: {ca_sc_lonely_cv, cb_sc_lonely_cv, cc_sc_lonely_cv and cd_sc_lonely_cv}).
financial_crisis	Binary variable to indicate acute financial crisis at Wave 4. 1 = has accessed a food bank in the prior 4 weeks, 0 = has not (derived from the survey variable {cd_foodbank_cv}).
income_decrease	Binary variable to indicate worsening financial situation. 1 = house hold equivalised income has reduced from wave 1 to wave 4, 0 = income is the same or greater (calculated from multiple variables, see text).

Table 3.4: Variables in the analysis for Paper 2

3.7 Paper 3

3.7.1 Using Secondary Users Service Data to understand inequalities

In paper 1, a service useage variable was used, but no actual health outcomes were available, in paper 2 survey data was used to investigate an aspect of health care that was subjective and also not recorded in the medical records. In this final piece of work I used a recorded health outcome variable at a person level and so this completes a triptic of different variable types as part of my approach to the multi-faceted issue of health services delivery and social inequality.

In this paper, I returned to the use of administrative data, analysing hospital records created for the purposes of tracking and allocating financial flows within the acute care system to examine deprivation effects in length of stay and death risk in patients hospitalised with COVID-19 in Greater Manchester. These data are drawn from the Secondary Uses Service Data Repository, a single repository for all English health care data used by commissioners and providers of NHS care for non-clinical purposes, including planning, commissioning, tariff payment and policy development. The records contain medical information in codes, but are not as such a care record and are not used to meet health care need, rather to account for and plan health care provision (NHS Digital 2022).

The data were made accessible in direct response to the COVID-19 pandemic crisis and my use of these data is tied to operational need within the health care service. In contrast to paper 1, these data are very high risk for re-identification as they contain patient home location (to the LSOA level), exact treatment location and personal data such as age, sex, ethnicity and coding for specific health conditions. For this work, I used a secure remote machine and a virtual desktop. In normal circumstances, these data may have been subject to the use of a secure physical location on an NHS site, or a 'safe room' however, given the need for timely operational research and the risk of disease transmission, all work was conducted from home using virtual means. These data and all code pertaining to the research remain on an NHS administered cloud machine.

Data are held in a relational database interrogated using SQL[8]. The management information team are able to draw down a static copy of the data for researchers to use in a secure environment. The data are held in multiple nested tables and so an understanding of the architecture and the relationship of tables to one another is critical to proper use of the resource. Each hospital episode relates to a specific procedure or event. A hospital spell within the admitted patient care tables may therefore contain multiple hospital episodes. We know that there has been within-hospital transmission of COVID-19, that is to say that people have contracted the virus after admission, and also that patients may be admitted for a health care need, and discover that they have a benign COVID-19 infection at the time of admission - hence their admission is actually not COVID-19 related. In order to simplify the complicated picture of infection and mortality cause, I selected

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[8] SQL is short hand for Structured Query Language and is a language used to communicate with relational database management systems.

only those cases with COVID-19 diagnosis codes as their *primary* diagnosis. That is to say, this was the reason they came to the hospital. A patient may then have other diagnoses on presentation, for example diabetes melitus and so on. These secondary diagnoses impact the risk which a COVID-19 infection poses and so co-morbidities were included in the model as a logarithm of a simple count.

At the time of the work, there had been reports of adverse mortality within Greater Manchester and indications of within Greater Manchester variation for outcomes and as such there was a need for further research to uncover local events to assist with planning and explore how the social gradient in health relates to health outcomes for COVID-19 in the city.

These data are an N=All sample and so selection of the cases to study was a vital part of the process of designing the research and the sample selection is shown in Figure 3.1

3.7.2 Location in paper 3

As in prior papers, I used an LSOA derived deprivation statistic (Index of Multiple Deprivation) to ascribe deprivation characteristics to individuals within the data to analyse outcomes for individuals. In addition, I aggregated outcomes by larger geographical units (here local authorities) to assess whether there are authority based differences in outcomes at a macro level. In these analyses, I considered mean survival and length of stay statistics for each authority, aggregating place based statistics to the authority level rather than considering individuals. The same issues arise here as in earlier

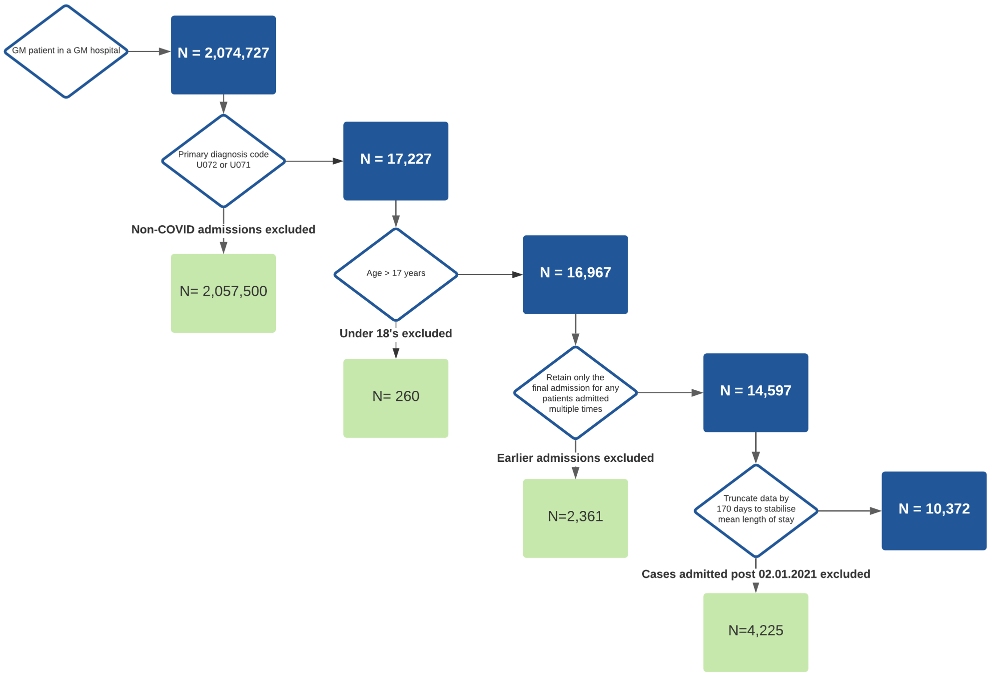

Figure 3.1: Flowchart of dataset sample selection for Paper 3

papers around the mis-classification of deprivation by the use of a census unit measure, but in the absence of more granular personal data, this is an appropriate approach, and one which is a well established compromise for health equalities research.

The availability of treatment and home location allowed me to enrich these data with information on air quality at a local level. These data are produced using models of particulates and nitrous oxides from data collected by a network of monitoring stations across the city. The data are made available by the Consumer Data Research Centre based at the University of Leeds (**cdrc˙access˙2017**).

3.7.3 Variables in the analysis

Variable name	**Description**
Length of Stay (LOS)	Difference between the date of admission and the date of discharge, measured in whole days. Decriptives here given for patients who survived only, N = 4,350. Source: SUS.
Died	Binary variable based on mode of discharge. 1 = died, 0 = survived. Source: SUS.
Deprivation	Index of Multiple Deprivation (IMD) decile for the respondent's LSOA as per registered address. A higher decile indicates lower deprivation. Source: English Indices of Multiple Deprivation.
Age	Age in years at the date of admission. Source: SUS.
Sex	Binary variable. 0 = Male, 1 = Female. Source: SUS.
Ethnicity	Four category ethnic coding derived from 16 standard ethnic groupings used within NHS data. Black, Asian, White and Other used here due to low numbers in some categories. Source: SUS
Home air quality	Index constructed by summing the standardised mean annual NO_2, SO_2 and PM_10 scores in $\mu g m^3$ for each LSOA. Source: Air quality domains of the Access to Healthy Assets and Hazards Index
Hospital site air quality	Same value as for Home air quality, but based on the site of the hospital episode. Source: Air quality domains of the Access to Healthy Assets and Hazards Index
Co-morbidity	The natural log of the count of diagnoses is used here as a proxy for co-morbidity based on the assumption that patients with higher diagnoses counts are likely to be those with greater co-morbities. The log of the count is used in this analysis. Source: SUS.
Timing of admission	Period 1 (reference) relates to all spells completed before 14/04/2020. Period 2 relates to all spells completed after 14/04/2020 but before 16/06/2020. Period 3 relates to spells completed after 16 June 2020. Source: SUS.
Multiple admission	Binary variable to indicate if this is a re-admission for COVID-19. Spells where patients have been subsequently readmitted within the data have been removed. 1 = this is the final admission of more than one admissions for this patient within the data, 0 = one admission only. Source: SUS.
Local authority	Local authority name (coded as dummy variables), included in the model for death only. Source: SUS.

Table 3.5: Variables in the analysis for Paper 3

3.7.4 Modelling SUS data

I used a logistic regression model to estimate parameters in the model for death risk, using a pseudo-R^2 measure to assess model fit.

To model length of stay I used a Poisson regression to estimate coefficients, as the data although theoretically continuous have the properties of a count variable. These investigations showed overdispersion and a Negative Binomial (NB2) model provided the most robust and coherent results. The α parameter was estimated using an auxiliary ordinary least squares regression without a constant in line with Cameron and Trivedi (2013).

For area effects, I used death rates of hospitalised patients at the Middle Super Output Area (MSOA) and Local Authority (LA) level using mean IMD deciles (aggregated from the lower super output area level), mean age from mid year population estimates as at 2019, and the proportion male residents from mid year population estimates as predictors. For the LA model, we were also able to include the proportion of Black, Asian and other ethnic minorities based on the 2011 census data. This allowed me to broaden the analysis to consider inter-area differences within the Greater Manchester city region.

Chapter 4

Paper 1: Investigating the impact of distance on the use of primary care extended hours

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Investigating the impact of distance on the use of primary care extended hours

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Abstract

Introduction

Poor access to general practice services has been attributed to increasing pressure on the health system more widely and low satisfaction among patients. Recent initiatives in England have sought to expand access by the provision of appointments in the evening and at weekends. Services are provided using a hub model. NHS national targets mandate extended opening hours as a mechanism for increasing access to primary care, based on the assumption that unmet need is caused by a lack of appointments at the right time. However, research has shown that other factors affect access to healthcare and it may not simply be appointment availability that limits an individual's ability to access general practice services.

Objectives

To determine whether distance and deprivation impact on the uptake of extended hours GP services that use a hub practice model.

Methods

We linked a dataset ($N = 25{,}408$) concerning extended access appointments covering 158 general practice surgeries in four Clinical Commissioning Groups (CCGs) to the General Practice Patient Survey (GPPS) survey, deprivation statistics and primary care registration data. We used negative binomial regression to estimate associations between distance and deprivation on the uptake of extended hours GP services in the Greater Manchester City Region. Distance was defined as a straight line between the extended hours provider location and the patient's home practice, the English Indices of Multiple Deprivation were used to determine area deprivation based upon the home practice, and familiarity was defined as whether the patient's home practice provided an extended hours service.

Results

The number of uses of the extended hours service at a GP practice level was associated with distance. After allowing for distance, the number of uses of the service for hub practices was higher than for non-hub practices. Deprivation was not associated with rates of use.

Conclusion

The results indicate geographic inequity in the extended hours service. There may be many patients with unmet need for whom the extension of hours via a hub and spoke model does not address barriers to access. Findings may help to inform the choice of hub practices when designing an extended access service. Providers should consider initiatives to improve access for those located in practices furthest away from hub practices. This is particularly of importance in the context of closing health inequality gaps.

Keywords

distance; primary care; deprivation; access

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Introduction

In 2005, member countries of the World Health Organisation committed to developing health financing systems such that all people have access to health services, known as ‘universal coverage’ [1]. Health inequalities are observed within and between countries across the world – even in developed economies with sophisticated health infrastructures such as the UK. Health inequities arise through the circumstances in which people grow, live and age – and the systems which are put in place to deal with illness when it occurs [2]. Good access to the right health service systems for dealing with illness when it is needed is therefore a fundamental tenant of universal coverage.

The Greater Manchester area has the fastest growing economy in the UK, however life expectancy in the city region is lower than other parts of England [3]. There are also significant spatial differences in life expectancy across the city region with a male life expectancy varying by over a decade (between some of the poorest and the most affluent areas) [4]. There is an even larger effect of deprivation on the healthy life expectancy experienced by Manchester residents with a gap of over 18 years for men and 13 years for women between the most and least deprived wards [4].

In 2016, Greater Manchester became the first city region in the UK to sign a devolution deal and since 2017 has taken control of a £6bn health and social care budget [3]. Addressing the health inequalities experienced by the residents of the city is central to the aims of the Manchester devolution project and a priority for policy makers and politicians in the area. The devolution project has also provided an opportunity for academics to explore previously unavailable datasets - through partnerships with the local NHS trusts - as local politicians and care commissioners seek to understand whether services are improving and how best to meet the needs of the local population.

Since 2014, Greater Manchester has piloted and subsequently rolled out extended access to general practice services. The service forms part of the regions devolution and health and social care strategy [3]. The extended access service includes appointments that are offered in addition to the usual non-core hours services (out of hours GP appointments, walk-in centres, accident and emergency departments and NHS 111)[1]. These appointments are delivered in person by general practitioners and practice nurses. The appointments are held at ‘hubs’ which are distributed across the main population centres within Clinical Commissioning Group areas (CCGs –responsible for the planning and commissioning of health services in a local area). The extent to which same-day and/or pre-bookable appointments are available, the time of the appointments and the availability of different medical disciplines are specified by the CCGs.

Extended access schemes have also been piloted nationally since 2013 and form a key component of the NHS (England) strategy for primary care by 2020/21 [12, 13]. All English CCGs are expected to provide extended access in the evenings and weekends in line with local demand from 2020.

Extended access appointments have been motivated by two main factors: a perception that rising emergency department (A&E) activity is partly driven by poor access to primary care, and poor patient perceptions of access to primary care services. The UK in common with many other countries reports limited access to primary care outside of core hours (deemed to be 9am-5pm) [5]. The King’s Fund [6] reported that the NHS is struggling to recruit and retain a sufficient number of general practitioners (GPs) to work in primary care. Majeed (2017) reported that ‘GPs are a scarce resource’ and that the NHS underestimates the shortage given the rising complexity of the role and the increase in patient need [7]. In the decade between 2003–4 and 2013–14, the number of A&E attendances rose sharply from 16.5 million to 21.8 million (32%) [8]. Research and Evaluation studies have found that extending access to primary care can reduce pressure on hospital settings [9, 10]. An Italian study using administrative data showed specifically that increasing the opening hours of primary care providers to 12 hours a day, resulted in a reduction in the rate of unnecessary emergency attendances of 10–15% [11].

While the evidence suggests extended access is likely to reduce A&E pressures, little is known with regards to the impacts the services have on patient perceptions of access. Studies have so far assessed uptake and use of extended access to understand which patients are being directly impacted. Whittaker et al. analysed the use of extended hours appointments in 5 clinical commissioning groups within Greater Manchester [12]. Using figures from the General Practice Patient Survey they showed that users of the extended hours service were typically younger than those using primary care services in core hours before the scheme was launched [12, 13]. Female patients were more likely to book appointments outside of core hours than males. Their study revealed significant spare capacity within the service and questioned whether this was the result of the way the service is delivered (e.g. via a hub model) or due to a lack of demand for the service.

There may be multiple reasons why spare capacity is seen in an extended access service. McIntyre et al. propose a conceptual framework of access as a multi-dimensional concept comprising three dimensions; availability, affordability and acceptability [14]. Under this, for good access there must be sufficient appointments such that there is availability. The patient needs to be aware that the appointments exist and attending an appointment must be affordable – not just financially but also in terms of the opportunity cost of time spent travelling and attending the service. Finally the service needs to be acceptable – patients need to be prepared to visit a practice or doctor who is not their regular GP, and GP practitioners themselves need to buy into this model so that it is promoted in their surgeries. The empowerment of an individual to use health care is affected by the different dimensions and barriers within these must be considered when determining whether or not a service is providing good access. Gulliford et al. report that groups may experience differing perspectives, needs and context which impact on their empowerment and so when considering the effectiveness of a policy, it is important to evaluate not just the supply of healthcare, but also the nature of the uptake and thus discover if any citizens remain marginalised [15].

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[1] Extended hours refers to normal primary care appointments offered outside of core working hours (9-6pm). This is distinct from out-of-hours services which are for emergency primary care. Out of hours services would include the NHS 111 service which might refer a caller to a GP led out of hours clinic at a central location such as a local hospital.

Distance has been found to be a significant driver for health care use and feeds into the aspects of access (e.g. the affordability and acceptability domains) that may help explain low uptake of an extended access service. Haynes et al. (1999) found that distance is a factor in attendance rates at both primary and acute care sites [16]. Controlling for the needs of the local population and the existing health provision, distance from an emergency care provider had a marked impact on the rate of episodes, with the greatest reduction being seen in psychiatric cases (37% over the five distance quintiles within the study). Distance from a GP surgery had a similar effect, reducing elective acute episodes by up to 15%. The National Audit Office conducted a multilevel regression analysis of GP practice level rates of attendance at accident and emergency departments. Out of hours, patients from practices located nearer to accident and emergency attended more than those who were further away. This was shown by a rate of attendance that was 2% lower for every additional kilometre that the practice is further away [18]. These results suggest that access to services is not geographically equitable and that fair access to NHS services is dependent on geographical location being considered as part of the commissioning process.

Considering out of hours services, distance matters again. The out of hours service is often accessed by first making a telephone call, and then attending a hub service for an appointment. These are often located in emergency care settings such as at a local hospital. A study of telephone data from the Devon out of hours service showed that call rates to the out of hours service varied with the straight line distance from the caller to the centre. This study also included measures of rurality and deprivation. Those living in deprived areas called the out of hours service more often, however, the further away the caller was from the emergency care setting where an appointment would be taken, the lower the rates of calls [18]. GP cooperatives are typically based in emergency primary care centres, and patients are frequently required to travel to be seen. Geography is a key determinant of access, but little is known about the extent of geographical variation in the use of out-of-hours services. Further investigating the progression of out of hours calls to either telephone or in person management, Turnbull et al. used logistic regression to demonstrate that increased distance using a straight line measure was associated with telephone, rather than face to face management, highlighting potential geographical inequity in access to in-person services [17]. Berchet and Nader (2016) observed geographical factors in accessing out of hours care in an international study with a number of OECD countries reporting the same distance effect. O'Reilly et al. examined the effect of distance and deprivation on use of an out of hours GP cooperative in Northern Ireland with four centres. The study showed that calls to the service were proportional to proximity to the centres with those living further away, representing fewer calls even when controlling for confounding factors [21].

Raknes et al. examined the utilisation of out of hours health services by municipality in Norway, calculating distances from population centroids to service providers. The study concluded that distance was important in service uptake, even in acute cases and as such, extreme distances could impact patient outcomes [22]. Smits et al. examined a small sample (N=20) of general practices in the Netherlands, related to five cooperatives classifying use as 'high' and 'low' for out of hours care. Greater distance from the out of hours provider was associated with lower use at a practice level [23].

In addition to distance, there are other factors that may influence uptake. Patients who are registered at larger GP practices attend accident and emergency departments less often with research showing that for every additional GP, the rate of attendance for a practice reduces by 4% [19]. When there are more GPs, there is greater provision of core hours services and this means that fewer patients need to attend accident and emergency. It is reasonable to posit that the level of provision of core hours services is likely to affect the extent of extended hours service use in a similar way. Where GP time is scarcer, the use of an out of hours or extended hours services may therefore increase.

There is extensive research in the field of health inequalities which demonstrates that there are clear relationships between social disadvantage and poorer health outcomes. The World Health Organisation [2] reported that in all countries, health follows a 'social gradient'. Asaria et al. [24] showed that the inequality gap in the supply of primary care was reducing, but had not been eliminated by public policy. However more recently, Bostock [25] wrote that the primary care workforce in deprived areas is reducing at a faster rate than more affluent areas. It follows therefore that the number of GPs serving a community and the deprivation of the patients within that cohort are likely to be correlated and both may in turn be associated with the rate of use of an extended hours service. Where GP time is scarce and there is a higher level of deprivation, demand may be even higher.

Continuity of care is important and valuable to patients for both psychological and quality of provision reasons. The concept of a medical "home" was associated with better outcomes for patients in a cross national study which included the UK [5]. The results of a patient survey in six practices in Sunderland (UK) showed that for working age patients, a choice of appointment time was six times more important than a shorter waiting time. Patients with chronic illnesses valued seeing a GP of their choice seven times as much as having a shorter wait time. The research concluded that speed of access for many patients is less important than GP choice or timing convenience [26]. Therefore, we might expect that extended services would be more likely to be used if provided by the patient's home practice than by another practice.

The current study considers all extended hours appointments in 2016 from four CCGs within the Greater Manchester area and seeks to investigate the impact of distance on the uptake of extended hours appointments in primary care. We hypothesise that practices which are located further away from a hub account for fewer uses per capita of the extended hours service, than those which are located nearer and that therefore distance is an impediment to access. If distance is a barrier then it may mean that this service does not improve access for all and that this geographical inequality has the potential to widen underlying socio-economic inequality in access.

Methods

Data on extended access appointment provision and use were collected by CCGs and submitted to the National

Table 1: The Hubs, practices, and registered populations within the four CCGs included in the final dataset

CCG	Number of hubs	Number of practices	Registered population
1	4	37	227,267
2	2	35	238,924
3	2	41	243,828
4	6	45	247,842

Table 2: Variables in the analysis

Variable in the analysis	Values
use_rate	Number of service uses per 1000 registered patients
mean_age	Mean age of patients at the practice[2]
female_proportion	Proportion of patients registered as female
min_dist	Distance to nearest hub in miles to one decimal place
hubs	Hub = 1, Non-hub = 0
imd_decile	Decile of Indices of Multiple Deprivation (IMD) score for the LSOA in which the home registered practice is located.Decile 1 relates to the least deprived areas, decile 10 to the most deprived
GP_per_1000	Number of full time equivalent GPs (doctors) per 1,000 registered patients
supply_measure	Percentage of respondents who could not get an appointment the last time they called their surgery, because of the time, the data or the unavailability of their preferred GP. Weighted Responses taken from the GPPS survey, 2015
CCG(1,2,3)	Dummy variable to indicate the CCG of the practice

Institute for Health Research Collaboration for Leadership in Applied Health Research and Care Greater Manchester (NIHR CLAHRC GM) as part of an evaluation of extended access services being delivered in Greater Manchester throughout 2016 [27]. Seven of the ten Greater Manchester CCGs were funded by Greater Manchester Health and Social Care Partnership (GMHSCP) to implement extended access, however, one did not implement the service during the evaluation period and another did not submit data. In addition, one CCG did not include GP practice codes so could not be used, resulting in a dataset covering extended access services in four CCGs. The appointments data extend from 01 January 2016 to 31 December 2016.

In 2016, there were 158 unique general practices within the four selected CCGs. These were served by fourteen 'hubs' Table 1.

Counts of appointments were generated at the practice level, these were aggregated to generate uses of service at an annual rate. The outcome variable for the analysis is the number of uses per 1,000 registered patients at each practice. The dataset included 44,787 appointments of which 32,041 were booked and 27,747 were attended. Removing uses from practices outside of each CCG area, reduced the appointments to 25,408 useable records (appointments). These appointments were complete (zero missingness).

Practice codes [26] enabled several practice-level characteristics to be matched into the data, these include:

- Practice postcodes [28]
- Index of Multiple Deprivation (based on postcode mapped to Lower Super Output Area (LSOA)) [29, 30]
- Latitude and longitude (based on Practice Postcode centre point, used to generate an inter-practice distance matrix) [31, 32]
- GP full time equivalents per 1,000 registered patients [33]
- Practice level registration data by age and sex [28]
- Measure of perceived supply derived from GP Patient Survey [13]

After matching practice level characteristics, the two variables were found to be incomplete: *GP full time equivalents* (21 missing, 13%) and *supply measure* (14 missing, 9%). A sensitivity analysis using binary logistic regression showed these to be unrelated to any other variable within the analysis. Missing at random values were imputed with the mean (of all four CCGs).

We included the hub/non-hub status of each practice as a binary variable, and the deprivation measure is the IMD decile, taken from the English Indices of Multiple Deprivation.

Variables used in the analysis are given in Table2. Appointments were grouped by practice to generate a count of uses for the year. The number of full time equivalent GPs working at every practice was also calculated per 1,000 registered patients.

To test whether there is a relationship between the use of an extended access service and distance we estimate count models of extended access service use with distance to the nearest extended access service and six additional covariates that we have reason to expect may predict service use. The

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[2] An interactive term for practice mean age and female proportion was included in preliminary modelling work but this did not improve the model fit or yield any further associations.

dependent variable is a measure of use per practice and as such is a count variable. Count variables are often modelled using a Poisson framework however this can be biased where over-dispersion is present. In such instances a negative binomial model is used to account for over dispersion in the data [34]. The α parameter was selected using an auxiliary ordinary least squares regression without a constant [38]. Equivalising the response by the number of registered patients at each practice transforms the count of appointments taken from a discrete to a continuous value. Although this might seem to violate a required assumption for a count model, the discrete value cannot be negative and has the fundamental properties of a count, that is to say that it relates to a number of instances over a defined period of time. The practice list size has therefore in effect been applied as a weight.

Analysis was conducted in Python using the open source packages Pandas, Statsmodels and Numpy [35–37]. Visualisations were conducted in Python using Matplotlib and Seaborn [38, 39].

Results

Baseline characteristics of the variables in the analysis are given in Table 3.

Table 4 shows the breakdown of analysed appointments across the four CCGs. There are volume differences between CCGs. Some practices may not have advertised the service, others may not have the underlying unmet need. Some CCGs offered a much less extensive extended hours service. Practices are nested within CCGs, and the CCG has been included as a fixed effect to control for between-CCG variability due to organisational structure and the way in which the extended hours service was provisioned. We are unable to provide geographical visualisations of these data as we are required to preserve CCG and practice anonymity.

Distance is important in predicting service use rate (Table 5). As the distance to the nearest hub increases, so the number of uses observed at a practice over the year decreases. Figure 1 shows the predicted annual use rate by estimated distance to the nearest hub practice.

For a non-hub practice at 1km from its nearest hub, the predicted use rate is around 30 per 1,000 registered patients per annum. At 5km this falls to fewer than 10 uses per 1,000 patients per annum. Once CCGs were included within the model to control for between area variability, a greater proportion of female patients registered at the practice was not associated with increased use of the extended hours service in this model, in contrast with previous findings [12]. No age association was found and deprivation was not associated with rate of use. Hub status was associated with higher use rates. GP numbers and supply issues were not associated with the use rate. There were significant differences between some of the CCGs and we suggest that this could be attributable to between CCG differences in how the extended hours program was implemented.

Discussion

This study sought to determine whether distance and deprivation impact on the uptake of extended hours GP services that use a hub practice model. In line with previous studies [18, 20], we found that distance is important when predicting the use rate of the hub service for an individual practice. Hub status had a statistically significant effect, and we propose that familiarity plays a part in use of an extended hours services with patients more likely to use the service when it is located at their normal registered medical ‘home’. We found no evidence that deprivation (as measured by the IMD decile of the home practice) was associated with lower use of the extended access service. The extent to which access to GP appointments has been improved through the extended hours service is difficult to discern from the data available. Female proportion was not significant in the model.

The presence of spare capacity in evaluations of extended access service uptake raises questions about whether access has improved for patients. Access is a multidimensional concept relying on availability, affordability and acceptability [14]. Availability may have improved through the generation of additional appointments; however, affordability and acceptability may still be restricted. We found that distance is an important factor in uptake. Distance from a hub location is a proxy for factors which affect the affordability dimension of good access. Practices which are further away from their nearest hub have much lower use rates of the service. The study considers appointments, aggregated to a practice level variable. Although these appointments are made and used by individuals, they are administrative units rather than people; uses rather than users. Individual motivations affect the underlying flow of appointments from the core provision to the extended hours, but there are also practice level effects, many of which are not captured here. The practice may serve a catchment with poor access to public transport or more restricted financial means restricting the flow of usage to an additional provider. The employment type prevalent in the

Table 3: Descriptive statistics for variables in the analysis

Variable	Mean	Standard deviation	Min	Max
use_rate	28.8	58.4	0	400
min_dist	2.02	1.59	0.0	7.44
mean_age	38.3	4.05	26.6	44.9
female_proportion	49.7%	1.9%	41.8%	54.5%
imd_decile	3.4	2.8	1	10
GP_per_1000	0.50	0.20	0.07	1.45
supply_measure	0.03	0.017	0.0	0.089

Table 4: Volume of use per CCG (N = 25,408 appointments)

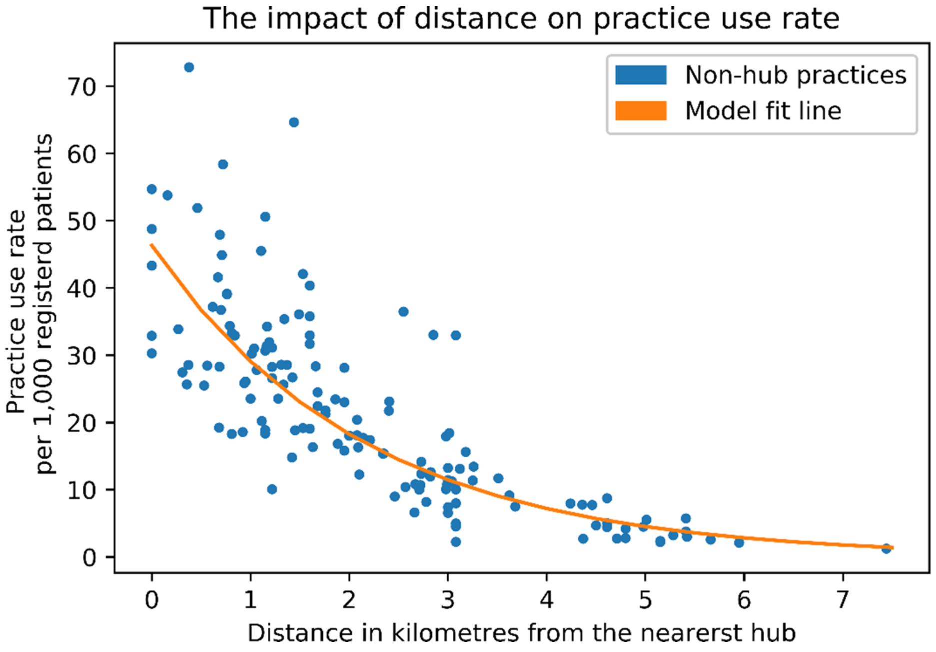
CCG	Number of attended appointments analysed	Appointments per 1000 registered population	Registered population
1	18,466	81.3	227,267
2	1,819	9.1	238,924
3	3,309	14.8	243,828
4	1,814	8.0	247,842

Table 5: Estimated model parameters (n = 25,408, AIC = 1,254.3, $\alpha = 1.46$)

	Estimate	Standard error	95% CI	
			[0.025	0.975]
Intercept	1.08	2.82	−4.45	6.60
min_dist	−0.28*	0.08	−0.44	−0.12
mean_age	−0.03	0.03	−0.09	0.03
hub	1.10*	0.39	0.33	1.86
female_proportion	0.08	0.06	−0.03	0.19
imd_decile	0.07	0.06	−0.04	0.19
GP_per_1000	0.49	0.53	−0.55	1.53
supply_measure	12.35	6.59	−0.57	25.28
CCG1	−1.43*	0.29	−2.00	−0.87
CCG2	−2.31*	0.29	−2.87	−1.75
CCG3	−2.62*	0.38	−3.37	−1.88

*indicates significant at the p<0.05 level.

Figure 1: Predicted annual use rate by distance to hub practice[3]



area may place time cost restraints which affect the ability for appointments to flow to a different location, an effect that increases with distance. There are effects at the CCG level which we are unable to explore with this dataset however it may be that different CCGs have advertised and implemented their extended hours services differently and that this has impacted upon the domains of access or simply through a lack of awareness that the service is available.

Familiarity may also be important in determining acceptability of appointments in distant locations – in many aspects of our daily lives, we are reticent to try out the unfamiliar and are often creatures of habit. It is therefore reasonable to expect that hubs which are further away may be

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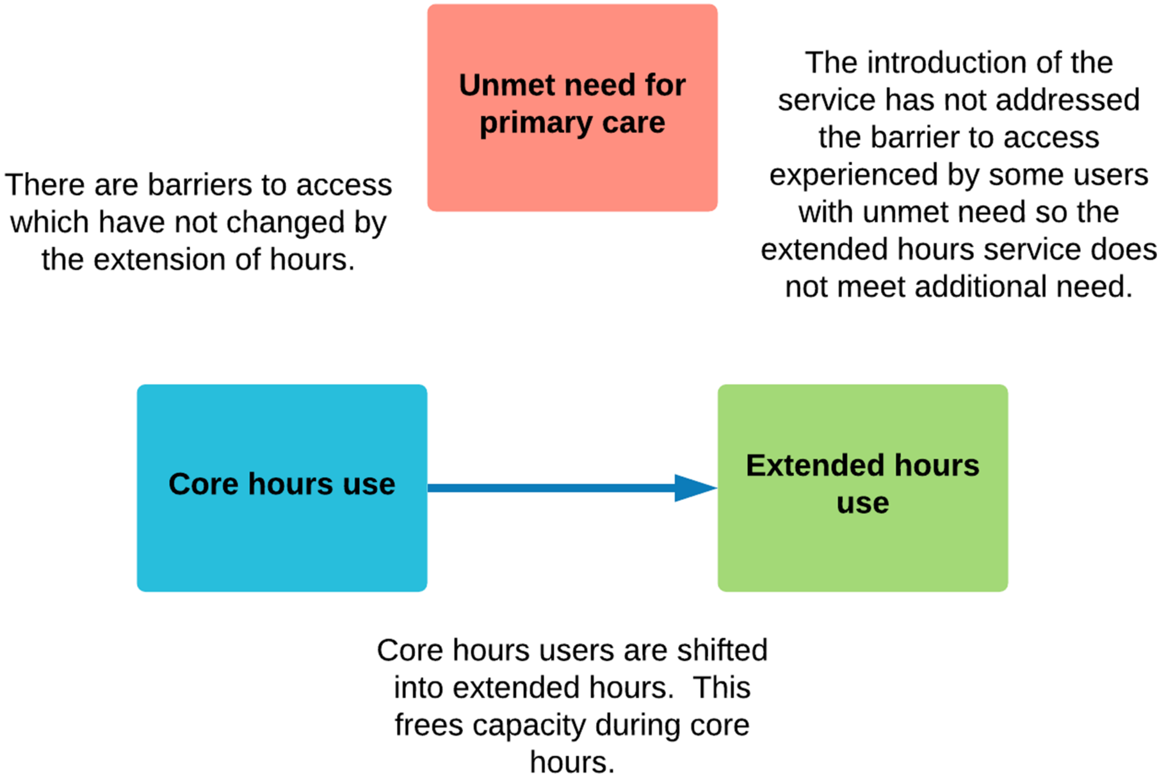
[3] This figure shows underlying data for non-hub practices, overlaid with a predicted fit line for the estimated model parameters using the mean for all variables except distance. Hubs have been excluded to allow better clarity of individual data points.

Figure 2: Unmet need remains unmet



less familiar and so the flow of appointments from the home practice into the extended hours service may be reduced. For hub patients, the implementation of the scheme simply offers them a wider window in which to experience the same service and greater flexibility in timing and so it makes sense that once a patient has decided to make an appointment to see a doctor, there is no structural barrier to the flow of usage between the core hours or extended hours service.

Research has found that having a medical "home" which is easy to access, leads to a more positive patient experience. Patients who see multiple doctors, report more errors in their care [5]. Accessing primary care through the extended hours service for patients of non-hub practices will necessarily involve travelling to an unfamiliar healthcare setting and the likelihood is that the patient will not see their usual core hours doctor. A hub service therefore threatens the concept of a medical home and there is a risk that the quality of primary care is eroded by the structure of the provision. The perception of eroded quality, concerns about having to repeatedly explain ongoing medical issues and the unfamiliarity of the setting may also pose additional barriers to using the extended hours service which are not measured in this study. It is proposed that the barrier to access for the service is to an extent a psychological one and as such the distance to the nearest hub is a good measure of dislocation from the service, even where users are opting to use hubs which appear to be further away.

Figure 2 provides an approach to visualising the above explanations for the results. The figure describes a use scenario where patients make use of the extended range of options, but the unmet need for primary care is not itself affected despite the extension of hours because the barrier to access for these patients has not been caused by the unavailability of appointments. Here a patient who would have used a core hours appointment is now choosing to use an extended hours appointment. This would increase free capacity during core hours but potentially does nothing to impact access for patients in the unmet need group. In this model, additional core hours provision may be wasted.

Figure 3 describes a use scenario where patients with previously unmet need are using the extended hours service as well as the core hours. Access has been enabled through two mechanisms – provision of additional choice over appointment timing, and consequential increase in core hours capacity. In this scenario, the barrier to access for this unmet need is the availability and timing of appointments, which has been addressed by the extended hours service provision.

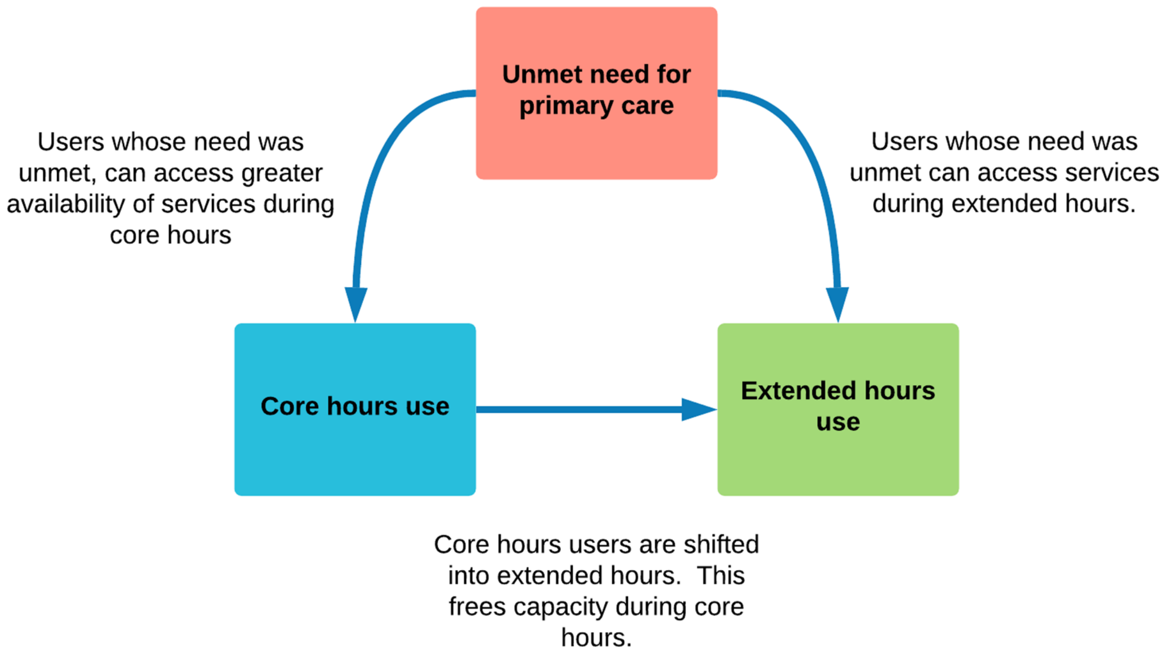
There are intermediate use scenarios which fall between these two theoretical examples – for example where unmet need is serviced by the extended hours only, with no core hours shift, or conversely where unmet need is met wholly through relaxation of overcrowding in core hours caused by core hours use shift.

Limitations

This study was limited by a lack of more granular geographical data and of detailed information at the individual level, particularly pseudo identifiers and a lack of home postcode data.

Only the home GP practice postcode is known for each use instance. The distances were calculated as a straight line between the home practice, and the nearest hub practice. The

Figure 3: Unmet need is met through two mechanisms



distance[4] travelled to attend an extended hours appointment is likely to be misclassified in all cases as patients living in the geographical extremes of each practice may need to travel significantly further or experience distance effects in the other direction. For patients at a hub practice, the minimum distance in this model is zero, however these patients are all likely to have travelled more than this to attend. For non-hub practices, the distance is likely to be underestimated in 50% of cases, assuming the registered practice is located at the centre of its catchment. This means that more than 50% of distances will be misclassified and an underestimate, but this is deemed to be a random effect and thus treated as a rescaling that does not introduce bias into the model.

The socio-demographic characteristics for each use instance were necessarily assigned at the practice level using the 2011 LSOA. Practices serve a catchment which may include a range of socioeconomic settings. Even within the same LSOA assigned to a deprivation decile, two streets of houses might be experiencing radically different socioeconomic circumstances. The use of practice postcodes as a proxy for patient location will have caused some misclassification which may have affected the performance of the IMD score in the model[5].The results of this study are specific to the four CCGs examined here and may not be generalisable across the rest of Greater Manchester or the UK. CCGs have the freedom to design the service as they see fit and so there may be structural differences and effects which impact the extent of uptake here, which do not apply elsewhere.

A measure of core hours capacity and use is not available in this dataset and so it is impossible to determine whether the use of the extended hours appointments represents a true increase in access, or whether it simply reflect a shift in uses for patients who already experienced an adequate level of empowerment or those who did not. The main consequence of this is that we are not able to distinguish between the candidate scenarios captured in figures 2 and 3. Further research using more detailed and comprehensive data is needed to clarify this important point.

Seasonal effects in utilisation were also not analysed here; it may be that there is still some compromise of availability during times of greater patient need, such as during the winter. Time stamp information is available in the dataset but the low quantity of data for some practices made it impossible to model using both time and practice level geocoding. Availability is not however the only determinant of whether a patient can access an appointment and so it is important to emphasise that spare capacity in the system does not necessarily mean that all need for primary care has been met, for example, the way in which patients were made aware of the service could also impact on uptake.

We do not know the health outcomes of service users and so the study does not explore whether or not the extension of primary care hours results in health benefits to the users or results in ineffective access and return visits to the patient's home practice.

Conclusion

The aim of providing primary care appointments outside of core hours is to improve access. The extension of hours

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[4] We tested network distances in the original modelling and the results were near identical. Network distances and the measure used here are highly correlated for this particular area (Pearson's coefficient 0.96). The principle of parsimony and replicability suggests that the Euclidean method is more appropriate in this case.

[5] The Modifiable Area Unit Problem is relevant to any measure at the LSOA level. In the paper this only applies to the index of multiple deprivation. It turned out to not be associated with the outcome measure after controlling for other factors, but this could simply be to do with the misclassification of the LSOA, rather than the lack of a deprivation effect itself. From the data we have, we cannot say. We have been forced to use the practice level deprivation, and acknowledge that this may misclassify uses but we have limited options here other than to have excluded it entirely. We have not used any other measure at the LSOA unit here e.g. disease burden.

as a mechanism of increasing access is predicated on the assumption that unmet need is caused by a lack of capacity at an appropriate time. This may be due to overcrowding of services in core hours, or it may be due to the unsuitability of core hours for some primary care users.

Patients want, and use, extended hours services; however distance and familiarity are two potential barriers to equal access for all. The study suggests that patients living further away use the service less. For patients who cannot travel, or are unwilling to accept an appointment somewhere other than their medical 'home', the extended hours service may not be an effective way of improving access.

A simple view would be that if there is spare capacity in the system, then all needs must be met. However this analysis provides evidence that spare capacity in the system does not of itself demonstrate that access issues have been eradicated. It may be that patients who are already empowered to access health care are simply being given more choice, with no increase in the provision for those whose needs are not currently met, or it may be that the increase in provision increases access. Provision of ever greater service volume without consideration of the way in which people are motivated to use it, risks leaving those groups with unmet needs behind and reporting spare capacity risks hiding this unmet need in the data.

Policy makers and health care commissioners need to understand the differences in the extent and nature of uptake to inform their design and evaluation of future services. They should consider whether or not this type of model works to provide additional access and may use the findings in this study to inform the selection of hub practices – perhaps focusing on practices which minimise the average distance travelled for patients, or where there is relatively greater evidence of constrained capacity. This is particularly of importance in the context of closing health inequality gaps as those who are least enabled to access services may be those who need them the most.

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Statement on conflicts of interest

All authors have completed the ICMJE uniform disclosure form at www.icmje.org/coi_disclosure.pdf and have the following competing interests: funding support from NIHR and from Greater Manchester Health and Social Care Partnership for this work; WW reports grant funding for other work from the Department of Health Policy Research Programme and NIHR. No other relationships or activities that could appear to have influenced the submitted work are declared.

Ethics statement

The study was reviewed by the University of Manchester's internal University Research Ethics Committee and approved under the low risk procedure and thus did not require UREC approval (ID: AMBS/16/05). The study involves anonymised administrative data and did not impact on the type of care patients received, consent by patients using the service was not required.

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Abbreviations

CCG:	Clinical Commissioning Group
GM:	Greater Manchester
GMHSCP:	Greater Manchester Health and Social Care Partnership
GP:	General Practitioner
GPPS:	General Practice Patient Survey
IMD:	Index of Multiple Deprivation
LSOA:	Lower Super Output Area
NHS:	National Health Service
NIHR CLARHRC GM:	National Institute for Health Research Collaboration for Leadership in Applied Health Research and Care Greater Manchester

Chapter 5

Paper 2: Wellbeing during the COVID-19 pandemic in the UK: a secondary data analysis

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Discover Social Science and Health

Research

An analysis of changes in wellbeing during the COVID-19 pandemic in the UK

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Abstract

Purpose We investigated the trajectory of wellbeing over the course of the first wave and sought to determine whether the change in wellbeing is distributed equally across the population. Specifically we investigated pre-existing medical conditions, social isolation, financial stress and deprivation as a predictor for wellbeing and whether there were community level characteristics which protect against poorer wellbeing.
Methods Using online survey responses from the COVID-19 modules of Understanding society, we linked 8379 English cases across five waves of data collection to location based deprivation statistics. We used ordinary least squares regression to estimate the association between deprivation, pre-existing conditions and socio-demographic factors and the change in well-being scores over time, as measured by the GHQ-12 questionnaire.
Results A decline in wellbeing was observed at the beginning of the first lock down period at the beginning of March 2020. This was matched with a corresponding recovery between April and July as restrictions were gradually lifted. There was no association between the decline and deprivation, nor between deprivation and recovery. The strongest predictor of wellbeing during the lock down, was the baseline score, with the counterintuitive finding that for those will pre-existing poor wellbeing, the impact of pandemic restrictions on mental health were minimal, but for those who had previously felt well, the restrictions and the impact of the pandemic on well-being were much greater.
Conclusions These data show no evidence of a social gradient in well-being related to the pandemic. In fact, well-being was shown to be highly elastic in this period indicating a national level of resilience which cut across the usually observed health inequalities.

Keywords Well-being · COVID-19 · Social gradient · Resilience

1 Introduction

In March 2020, in response to the rising prevalence the disease in the UK, the government followed many others in declaring a 'lock-down' where citizens were required to stay at home beyond a very limited number of sanctioned reasons [1]. Mass gatherings were banned, travel was restricted. Leaving the home was restricted to those working in so-called 'key-worker' roles such as healthcare, education and the food system. Non key-workers were permitted to exercise alone outside of the home once daily, and to make trips for essential supplies. All non-essential services were closed including shops and leisure facilities. Non-emergency care was seriously compromised with many routine care services stopping for several months including cancer diagnostics, chemotherapy, surgery and outpatient clinics.

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We hypothesise that as a result of the pandemic and the accompanying lockdown, wellbeing has been impacted and that there are likely to be widespread indirect effects important to policymakers and health professionals as the population recovers. Studies using the UK Household Longitudinal Study show that there has been a deterioration in the average mental health of respondents when comparing data waves before and early in the pandemic. Proto and Quintana-Domeque [2] report that the extent of the deterioration varies by ethnicity and by gender. Pierce et al. [3] explored the trend in UK mental health, demonstrating that there had been a deterioration compared with pre-COVID-19 trends, highlighting greater increases for younger adults, women, and people living with young children. Google Trends data showed an increase in search terms for boredom, loneliness, worry and sadness indicating mental health was impacted by the lockdown [4]. A study of 6142 adults from 18 countries within the Middle East and North Africa in May and June 2020 concluded that the pandemic was associated with a mild psychological impact, with half the sample reporting feelings of being horrified, helpless or apprehensive [5]. Holmes et al. call for resources to be deployed to understand the varied effects, collecting data and conducting multidisciplinary research to ensure efficient targeting of policy mitigations [6]. The authors specifically reference mental health, and the growing threat of virus mitigation measures, alongside the potential physiological effects of contracting the virus on brain function and mental health in patients testing positive with COVID-19.

In this paper, we use the UK Household Longitudinal Study, Understanding Society [7] to investigate the trajectory of wellbeing over the course of the first wave (defined as April–July 2020) and analyse whether any change in wellbeing is associated with social and demographic factors. In the next section we discuss the background to the pandemic and factors which may affect wellbeing. In Sect. 3, we introduce the dataset used and the methods applied. Results are presented in section 4. Section 5 contains the discussion of findings, followed by an appraisal of the strengths and weaknesses of the work in Sect. 6. We conclude in Sect. 7.

2 Background: factors affecting wellbeing in a pandemic

The global pandemic has been a period of extreme stress and challenge. Communities and individuals have needed to rapidly adapt to the developing situation and in many instances, significant adversity. The ability to adapt to the changing health and social landscape at an individual and community level may affect wellbeing, and the extent to which communities and individuals are resilient to these stresses may influence the nature and duration of this impact.

Morton and Lurie [8] present domains of community resilience. At an individual level, physically and mentally well individuals are more resilient, with better underlying population health contributing to this individual resilience. Conversely, individuals with poorer underlying health, or with under-treated chronic conditions, find it more difficult to re-establish a health promoting way of life in the aftermath of adversity and are thus less resilient to any challenges they face. Individual mental resilience enables individuals to adopt positive adaptations in response to (and despite) external stress factors, but this mental resilience can be impaired by changes to the normal social life of an individual, for example through disruption of social networks. This type of disruption impacts all actors within the network and thus also leads to reduced population health at the community level.

The pandemic has disrupted our social existence and many of the support structures in place to support those with poor underlying mental health and other chronic conditions [9]. Outcomes for individuals may therefore have been impacted by not just by their own personal resilience, but also by the adaptation of their community and the resilience of the organisations upon which their communities depend.

Controlling the spread of COVID-19 continues to be a priority to protect the ability of the healthcare system to provide care for those who need it, and to reduce the number of excess deaths attributable to the disease. However, the measures taken have impacted incomes, social contact and job security. These factors are all known to contribute to an individual's ability to live a healthy life and so we can expect to see an impact on long term health [10]. The Trussell Trust reported a rise of 122% in emergency food parcels for children during March 2020, compared to 2019 [11]. Those on a low wage, in particular the young, and women, were seven times more likely to work in sectors required to close by the COVID-19 restrictions with a third of employees in the bottom decile of the income distribution working in a closed sector, compared with only 5% of those in the top decile [12]. Economic contraction is expected to lead to an expected additional 3.5 million claims for universal credit from the UK welfare system [13]. As the Health Foundation have observed, pre-existing inequalities are likely to cause uneven impacts of the virus, and it follows that complex patterns of health inequity will result [14].

For many people in the UK, the pandemic restrictions have either reduced incomes, or increased the threat of financial stress in the future [15, 16]. This may continue for some time, a recession is underway with large scale unemployment [17]. Unemployment is associated with excess mortality [18]. Individuals need money to meet their material needs and to participate and engage in health promoting activities, or being able to afford fresh goods and the time to prepare meals using them. Having insufficient money is stressful, and living with disadvantage can make a person more likely to engage in unhealthy behaviours. A systematic literature review by Benzeval et al. [19] has shown that the effect that having insufficient financial resources has on health, can further impede individuals' education and employment causing an ill-health and income negative feedback loop.

Age can be a factor in mental health. A study of older adults in Hong Kong showed that during the 2003 Severe Acute Respiratory ("SARS") pandemic, suicides in the age 65+ age group increased by 30%. This increase was attributed to fears of being a "burden" to family during the outbreak, but also social disengagement, mental stress and anxiety [20].

For patients living with a long term condition, social engagement and access to informal healthcare services such as support groups is part of ongoing self management. For example, Reeves et al. [21] studied 300 patients with diabetes or chronic heart disease living in deprived areas of the North West of England. The authors found that self management, and physical and mental health were supported by social involvement with groups and people. Patients increased their use of their social networks as their care needs increased, showing a dynamic effect that was reflected in financial savings to the care providers. Social networks act for this cohort as a support to and a substitute for more formalised health care services.

This social network effect may have been significantly disrupted by the COVID-19 pandemic leading to increased social isolation and potentially loneliness. At a time when care services were stretched by patients requiring care for COVID-19, patients living with a long term care need may have needed to draw more on this social network for their own self-management as access to formalised healthcare settings became restricted [22]. Access to groups, socialising and networks including family and friends was at the same time restricted for all, and particularly for those living with significant co-morbidities who were instructed to "shield" for a period of 3 months [23]. Support for self-management of long term conditions is a networked and collaborative construct, as opposed to merely based on the action of individuals, and so a time of significant social isolation may well have caused a break down in self-management of health and wellbeing for those with longer term care needs [24–26]. Not everyone who experiences social isolation, feels lonely and indeed loneliness may occur without social isolation, however Emerson et al. [27] demonstrated that loneliness was also associated with wellbeing for a representative sample of people with and without a disability. Coyle and Dugan [28] studied older adults, showing that loneliness is associated with poorer mental health.

The highly infectious nature of the COVID-19 virus necessitated significant organisational changes for health care services on a global scale. In a multinational survey, resource reallocation from chronic disease to COVID-19 disrupted the continuity and the quality of care across all countries, with specific impact on diabetes, chronic obstructive pulmonary disease and hypertension [29]. Elective surgeries and outpatient clinics were cancelled with many care appointments postponed and most care moving to remote provision by teleconsulting [30]. In the early stages of the first wave, evidence of risk factors for infection and mortality had not yet emerged and a crisis in demand for respiratory care de-prioritised other areas of the health care system. Health care service overcrowding affected the resourcing and facilitation of ongoing treatment and palliative care for conditions such as cancer [31]. Diagnoses were reported to be delayed as services for screening and testing were suspended and many patients were reticent to engage with healthcare services for fear of contracting the virus in a hospital or other setting [32]. Maringe et al. [33] predict over 3000 excess cancer deaths in the next five years as a result of delays to diagnostic and treatment services, in a sample of 93,607 patients suffering from one of four specific tumour types. In the case of diabetes care, the strain on emergency health care services required many medical staff to be seconded to alternative roles, further compromising the availability of specialist services. Nagi et al. [34] report a reduction in acute admissions for diabetes and related endocrine disorders and a reduction in investigations. Standard outpatient clinics were closed and cancellation of face to face clinics alongside a reduction in availability of services, caused the care to be delivered to be sub-standard in addition to there being concerns of "important unmet clinical need".

Using questionnaire responses from the COVID-19 modules of Understanding Society [7], we examine the change in wellbeing for a sample of respondents in England[1] during the lock down period associated with the UK's 'first wave' of COVID-19 infections using the twelve question General Health Questionnaire as a proxy measure for wellbeing.

We ask the following research questions:

1. Is the reported initial decline in wellbeing distributed equally across all groups regardless of deprivation?
2. Is the reported initial decline in wellbeing the same for those with pre-existing medical conditions?
3. Did wellbeing change overall during the course of the first wave?
4. Has any overall change in wellbeing been experienced equally across those in deprived areas or with pre-existing medical conditions?
5. Are there community level characteristics which are protective against poorer wellbeing?

3 Data and methods

The data are taken from the first four waves of the Understanding Society COVID-19 survey, with wave nine data used as a baseline [7]. The outcome variable is the General Health Questionnaire (GHQ-12) caseness score for each survey.

The twelve item General Health Questionnaire (GHQ) is a validated measure of mental distress and is considered robust in longitudinal data samples [35]. Each question is rated on a 1–4 Likert scale with the answer 4 indicating the response associated with the poorest wellbeing for each question. The measure includes generalised questions about concentration, sleep, decision making, feelings of worthlessness, confidence, stress, and happiness. The GHQ index variable is the sum of responses to the twelve questions. The maximum score for a complete questionnaire is 48 and the minimum is 12. Question and response texts are given in Appendix A.

The caseness variable is computed by recoding all responses to a binary 1/0 value. Responses of 1 and 2 are recoded to 0, indicating no change from usual, whereas 3 and 4 and recoded to 1. Summing over the twelve questions gives the caseness score. A caseness score of 1–2 is considered to indicate mild psychiatric illness [36].[2]

Valid cases are selected as those who responded to all five waves of data.[3]

The longitudinal response rate to waves 1 through 4 of the COVID-19 survey is 21.8%, representing 9,603 valid cases UK wide. 58.3% of respondents were female, compared with 53.2% in the survey sample. Of these 8379 resided in an English Lower Super Output Area during the wave 1 COVID-19 data collection and were included in the analysis.

The mean age of respondents in England is 55.4 years (SD 15.6) compared with the overall Understanding Society sample mean age of 49.1 years (SD 19.3)

Logistic modelling of longitudinal response across the four waves of data collection, identified sex, ethnicity, age and baseline GHQ-caseness (as recorded in wave 9 of the main survey) as predictors of response.

There are only 786 valid English non-white respondents (9.4%). In the overall sample 20.3% are non-white ethnicities suggesting an non-random missingness and an under representation of BIPOC communities within the data. This is accounted for in the models by including ethnicity as a co-variate regardless of its effect.

The extent of decline in wellbeing is measured by the change in GHQ caseness score between wave 9 of the main survey and wave 1 of the COVID-19 survey. The progression of wellbeing during the first pandemic wave is defined as the change in this score between waves 1 and 4 of the COVID-19 survey. The base line is selected as wave 9 of the main survey as this was the most recent dataset available at the time, and data collection occurred well before the emergence of the pandemic.

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[1] Non-English cases were excluded from the analysis as deprivation index data is not comparable across the home nations.

[2] For more information on the questionnaire see https://www.gl-assessment.co.uk/assessments/products/general-health-questionnaire/

[3] There are 8379 valid cases from 6010 unique households. 4553 responses came from respondents where another person in their household also responded to the survey. 3826 respondents were the only respondent in their household—this may be because of non-response or because of them being a sole individual household. We randomly sampled the respondents to create a dataset containing no duplicated households (6010 valid cases) and repeated the modelling. There was no substantive change in the results or findings and so the models are reported here for the full set of valid cases (8379). Household effects are deemed to be negligible in respect of this research although we acknowledge that there may be a household level effect within response rates but this is not captured nor investigated as part of this work.

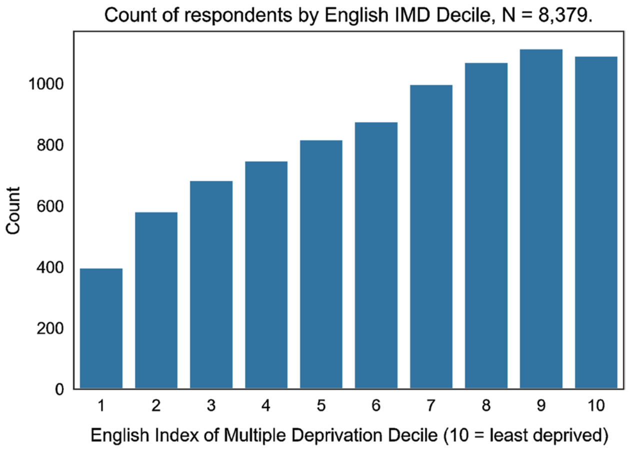

Fig. 1 Distribution of respondents by IMD Decile

The response to a question about loneliness is used in different forms in both models. Modelling the decline, we compared the loneliness response for wave 1 of the COVID-19 data collection with the baseline and constructed a categorical variable to capture the trajectory of loneliness for respondents with four responses:

- remaining lonely (having been lonely previously),
- becoming lonely (having not felt lonely before),
- no longer feeling lonely (having felt lonely before),
- not having experienced loneliness either before or at the beginning of the lock-down.

Using this variable as a series of dummies within the model provided the same result as simply using the response to the first wave of COVID-19 data collection and therefore—for reasons of parsimony—we use the variable *lonely* in the model. The recovery model uses a cumulative score to capture persistent or frequent loneliness over time.

The variable *income_decrease* is derived from the household composition and household earnings amounts. The household makeup was summed using variables[4] which correspond to the number of adults residing in the household and those[5] which correspond to the number of children within the household. This was then equivalised to account for the differing costs of adult and child residents using the formula given by the OECD as an appropriate method for equivalence [37]: $household\_equivalence = 1 + 0.5(adults) + 0.3(children)$.

The income change was computed using the baseline and third wave household income values, equivalised to an annual figure[6]

The economic impact of the income decrease was calculated by scaling the change in income between the baseline and wave 3, by the equivalised household size and then recoding this variable to show whether or not income had decreased during the period of the lockdown.

Using respondent geography, each response was assigned a deprivation decile corresponding to home location for wave 1 of the COVID-19 data collection using the 2019 updated English Indices of Multiple Deprivation (IMD) [38]. The variable *community_cohesion* was compiled from four questions asked in the third wave of data collection, in June 2020. Questions asked whether a respondent spoke regularly with neighbours, trusted those who live in their community, found neighbours to be helpful and whether or not they got along with people in their community. The responses on a Likert scale, were re-coded and summed to give a composite score for the respondent's neighbourhood.[7]

In 129 cases Lower Super Output Area (LSOA) changed during the period. 5 cases changed more than once, of which 4 reflected a move away and then back to an LSOA of origin. LSOA of origin is defined as the relevant LSOA for determining deprivation. Respondents are skewed towards areas of lower deprivation. 2206 respondents live within LSOA's

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[4] *cc_hhcompc*, *cc_hhcompd* and *cc_hhcompe*.

[5] *cc_hhcompa* and *cc_hhcompb*.

[6] using the variables *cc_hhearn_period, cc_blhhearn_period, cc_hhearn_amount and cc_blhhearn_amount*. The *_period* variables give information on whether the figures given for household income are weekly, fortnightly, monthly or annual.

[7] The variables from Understanding Society used to compile this score were those with the codes: *scopngbhh, nbrcoh3, nbrcoh2 and nbrcoh4*

Table 1 Variables in the analysis

Variable	Mean (male/female)	Std (male/female)	Missing	Notes
wellbeing_decline	0.606/1.30	2.87/3.67	0	Change in GHQ-12 caseness score from wave 9 of the main survey (*i_scghq2_dv*) to wave 1 of the COVID-19 survey *ca_scghq2_dv*).
baseline_wellbeing	1.24/1.80	2.58/3.04	0	GHQ-12 caseness score from wave 9 of the main survey (*i_scghq2_dv*).
wellbeing_recovery	0.458/1.00	2.54/3.27	0	Change in GHQ-12 caseness score from wave 1 (*ca_scghq2_dv*) to wave 4 (*ca_scghq2_dv*) of the COVID-19 survey. Positive values indicate a reduction in the score, an improvement in wellbeing.
age	56.8/53.3	15.4/15.7	0	Age in years, calculated from birth year (renamed from survey variable: *ca_age*).
sex			0	Sex, binary. 1 = Female, 0 = Male. (recoded from survey variable: *sex_dv*).
community_cohesion	14.8/14.9	2.7/2.8	20	Variable (derived from questions on neighbourhoods: *scopngbhh, nbrcoh3, nbrcoh2 and nbrcoh4*).
imd_decile_2019	6.3/6.2	2.7/2.7	0	English Indices of Multiple Deprivation decile for the respondent's LSOA as at wave 1 data collection [imputed from 38].
eth_minority			26	Binary variable to indicate white and non white ethnicities. 0 = White 1 = Black, Asian and Minority Ethnic (derived from the survey variable *race_dv*).
health_condition			0	Binary variable to indicate underlying health conditions. 0 = no health condition, 1 = health condition. Taken at July data collection as those diagnosed during the COVID-19 survey period are likely to have been living with symptoms and accessing care for an undiagnosed condition during the period. (derivation of the survey variable: *cd_ff_hcondhas*).
lonely			0	Binary variable to indicate experience of loneliness in the 4 weeks prior to the wave 1 data collection. 0 = has not experienced loneliness, 1 = experienced loneliness some times or often. (derived from the survey variable *ca_sc_lonely_cv*).
always_lonely	0.97/1.54	1.4/1.6	2	Sum of binary variables over waves 1 to 4 to give a score for persistent loneliness. Max = 4, min = 0. (calculated from derivations of four survey variables: *ca_sc_lonely_cv, cb_sc_lonely_cv, cc_sc_lonely_cv and cd_sc_lonely_cv*).
financial_crisis			3	Binary variable to indicate acute financial crisis at Wave 4. 1 = has accessed a food bank in the prior 4 weeks, 0 = has not (derived from the survey variable *cd_foodbank_cv*).
income_decrease			0	Binary variable to indicate worsening financial situation. 1 = house hold equivalised income has reduced from wave 1 to wave 4, 0 = income is the same or greater (calculated from multiple variables, see text).

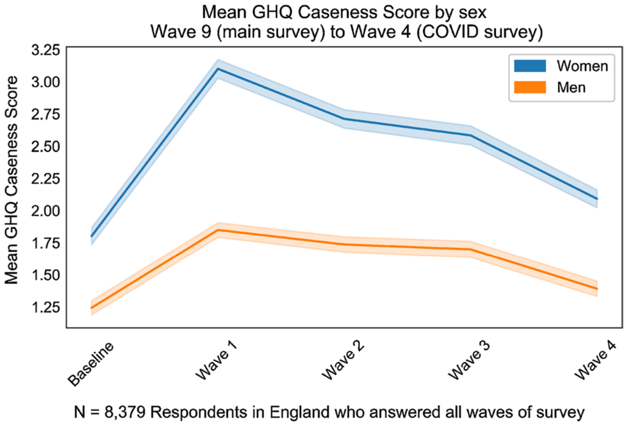

Fig. 2 Mean GHQ Caseness Score over time, by Sex, with 95% confidence interval

ranked in the bottom two deciles for deprivation, compared with 5150 in the top two deciles. The mean IMD decile for a respondent was 6.3 (SD 2.7) where 10 reflects the least deprived areas (Fig. 1).

43% of the men (N = 1523) and 47% of the women (N = 2.287) in the analysis had no underlying health conditions. Of those reporting an underlying health condition, 57% were women (N = 2602) in line with the overall sex distribution of respondents.

Parameters in the regression model were estimated using using ordinary least squares regression with wave 4 longitudinal weights, using R^2 as a measure of model fit. The variables used in the analysis are described in Table 1.[8]

The model was constructed in three steps (A, B and C) corresponding to underlying demographic factors (A), baseline GHQ scores (B) and variables which correspond to specific pandemic lock down phenomena (C). Non-significant variables are retained throughout as controls for model equivalence.

We note that using the same GHQ-12 questions from the Understanding Society survey and its predecessor the British Household Panel Survey from 1999 to 2016, Brown et al. [39] showed that under reporting bias for mental health was greater for men. For this reason we elected to produce separate models for men and women.

Initial model specifications are can be seen in Eqs. (1) and (2) below.

$$\begin{aligned} wellbeing\_decline = &\beta_0 + \beta_1(baseline\_wellbeing) \\ &+ \beta_2(lonely) + \beta_3(age) \\ &+ \beta_4(community\_cohesion) + \beta_5(imd\_decile\_2019) \\ &+ \beta_6(health\_condition) + \beta_7(eth\_minority) \end{aligned} \tag{1}$$

$$\begin{aligned} wellbeing\_recovery = &\beta_0 + \beta_1(baseline\_wellbeing) \\ &+ \beta_2(wellbeing\_decline) + \beta_3(age) \\ &+ \beta_4(community\_cohesion) + \beta_5(imd\_decile\_2019) \\ &+ \beta_6(\mathrm{eth\_minority}) + \beta_7(health\_condition) \\ &+ \beta_8(always\_lonely) + \beta_9(financial\_crisis) \\ &+ \beta_{10}(income\_decrease) \end{aligned} \tag{2}$$

Missing data within the valid cases were imputed with the mean value for the variable, with the exception of ethnicity where "white" was imputed. The level of missingness within the selected cases is very low (see Table 1). However, as a precaution, sensitivity analysis was conducted by re-running the regression models after dropping all cases with missing values, and comparing to the models with missing values imputed. The models were stable with minimal change in the magnitude or direction of estimated coefficients.

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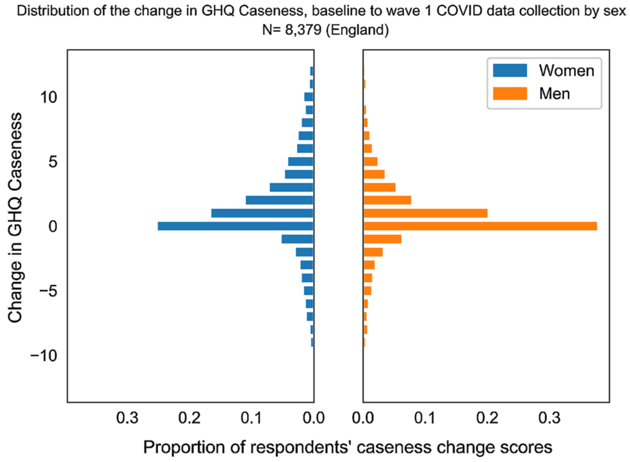
[8] The variables are a mixture of derived, re-coded, calculated, imputed and original variables. For readability all variables have been given plain English names; the relationship between the analysis variables and the ones in the survey dataset can be found in the notes section of Table 1.

Table 2 Mean caseness scores for males and females

	Mean	Std	Sex	95% CI Lower	95% CI Higher
Baseline	1.80	3.05	Female	1.74	1.87
	1.24	2.58	Male	1.19	1.30
Wave 1	3.10	3.37	Female	3.03	3.17
	1.85	2.65	Male	1.79	1.91
Wave 2	2.71	3.34	Female	2.64	2.78
	1.74	2.78	Male	1.68	1.80
Wave 3	2.58	3.46	Female	2.51	2.66
	1.70	2.93	Male	1.64	1.76
Wave 4	2.09	3.24	Female	2.02	2.16
	1.39	2.79	Male	1.33	1.45

Fig. 3 Distribution of the change in GHQ Caseness from baseline to wave 1, by sex



4 Results

Mean wellbeing scores show a clear peak and decline with the peak occuring in April during the first wave of data collection. Mean scores have recovered to almost the baseline (main wave 9) by July (COVID-19 wave 4) when an end to shielding was announced and much of the economy reopened, albeit with restrictions in place to ensure continued social distancing. The increase in scores between the baseline and July 2020 are consistent with the trend in scores over time reported elsewhere (see Figs. 2, 3; Table 2) [3].

The difference between men and women in the mean figures for the baseline is statistically significant ($t = 8.8$, $p < 0.05$) as is the difference in the mean change for men and women between the baseline and April data collection ($t = 9.3$, $p < 0.05$).

Women suffered, on average an increase of 1.3 in the GHQ caseness score (72% increase on baseline) between wave 9 and the first COVID-19 wave, compared with 0.61 for men (51% increase on baseline). This indicates a difference in the impact of the pandemic on women's wellbeing consistent with reports that women have been unequally impacted [40, 41].

4.1 Modelling the decline in wellbeing

An increase in the GHQ caseness score equates to a decline in wellbeing. Model 1C explains 36.7% of the variance in the wellbeing decline for women, and 33.1% for men (Table 3). Variance inflation factors were below two for all variables and all permutations of the model, indicating no problematic multi-colinearity. Pearson's correlations for all variable pairs showed no correlations over 0.5.

Table 3 Model 1: parameter estimates for the decline

		Male	Std. error	Female	Std. error
Model 1A	Intercept	0.316	(0.175)	1.393*	(0.141)
	age	0.005	(0.003)	– 0.009*	(0.002)#
	eth_minority	0.204	(0.188)	– 0.425*	(0.151)#
	imd_decile_2019	0.007	(0.017)	0.017	(0.014)
	health_condition	– 0.178	(0.104)	– 0.104	(0.083)
	R^2	0.2%		0.4%*	
Model 1B	Intercept	1.973*	(0.157)	3.383*	(0.126)#
	age	– 0.013*	(0.003)	– 0.029*	(0.002)#
	eth_minority	0.311	(0.161)	– 0.116	(0.129)#
	imd_decile_2019	– 0.021	(0.015)	– 0.021	(0.012)
	health_condition	0.291*	(0.090)	0.491*	(0.072)
	baseline_wellbeing	– 0.531*	(0.014)	– 0.595*	(0.011)#
	R^2	25.9%*		26.9%*	
Model 1C	Intercept	1.261*	(0.230)	1.834*	(0.181)
	age	– 0.001	(0.003)	– 0.01*	(0.002)#
	eth_minority	0.266	(0.154)	0.041	(0.121)
	imd_decile_2019	– 0.006	(0.014)	0.005	(0.011)
	health_condition	0.156	(0.086)	0.27*	(0.067)
	baseline_wellbeing	– 0.6*	(0.014)	– 0.671*	(0.010)#
	ca_lone	1.817*	(0.091)	2.518*	(0.067)
	community_cohesion	– 0.025	(0.015)	– 0.019	(0.011)#
	R^2	33.1%*		36.7%*	

*Indicates significant at the $p<0.05$ level. # indicates Clogg test statistic > critical value of 1.96

The model build using a stepped approach shows that underlying demographic factors age, ethnicity, deprivation and pre-existing health conditions on their own (model 1A) explained little of the variance in GHQ scores (R^2 of less than 1% for both male and female models).

Introducing baseline scores from wave 9 in model 1B explained 25.9% and 26.9% of the variance for males and females respectively. Those with higher baseline scores, experienced less of a decline in wellbeing. Clogg test statistics (critical value 1.96) comparing parameter estimates between the two sexes show that the effect of this was stronger for women than for men. The difference in effect size however, although statistically significant, is small and does not offset the underlying result that women were affected more heavily than men (represented in these models by the large differences in the intercepts).

Model 1C shows the impact of introducing pandemic phenomena of loneliness and community cohesion into the estimates for well being. In this final model, for women, age, pre-existing health conditions, baseline and loneliness are associated with a decline in well being however age and underlying health conditions explain very little of the variance and have small effect sizes. The loneliness variable explains an additional 9.8% of variance (total R^2 of 36.7%) with a much larger effect size. For men the baseline and loneliness variables are significant. Introducing the loneliness variable explains an additional 7.2% of the variance (total R^2 of 33.1%). The difference in parameter estimates for the association between loneliness and the response variable between the sexes was not statistically significant (using a Clogg test).

Ethnicity and deprivation were not significant in the models for decline.

4.2 Modelling the bounce back

The model for the recovery included further variables reflecting ongoing loneliness, and the onset of any acute financial crisis, as well as a measure of income stability. Women recovered a mean score of 1.0 (std 3.3), men to a mean of 0.46 (std 2.5). Compared with the baseline figure, the mean score had increased by 0.23 (std 3.3) but there was no statistically significant difference between men and women in this increase, at the 95% confidence level. The coding for the response variable within this model is reversed for more simple interpretation—a positive value relates to a decrease in the GHQ caseness score.

Table 4 Model 2: parameter estimates for the wellbeing recovery

		Male	(std err)	Female	(std err)
Model 2A	Intercept	0.148	(0.163)	1.195*	(0.126)
	age	0.003	(0.003)	– 0.01*	(0.002)#
	eth_minority	– 0.056	(0.175)	– 0.375*	(0.135)
	imd_decile_2019	0.029	(0.016)	0.014	(0.012)
	health_condition	– 0.122	(0.097)	0.052	(0.074)
	R^2	0.2%		0.3%*	
Model 2B	Intercept	– 0.805*	(0.156)	– 0.702*	(0.117)
	age	0.009*	(0.003)	0.007*	(0.002)
	eth_minority	– 0.205	(0.157)	– 0.324*	(0.115)
	imd_decile_2019	0.039*	(0.014)	0.026*	(0.011)
	health_condition	– 0.265*	(0.088)	– 0.235*	(0.064)
	baseline_wellbeing	0.257*	(0.016)	0.343*	(0.011)#
	wellbeing_decline	0.475*	(0.016)	0.538*	(0.010)#
	R^2	19.4%*		27%*	
Model 2C	Intercept	– 0.509*	(0.236)	– 0.423*	(0.176)
	age	– 0.001	(0.003)	– 0.005*	(0.002)
	eth_minority	– 0.127	(0.155)	– 0.316*	(0.115)
	imd_decile_2019	0.02	(0.014)	0	(0.011)
	health_condition	– 0.15	(0.086)	– 0.114	(0.063)
	baseline_wellbeing	0.375*	(0.018)	0.46*	(0.013)#
	wellbeing_decline	0.56*	(0.016)	0.628*	(0.011)#
	community_cohesion	0.039*	(0.015)	0.053*	(0.011)
	always_lonely	– 0.397*	(0.029)	– 0.403*	(0.021)
	financial_crisis	– 0.925*	(0.479)	– 0.965*	(0.244)
	income_decrease	– 0.039	(0.116)	– 0.351*	(0.088)
	R^2	23.5%*		30.7%*	

*Indicates significant at the $p<0.05$ level. #indicates Clogg test statistic > critical value of 1.96

As for the decline, model A (Model 2A, Table 4) includes only variables related to sociodemographic characteristics. These models again described less than 1% of variance for males and females respectively.

The baseline figures introduced in model 2B increased the R^2 value to 19.4% and 27% for males and females, replicating the effect seen in the decline models. A higher baseline score from before the pandemic and a greater decline in the intial phase, were both predictive of a stronger recovery. Again their was a difference in the baseline parameter between the male and female models within women recovering more strongly for a given baseline score for both the pre-pandemic and the decline variables.

Model 2C introduces cohesion and loneliness as in the model for decline, but also includes variables which reflect the financial pressure of the lockdowns. The introduction of these pandemic factors explains a further 4.1% and 3.7% of variance for men and women respectively. Acute financial crisis was associated with a reduction in recovery for both males and females. Substantial changes in income over the period was associated with poorer recovery for women, but not for men. Although age and ethnicity were statistically significant in this model for females, the effect size is very small. Living in a cohesive community was significant for both sexes (and these parameter estimates were not statistically different between the male and female models).

The models indicate that the most important factor in the size of a person's 'bounce back' is in fact the size of the original decline. Loneliness and acute financial crisis were statistically significant for both men and women, age, ethnicity and reduced income was significant for women but not men.

5 Discussion

Times of adversity and extreme stressful events have been linked with increased risk for poor well-being [42, 43]. There has been much concern in the media about the mental health and wellbeing impact of the COVID-19 crisis on people who have undergone an unprecedented change and restriction to their lives. Our research here suggests that although the first wave was associated with an overall decline in wellbeing, the removal of lock down restrictions was also associated with a recovery.

The study set out to uncover differences in the extent of the decline in wellbeing and subsequent recovery. We predicted that there would be an association of deprivation and decline in wellbeing. The removal of services and support networks for those with long term health conditions was expected to cause a greater decline in wellbeing and a reduced ability to recover. We also considered whether there would be effects attributable to ethnicity and sex.

We expected wellbeing trajectories to differ along sex, ethnicity, deprivation and underlying health lines, and that some of these differences would be explained by the impact of stress (specifically financial crisis), the level of community support experienced (community cohesion) and the extent of social isolation experienced by respondents (measured by loneliness).

The models here do not show the expected differences between groups. For this sample, wellbeing declined, but then gradually improved over the course of the first wave, returning nearly to the baseline level by July. Wellbeing in this context can therefore be considered to be elastic, that is to say that although there appear to have been negative impacts on wellbeing at the beginning of the first lock down, these impacts were lessened over time as restrictions reduced demonstrating a bounce back effect and a capacity for rapid recovery.

This is consistent with a level of adaptation, and may indicate some implementation of specific coping strategies by the respondents within the data. Indeed, some participants may have experienced a degree of post traumatic growth [43–45] whereby the imposition of adversity results in an improvement in wellbeing as those faced with the stress, draw on strengthened personal and social systems to thrive despite the situation in which they find themselves.

Deprivation appeared to show no impact on changes in wellbeing. The sample was skewed towards the less deprived deciles and so this may be a non-response issue, with those suffering the greatest deprivation, least able to engage with the survey, through poor mental health, or simply through having the means to respond online. Deprivation was assigned to respondents at the LSOA level which is in itself problematic as each LSOA represents approximately 1,500 individuals and thus may be heterogeneous with respect of deprivation.

Deprivation can be considered to be a pre-existing vulnerability which increases a person's susceptibility to a disruption of any form and certainly deprivation could well be expected to have increased vulnerabilities to the social, economic and health impacts of the pandemic, particularly considering the evidence linking increased deprivation with poorer health outcomes [46]. However, the expected negative association of deprivation and health is not one that has been found universally in previous studies (e.g. [47–49]). The results of studies into health outcomes in deprived areas can sometimes be counter-intuitive and several investigations have shown that communities record better health outcomes than might be predicted from socio-demographic factors. These communities can be said to display 'health resilience' that is to say, they outperform expectations on certain measures.

No effect was detected here so it is possible that the expected social gradient in health has been cancelled out by additional resilience in the poorest communities. The social gradient implies that wealthier areas would experience less of a decline in well being but in fact many people in these communities were subjected to a level of stress to which they would be unaccustomed given their usual level of financial comfort and position of privilege in society. The threat of furlough, home working, home schooling and removal of a normal social life, may have been a sufficiently adverse effect on the better off that the mental health impact of the crisis has in fact been felt more equally than is usually the case for many other health measures. This observation may align with Holmes and Rahe [50] work on stress which proposes that life changes are the primary driver for reductions of wellbeing.

Women experienced a greater drop in wellbeing (a rise in the caseness score) than men, however at the end of the first wave there was no difference in the change in wellbeing between men and women. Self reported health is a combination of underlying health and reporting behaviour. Self reported mental health metrics are affected by misreporting, a potential impact of the continued stigma around mental health. Studying the same GHQ-12 questions from the Understanding Society survey and its predecessor the British Household Panel Survey from 1999 to 2016, Brown et al. [39] showed that this under reporting bias was greater for men. This may mean that the signal in these data showing a worse decline for women, is actually a factor of reporting bias. The baseline of the scores showed lower mental wellbeing for women than for men, the change was then greater for women than men, matched with a greater improvement. The uniformity of the elasticity across the sexes and the lack of lasting difference would tend to support a theory that the difference seen here can be attributed to reporting.

There was a low response rate amongst ethnic minority members of the panel with only half the expected number of respondents coming from an ethnic minority background of any type (approximately 10% from ethnic minorities in this sample, compared with 20% in the underlying survey panel). This necessitated the collapse of the detailed ethnicity variable to a binary ethnic minority/white measure. This is problematic because clearly people from different ethnic minority backgrounds are not homogeneous and may well have had experiences of the pandemic which varied by ethnicity for example due to the differing experiences of and relationships to family and community within different ethnic groups. The use of a binary variable also necessitates the categorisation of people with dual heritage into either "minority" or "white" and confounds British ethnic minority respondents with immigrant populations. Use of binary variables for ethnicity is problematic where the dominant research narrative considers the white perspective as central, and the ethnic minority perspective as "other". Ethnicity was significant in the recovery model for women (model 2), An ethnic minority background was associated with a smaller "bounce back". This may be because ethnic minority females suffered a smaller decline in wellbeing which was not detected in the modelling, or there maybe a resilience factors at play. However, the effect size and the overall contribution towards the explanation of variance small.

Age was significant for women in the decline of wellbeing and the recover but in both instances with a small effect size. Older people suffered a smaller decline in their wellbeing, and then a smaller recovery as the wave progressed. The mean age of respondents was skewed towards the older members of the panel. This may have reflected older people having more time on their hands relieved of their normal social lives and also perhaps the care burden for grandchildren, whereas younger adults were more likely to be juggling full time work from home whilst also caring for and schooling children. Poorer wellbeing in younger groups may also have contributed to non response.

Experiencing loneliness was predictive of a decrease in wellbeing in April for men and women and was a main contributor to the variance explanation in the model for wellbeing decline (Model 1C). Ongoing loneliness was statistically significant in the model for wellbeing recovery (Model 2C). Men and Women displayed the same effect. People who experienced continued loneliness using this measure, recovered less well as the pandemic progressed. There may be a stigma related to admitting that you are experiencing loneliness and so a bias in the response variable. The difference emerging between those who are lonely and those who are not is also indicative of the different ways in which people experienced the progressive loosening of restrictions. Some people opted to remain isolated, out of concern for their health, or because of shielding advice, whilst others made the most of new "freedoms". Many of the coping strategies and adaptation mechanism which mediate resilience to external stress are constituted through family mechanisms and social interactions and relationships. Green et al theorise that "Multilevel attachments" are protective against life's stresses [51]. For example, as Walsh et al observe families can adapt in times of crisis, and family relationships can mitigate against poor wellbeing [52]. Strength of the family and other social relationships can also therefore provide a path to adjusting to stressful situations and recovering from poor wellbeing. Similarly, Walsh et al write about the impact of belief systems and spirituality as a mediator for resilience [52]. During the pandemic, places of worship were closed and families were not able to be together. This measure of loneliness may well be reflecting this element of the restrictions and thus the framework of family resilience was disrupted by the pandemic and resulted in a reduction of wellbeing for those impacted through the removal of these important mechanisms.

Health inequalities follow a social gradient but in our final models for wellbeing decline (1C) and recovery (2C) deprivation was not associated with the response variable. The social gradient for health was not therefore replicated in these data when considering mental well being. This may be due to an overriding community effect which was present at the national level during the first wave. Many impacted directly by COVID-19 as a disease have suffered a devastating impact, through loss of their own physical health or bereavement. Indirect effects of the pandemic will take some time to uncover, but will include long term unemployment, and projected adverse outcomes in other health conditions as discussed in the introduction. These are likely to follow a social gradient but as the data used here were collected during the earliest stage of the crisis, the longer term impact of the pandemic's duration and severity will not have impacted upon the mood of those responding.

The financial impact of lockdown differed widely dependent on employment sector and to an extent caring responsibilities as school age children remained for the most part, in the home. For respondents in the sample, an acute financial crisis resulting in food bank use was predictive of a worse mental recovery and this is consistent with expectations around stress and mental health. However, for women, a negative change in income also predicted worse recovery. That this is different for men and women is of interest. The income variable is set at the household level so this may reflect a response which differs by gender to the same phenomenon. It may also reflect the unequal caring burden placed upon women and in fact be a example of increasing marginal returns. Women within the analysis were already suffering worse well being and a greater decline in the pandemic. The addition of reduced income may have thus been incrementally more stressful for them, given that they were, already suffering poorer wellbeing.

We expected that in communities where people are more likely to speak to each other and where respondents report having neighbours they can rely on for help, the negative impact of the pandemic would be mitigated. In the model for decline, the measure of community cohesion was not significant however in the recovery, this variable was associated with a stronger recovery for both men and women. This perhaps may be indicative of the physical reality of the lockdown, during the lockdown phase access to the social capital that community cohesion represents would be constrained and therefore its availability for mitigation may be limited. Once lockdown restrictions were eased then access to that social capital may also be released. We may also speculate that people's experience was influenced by the narrative of how they should react and process the tragedy around them. There were many communities which strengthened over this time with neighbours helping each other and local benefit groups delivering supplies to those isolating, shielded individuals and the elderly. Not for the first time in a British tragedy, media and politicians made reference to the "Blitz Spirit" and the rhetoric of survival, courage, fortitude and being 'in this together', using collective actions such as the "Clap for Carers" to further emphasise a message of solidarity. This cultural environment of resilience, may have been a universal protective factor at a national level, facilitating the observed elasticity of mood, moreover at a local level, the removal of traffic from streets, the necessity of restricting contact to only those who you saw on a daily permitted errand or exercise session may have emphasised the importance of living in a cohesive community for mental health, reflected here in the model for recover. Linkov and Trump write about communication as a key factor in resilience ([53], p 109). Effective communication from policy makers and health care systems whilst under stress is critical in encouraging behaviour from the population which does not lead to a breakdown of those mechanisms brought in to reduce risks - in this case, COVID-19 lock down restrictions and guidance on preventing disease transmission. So the outcome observed here is consistent with the relatively good communication during the early pandemic and consequential widespread compliance with pandemic restrictions observed in the first lock down.

The ability of a person to return to normal levels of well being after a negative experience is also considered within the adaptation and coping literatures. The adaptation framework proposes that adverse experience may result in an initial reduction in wellbeing, but over time the person affected can adapt and subjective measures of wellbeing will consequently return to prior levels [54]. Coping theory describes the development of behaviours that aim to reduce stress (although this framework does not presume that any coping mechanism will in fact be successful whereas the concept of adaptation is deemed to be inherently positive) [55]. We acknowledge that adaptation is plausible explanation of the findings, however we prefer an explanation in terms of 'recovery'. Given the real changes in situation as the pandemic progressed, with a lockdown followed by a relaxation which map on to the observed changes, we consider recovery as a more parsimonious theoretical framework for the phenomenon of improving wellbeing scores.

6 Strengths and limitations

The sample does not include care home residents and non-response was greater amongst younger people and people from ethnic minority backgrounds. The finding of elasticity cannot therefore be generalised to the whole population. Poor mental well being may well have contributed to the non response and therefore those who were most adversely affected by the pandemic, may have been structurally excluded from the data.

The research uses only those responses submitted online and so this may also exclude certain groups. For many families during the school closures, devices were shared between parents working from home, and children completing online learning. This may have created an additional barrier to completion. For many working from home, even in the absence of competition for access to an appropriate device and with a stable home internet connection, screen fatigue from long hours spent working remotely may have reduced the response rate amongst certain types of workers. Those who do not have an internet connection through choice, or through a lack of means are also excluded here. We have no direct data on these issues but recent work by Schaurer and Weiss [56] did find evidence of selection bias in online survey data collected during the pandemic and so this could have had an impact on our results.

In care homes, many residents live with dementia. To reduce infection risk in this vulnerable population, many in homes and in the community were confined to quarters as quarantine measures took place and there is evidence that this has hastened an irreversible decline in speech, social skills, functional skills and memory [57]. These people are excluded from the analysis and as such the finding that people "bounced back" as restrictions were lifted may not to apply in these contexts.

The remains a stigma around mental health and as such a form of social desirability bias exists within mental health self reporting. This may have impacted on the reliability of the measure used here and there may be some under-reporting within the data. Under-reporting behaviour has been shown to differ between groups and this may therefore have masked signals within the models.

More detailed and targeted data collection is needed to understand the experience of people from ethnic minority backgrounds. The increased non response rate in these data suggest some kind of systematic bias during the COVID-19 data collection. No signal has been found to suggest a differing experience of mental health during the pandemic but this may simply be due to missing responses.

The dataset is rich with additional variables which could have been included, for example the number of children in a household and patterns of domestic work. They are not included in this study however the consideration of the impacts of these and other variables of interest in addition to those considered here is an interesting areas for future research.

We note that recent related work has been carried out by Pierce et al [58]. They also considered five waves of Understanding Society, but used latent class analysis to classify respondents according to GHQ trajectories and then used demographics to predict group membership. They did find some factors that were not significant in our study were predictive of class membership in their analysis. This existing work complements the work we have done here providing a perspective about types of multi point trajectories. However the the key findings of the current paper that the biggest predictor of the initial dip was the baseline score but this was inverted against expectation, (with loneliness being the second biggest predictor) are derived from our focus on specific transitions. Both papers provide useful insights from different perspectives.

7 Conclusion

The challenges of social disruption, financial insecurity and changes to our routines resulting from the pandemic might be expected to be long lived and the structures and process of our normal social existence are impacted by contextual risk and pre-existing vulnerabilities [46].

When faced with the unprecedented events of the global pandemic, government sought to implement a risk management strategy, aiming to reduce and mitigate risks from the spread of disease. These measures were restrictive and represented a change to our everyday existence, as well as having widespread economic impact and thus were susceptible to unintended consequences such as a fall in population well being, or a consequent crisis in accessing healthcare. As we continue to experience COVID-19 and its transition to an endemic disease, as a society we are shifting to a resilience model where the systems and individuals are prepared and efforts to control the disease are concentrated on promoting a robust health and social system that reduces the disruption to the economy and to our normal social existence.

There have been clear losses in both the immediate and the long term for many of us. Our social skills, working practices and emotional wellbeing have been challenged by the emergence of this novel disease. These data show however, that in the first wave, these harms have to an extent been mitigated at the population level, and suggest that there has been a return to 'normality'.

This analysis of the COVID-19 survey datasets from the first wave of global pandemic in 2020, show interesting and counterintuitive results. We found no evidence of a social gradient in wellbeing related to the pandemic. In fact, although mental health and wellbeing certainly suffered during the lock down, wellbeing was shown to be highly elastic in this period indicating a national level of resilience which cut across the usually observed health inequalities.

Further research is needed to target those groups who may be excluded from this dataset, but the data would suggest that national efforts to "raise our spirits" may in fact in this context have been useful and effective. This may lend weight to arguments for other nationally led initiatives to improve mood in times of crisis, for example additional national holidays. Critically, over the time period that the COVID-19 datasets were collected a recovery took place. That duration coincided with the first national lock down and the eventual removal of most restrictions for most places in the UK. It would therefore follow that the best policy to improve the nation's mental well being and to protect vulnerable people from the worst mental illness, is to pursue policies which suppress the pandemic such that the domestic economy can in the widest possible spheres, reopen and people's pre-pandemic work and social existences can resume.

Author contributions JM completed the analysis and first draft of the paper. ME input into the construction of the analysis and commented and added to drafts of the paper. Both the authors read and approved the final manuscript.

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Data availability The data used in this study were extracted from the Understanding Society survey dataset which may be downloaded from the UK data archive.

Code availability Not applicable.

Declarations

Ethics approval and consent to participate No ethics approval was needed as the data were deemed to be anonymised secondary data.

Consent for publication Not applicable.

Competing interests The authors have no conflicts of interest to declare that are relevant to the content of this article.

Appendix A

The questions in the General Health Questionnaire module of the Understanding Society participants questionnaire are reproduced here for clarity [7]. Participants are instructed that the questions are about how they have been feeling over the last few weeks.

scghqa [GHQ: concentration]

Have you recently been able to concentrate on whatever you're doing?

1. Better than usual
2. Same as usual
3. Less than usual
4. Much less than usual

scghqb [GHQ: loss of sleep]

Have you recently lost much sleep over worry?

1. Not at all
2. No more than usual
3. Rather more than usual
4. Much more than usual

scghqc [GHQ: playing a useful role]

Have you recently felt that you were playing a useful part in things?

1. More so than usual
2. Same as usual
3. Less so than usual
4. Much less than usual

scghqd [GHQ: capable of making decisions]

Have you recently felt capable of making decisions about things?

1. More so than usual
2. Same as usual
3. Less so than usual
4. Much less capable

scghqe [GHQ: constantly under strain]
Have you recently felt constantly under strain?

1. Not at all
2. No more than usual
3. Rather more than usual
4. Much more than usual

scghqf [GHQ: problem overcoming difficulties]
Have you recently felt you couldn't overcome your difficulties?

1. Not at all
2. No more than usual
3. Rather more than usual
4. Much more than usual

scghqg [GHQ: enjoy day-to-day activities]
Have you recently been able to enjoy your normal day-to-day activities?

1. More so than usual
2. Same as usual
3. Less so than usual
4. Much less than usual

scghqh [GHQ: ability to face problems]
Have you recently been able to face up to problems?

1. More so than usual
2. Same as usual
3. Less able than usual
4. Much less able

scghqi [GHQ: unhappy or depressed]
Have you recently been feeling unhappy or depressed?

1. Not at all
2. No more than usual
3. Rather more than usual
4. Much more than usual

scghqj [GHQ: losing confidence]
Have you recently been losing confidence in yourself?

1. Not at all
2. No more than usual
3. Rather more than usual
4. Much more than usual

scghqk [GHQ: believe worthless]
Have you recently been thinking of yourself as a worthless person?

1. Not at all
2. No more than usual

3. Rather more than usual
4. Much more than usual

scghql [GHQ: general happiness]
Have you recently been feeling reasonably happy, all things considered?

1. More so than usual
2. About the same as usual
3. Less so than usual
4. Much less than usual

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Chapter 6

Paper 3: Length of Stay and Survival of Hospitalised COVID-19 Patients in Greater Manchester

Murphy, J., Elliot, M., Ravindrarajah, R. and Whittaker, W. *Length of Stay and Survival of Hospitalised COVID-19 Patients in Greater Manchester.*

This paper has been presented to the Greater Manchester Health and Social Care Partnership COVID-19 response cells and is currently undergoing peer review for publication.

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Deprivation effects on length of stay and survival of hospitalised COVID-19 patients in Greater Manchester

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Abstract

Introduction
The World Health Organisation declared a global pandemic in March 2020. The impact of COVID-19 has not been felt equally by all regions and sections of society. The extent to which regional, socio-demographic and deprivation factors have adversely impacted on outcomes is of concern to those looking to 'level-up' and decrease widening health inequalities.

Objectives
In this paper we investigate the impact of deprivation on the outcomes for hospitalised COVID-19 patients in Greater Manchester during the first wave of the pandemic in the UK, controlling for proven risk factors from elsewhere in the literature.

Methods
We fitted Negative Binomial and logistic regression models to NHS administrative data to investigate death outcomes and length of stay for surviving patients in a sample of adult patients admitted within Greater Manchester (N= 10,372, spell admission start dates from 30/12/2019 to 02/01/2021 inclusive).

Results
Deprivation was associated with death risk for hospitalised patients (-0.0224, [-0.0368,-0.0062]), but not for length of stay. Male sex, co-morbidities and older age was associated with higher death risk. Male sex and co-morbidities were associated with increased length of stay. Black and other ethnicities stayed longer in hospital than White and Asian patients. Period effects were detected in both models with death risk reducing over time, but the length of stay increasing.

Conclusion
Deprivation is important for death risk, however the picture is unclear and the results of this analysis suggest that the reported excess mortality and deprivation linked reductions in life expectancy, may have occurred in the community, rather than in acute settings.

Keywords
COVID-19; inequality; administrative data; deprivation

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1. Introduction

Successive reviews of health inequality in the UK over the past forty years [5, 1, 15, 17] have revealed a widening gap in health outcomes between the rich and the poor. Increasing deprivation is typically associated with poorer health outcomes [13, 20, 21, 23]. The Marmot strategic review of Health Inequalities in England conducted in 2010 concluded that the social gradient in health identified first by Black [5], and subsequently by Acheson [1], persists in the UK and that reducing health inequalities is a matter of fairness and social justice. The report showed that people in the poorest areas on average had a life expectancy seven years below those living in the richest areas and for healthy life expectancy, that is to say the proportion of life lived without disability, the gap was seventeen years.

Since the first Marmot Review, progress in addressing health inequalities in England has been, at best, slow. In a follow up report in 2020, Marmot et al. showed both that improvements in life expectancy have stalled and that the social gradient of health has become even steeper. In some groups life expectancy has actually decreased in the past decade and the largest decreases have been in the most deprived areas, with a spatial element highlighting that deprived communities in the North have suffered disproportionately compared with wealthy areas of London. The gradient in healthy life expectancy has also worsened, with the most deprived areas experiencing more of their already shorter lives living with ill health [17].

Marmot and Allen [18] cite this lack of progress as a contributing factor to the poor state of health of the population of England immediately even before the declaration of a global pandemic in March 2020 [28]. Against this backdrop of growing health inequality, the burden of COVID-19 disease and mortality has also not been felt equally across the UK. Kontopantelis et al. [14] reported geographical and social patterns in excess mortality during the first wave of COVID-19 in the UK (February-July 2020) with excess mortality varying from 1 per 100,000 of population in Wales, to 26 in 100,000 in the West Midlands. In Greater Manchester, Marmot et al. [16] reported that COVID-19 related mortality was 25% higher than that for England as a whole. Life expectancy in the city region is lower than the national average for England [10] and indeed this spatial inequality can be found within Greater Manchester itself [22]. For men, the difference in life expectancy between the most and least affluent wards is 18 years, and for women 13 years. This social gradient of life expectancy is mirrored in mortality from COVID-19 with Marmot et al. [16] reporting a stronger association between deprivation and mortality in Greater Manchester than other areas in England.

2. Background

2.1 Risk factors for severe and fatal COVID-19 infection

Evidence has emerged that there are a number of risk factors for severe and fatal COVID-19 infection. Older age groups are more at risk of hospitalisation and death, and men are more likely to be at an increased risk of severe infection [30, 12].
Drefahl et al. [8] linked recorded COVID-19 deaths in Sweden up to May 2020 to high quality personal records. Using individual level survival analysis the authors showed that being male, having lower income and lower education levels all predict higher risk of death from COVID-19 even after controlling for the others. They conclude that the virus was, at that time, exerting an unequal burden on the most disadvantaged.

Williamson et al. [29] conducted a large cohort study of COVID-19 related deaths in England using primary care data (N = 17,278,392 patient records, N = 10,926 deaths). The authors found that male sex, greater age and deprivation to be associated with increased mortality. Underlying health conditions (diabetes, asthma and others) were also linked with increased mortality as was ethnicity, with black and South Asian people more likely to die. The study used only records from one particular provider of general practice electronic health record software and was conducted earlier in the pandemic. Period effects were not examined and there was a high level of missingness in the ethnicity characteristics of patients included (26%). The analysis did not include any measure of place.
Air pollution and COVID-19 have been linked in England at the regional level [25]. Controlling for age, population density and income, the authors showed positive association between the concentration of air pollutants (specifically nitrous oxides) and COVID-19 mortality. The study also demonstrated that PM2.5 particulates were linked with increased case numbers in areas of higher concentrations.

2.2 Length of Stay

Evidence on the predictors of length of stay in hospital of COVID19 patients is mixed. Shryane et al. [24] investigated the length of stay of patients admitted to intensive care (ICU) between March and May 2020 using data from the COVID-19 hospital surveillance system (CHESS) in England. Changes in admission policy were found to be confounders of clinical knowledge of the dis- ease in this early stage of the pandemic and the earliest admitted patients spent significantly longer in ICU than those admitted after April. Sex and ethnicity were not found to be related to the length of stay and there was a non mono- tonic association with age (noting that this study also included non survivors which will have impacted the length of stay for older patients given their higher mortality risk). Vekaria et al. [27] used four variables to predict length of stay for hospital admissions in a hospital in Manchester using different methods to model path- ways to outcomes (discharge/death). In addition to sex and age, the authors found that the stage of the pandemic was predictive of the total length of stay, and that patients admitted to ICU who survive, have longer hospital stays.

Female sex, and kidney or liver disease were associated with longer lengths of stay in a retrospective cohort analysis of patients with COVID-19 in Hefei, China, in the earlier stage of the pandemic, excluding patients who died [11].

2.3 Research Questions and Motivation for this Research

Given the literature cited above linking deprivation with poorer health out- comes, the documented excess mortality experienced by the population of Greater Manchester and the indications of within Manchester variation, there is a need for further research to explore the social gradient of COVID-19 health outcomes within GM and whether the nationally researched picture of the determinants of COVID-19 outcomes are relevant to the Greater Manchester context. The authors secured access to administrative hospital data for the whole of

the GM population covering the course of the pandemic which provides us with a valuable opportunity to study this issue in depth. In this paper, we examine the effects of risk factors on the outcomes of hospitalised COVID-19 patients in Greater Manchester to assist in service planning as we transition to the disease becoming endemic, and to inform policy targeted at ’levelling up’ between the most and least disadvantaged communities.

We address the following research questions:

1. Does deprivation predict the risk of death from COVID-19 in Greater Manchester hospitals.
2. Does deprivation predict the length of stay for severe cases of COVID-19 in Greater Manchester.

To operationalise these questions, we use NHS administrative data to investigate severity of disease and death for patients hospitalised with COVID-19 in the first wave of the pandemic in Greater Manchester.

We hypothesise that patients from more deprived areas who survived hospitalisation were more likely to spend longer in hospital, and that the risk of death would be associated with deprivation and other demographic factors. In section 3 we introduce the dataset used and the methods applied. Results are presented in 4. Section 5 contains the discussion of findings, followed by an appraisal of the strengths and weaknesses of the work in section 6. We conclude in section 7.

3. Data and Methods

3.1. Secondary Uses Service Data Repository

The data are drawn from the Secondary Uses Service (SUS), a single repository for English healthcare data. The information collected for SUS is used by commissioners and providers of NHS care for non-clinical purposes including healthcare planning, service commissioning, tariff payment and policy development. Data Access was facilitated through the Greater Manchester Health and Social Care Partnership, the devolved body responsible for health and social care in the ten boroughs of the GM city region. These data contain records of all hospital spells. Each hospital spell is built from tables of hospital episodes. A single spell may relate to multiple hospital episodes for the same patient.

The data contain only completed spells and so any patients admitted during the study time frame who remained in hospital past 24/06/2021 (the end of the data made available for this work) are excluded. The inclusion criteria for the sample were patients who were:

1. hospitalised within the Greater Manchester region,
2. aged 18 or over on admission, and
3. registered at a GP surgery within Greater Manchester.

We selected only those episodes for which the primary diagnosis code is related to COVID-19, that is to say the primary diagnosis for the episode is either U071 or U072 in the ICD coding system (suspected or confirmed COVID- 19 illness). Where a unique patient ID re-occurred, the latest admission was selected and earlier admissions excluded. The final dataset included N = 10,372 hospital spells. The dataset creation path is shown in Figure 1. Descriptive statistics for the final sample are presented in section 3.5. When a patient was readmitted for a further spell within the dataset time- frame, we selected only the latest spell relating to that unique ID. From this set of 10,732 spells, 3,268 resulted in a death. Of the surviving 7.104 patients, we are unable to determine if there were subsequent admissions for these patients during which they died, or if they died outside of hospital subsequent to their discharge from a spell within the data. This is a limitation of the dataset - it contains only finished spells and so patients who are still in hospital who were admitted within the timeframe, do not appear in this analysis.

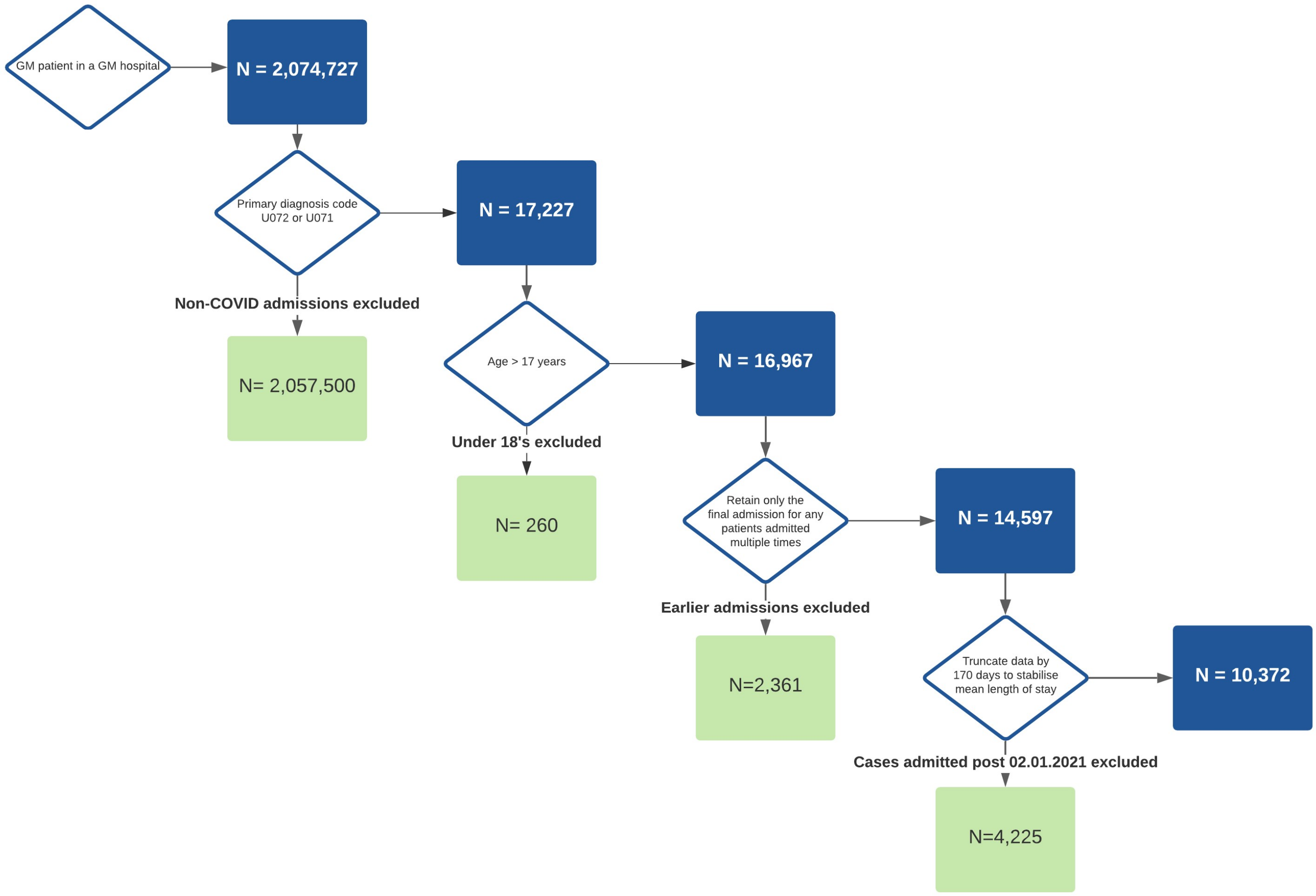
Length of stay (LOS) is computed using a simple date difference between the admission and discharge dates for the spell.

Survival is determined from the discharge destination field within the SUS data. Patients discharged into any kind of residential or home care are counted as survived, and this date of discharge is considered to be the end of the hospital stay. We did not investigate subsequent deaths of patients hospitalised with COVID-19 as we do not have data on deaths outwith the GMHSCP acute settings.

3.2. Variables used in the analysis

In national level studies in the UK and elsewhere, age, sex and the week of admission (stage of the pandemic) have been shown to be important for length of stay [24, 27, 11]. Deprivation has been associated with increased COVID-19 mortality, as has ethnicity, age, underlying health conditions and sex [29, 8, 30, 12]. Air quality has been associated with increased mortality [25]. Marmot et al. [16] write that there are area differences in mortality in Greater Manchester and so for this reason, local authorities are included in the model for death. The variables used in the analysis have been selected based on existing literature and are detailed in Table 1. We compared Variance Inflation Factors and Pearson’s Correlation for all variables and did not find any multi-colinearity (defined as no Pearson’s correlation of greater than 0.7 and no Variance Inflation Factor above 2).

Figure 1: Dataset sample selection



For length of stay, we included the a dummy measure for whether the patient died during the spell (the ’death’ variable) and all cases in the data to account for selection bias in the model. Death in these data is in fact all-cause mortality as we do not have the death certificates from which to select only patients for whom the cause of death is recorded as COVID-19.

The length of stay is time dependent. For admissions early in the period, there were very low numbers with some long lengths of stay. The length of stay then became more stable as the number of cases increased (see Figure 3.)

3.5. Descriptive Statistics and Missing Data

Low numbers necessitated the collapse of ethnic coding into four broad categories. Men outnumber women in the data (N = 2,835 males, N = 2,226 females) across all ethnic groups as shown in Table 2. Where ethnicity is not missing (N = 4,676), 83% of patients were white (see figure 4).

The mean age for men (68.1 years [std 16]) is lower than for women (69.1 years [std 18]). 33.8% of men died, compared with 28.4% of women (see Figure 5). Of the 10,372 unique patients, 9,560 have only one recorded hospital spell in the dataset. 751 patients have two spells, and 61 patients have three or more spells.

The death rate for spells which were the last in a series of more than one admission for a COVID-19 infection was lower (0.26) than for first admission spells (0.32). 6,174 (57%) of the spells concluded in period 3 (see Table 3). The mean length of stay for was 10.9 days (std 14.5).

The distribution of lengths of stay is shown in Figure 6 where 29 patients with stays over 100 days are removed for clarity; the maximum length of stay within the data is 321 days. This distribution includes the length of stay for patients who died in hospital.

Table 1: variables in the analysis

Variable	Mean	Std	Missing	Notes
Length of Stay (LOS)	10.9	14.5	0	Difference between the date of admission and the date of discharge, measured in whole days. Descriptive statistics are given for patients who survived only, N = 4,350. Source: SUS.
Died	0.32	-	0	Binary variable based on mode of discharge. 1 = died, 0 = survived. Source: SUS.
Deprivation	3.8	2.8	0	Index of Multiple Deprivation (IMD) decile for the respondent's LSOA as per registered address. A higher decile indicates lower deprivation. Source: English Indices of Multiple Deprivation [19].
Age	68.6	16.8	0	Age in years at the date of admission. Source: SUS.
Sex	0.44	-	0	Binary variable. 0 = Male, 1 = Female. Source: SUS.
Ethnicity	-	-	471	Ethnicity variable collapsed to four categories (White, Black, Asian, Other) due to small numbers. Source: SUS.
Home air quality	0.04	2.61	0	Index constructed by summing the standardised mean annual N O2, SO2 and P M10 scores in µgm3 for each LSOA. Source: Air quality domains of the Access to Healthy Assets and Hazards Index [7].
Hospital site air quality	0.71	2.86	0	As for Home air quality, but based on the site of the hospital episode. Source: air quality domains of the Access to Healthy Assets and Hazards Index [7].
Co-morbidity	2.91	0.73	0	The natural log of the count of diagnoses is used here as a proxy for co-morbidity based on the assumption that patients with higher diagnoses counts are likely to be those with greater co-morbities. The log of the count is used in this analysis. Source: SUS.
Timing of admission	-	-	0	Period 1 (reference) relates to all spells completed before 14/04/2020. Period 2 relates to all spells completed after 14/04/2020 but before 16/06/2020. Period 3 relates to spells completed after 16 June 2020.
Multiple admission	-	-	0	Binary variable to indicate if this is a re-admission for COVID-19. Spells where patients have been subsequently readmitted within the data have been removed. 1 = this is the final admission of more than one admissions for this patient within the data, 0 = one admission only. Source: SUS.
Local Authority	-	-	0	Local authority name (coded as dummy variables), included in the model for death only. Source: SUS.

Figure 2: Length of stay by dataset size

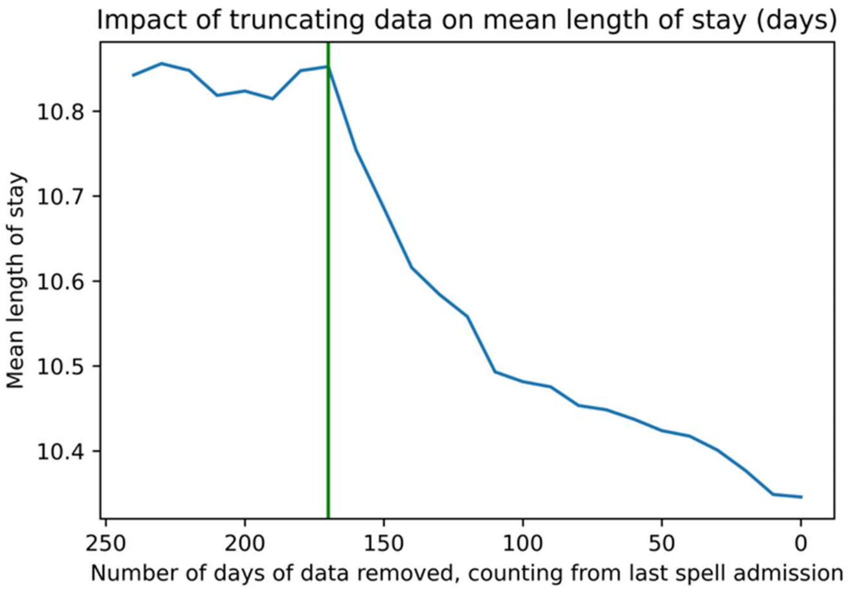


Figure 3: Length of stay by admission date

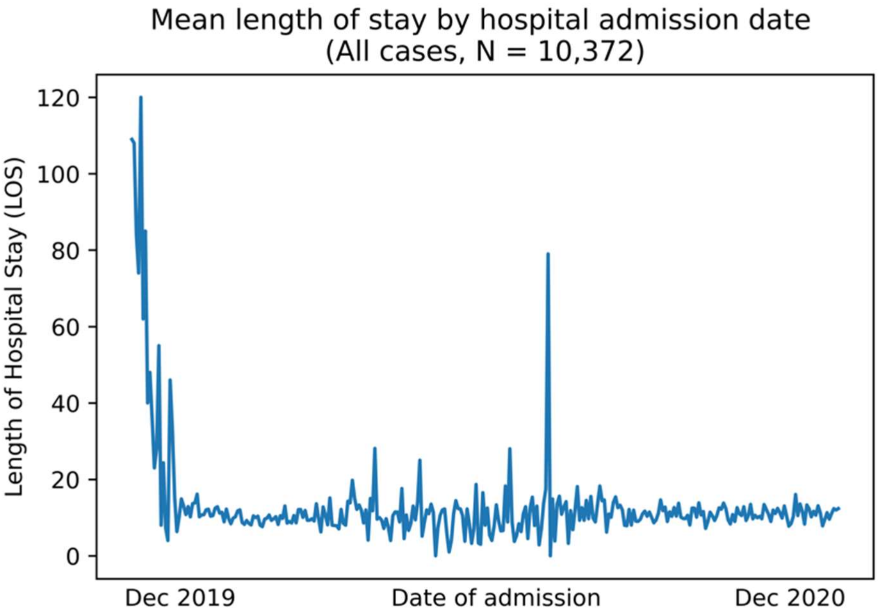


Figure 4: Ethnicity breakdown by sex, N = 10,372 total cases, N = 9,691 with valid responses for ethnicity

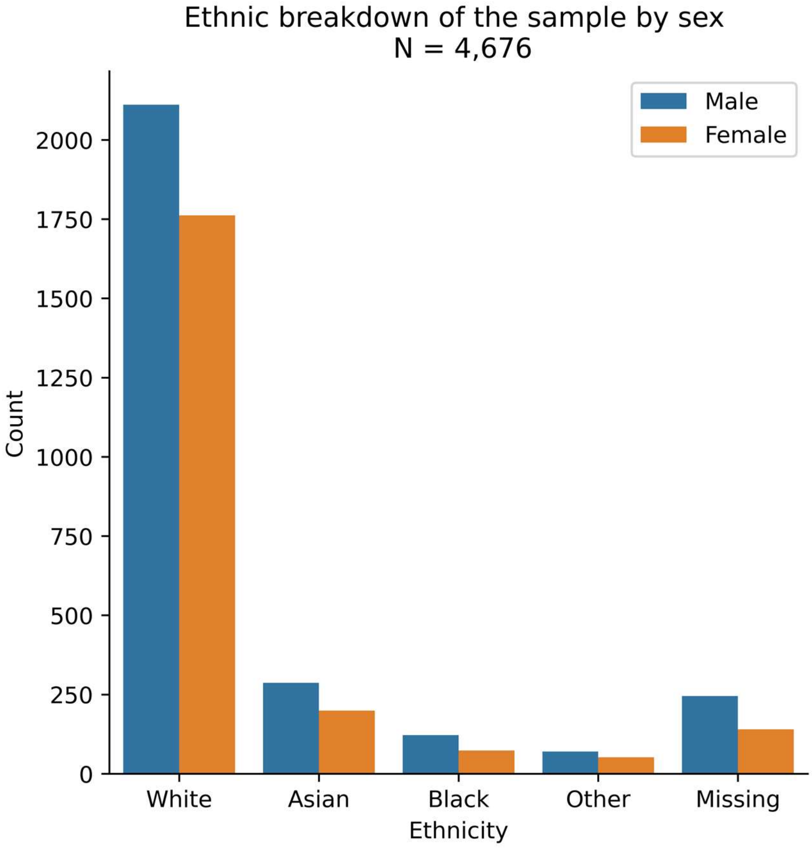


Figure 5: Deaths by sex, N = 1-,372

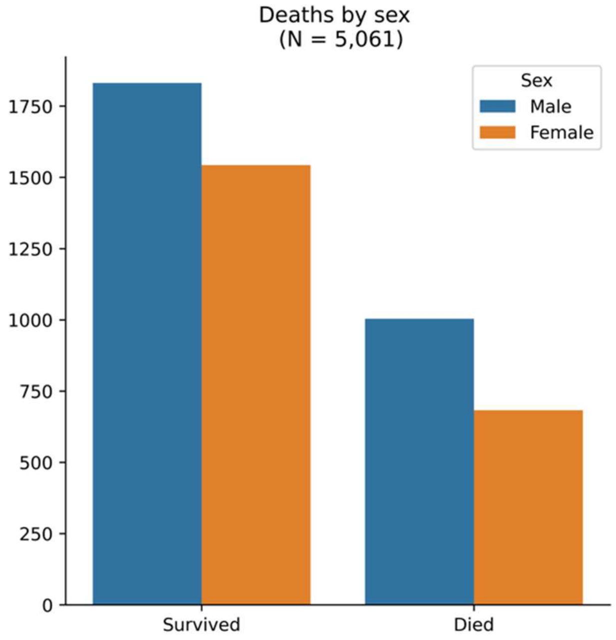


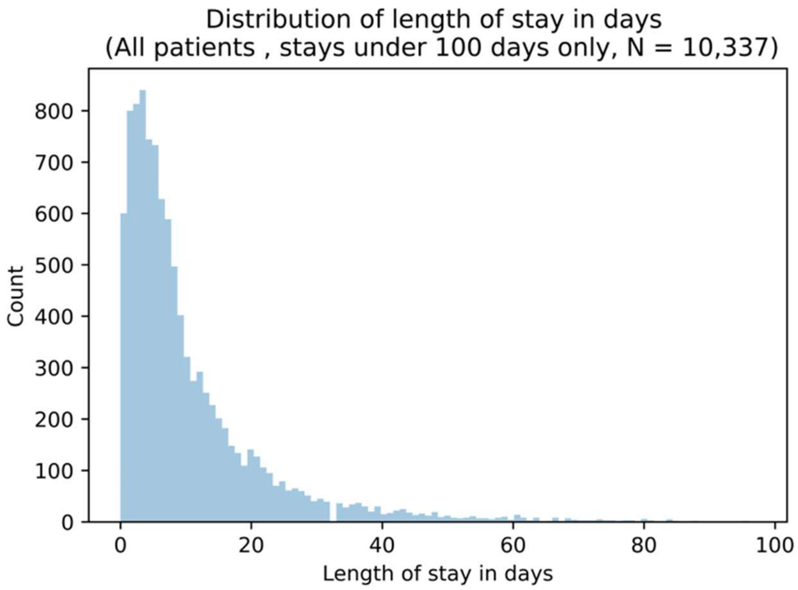
Table 2: Sex by ethnicity, N = 10,372

Sex	White	Asian	Black	Other	Missing
Female	3,570	470	137	93	247
Male	4,397	679	203	142	434
Total	7,967	1,149	340	235	681

Table 3: Date of spell conclusion

Date of spell conclusion	Period	Number of spells
Before 14/04/2020	1	1,547
Between 14/04/2020 and 16/06/2020	2	2,651
After 16/06/2020	3	6,174

Figure 6: Distribution of length of stay in days



4. Results

4.1. Models

Table 5 shows the results of the logistic model for survival.

Shryane et al. [24] identified a non-monotonic relationship between length of stay in the Intensive Care Unit and age. Using the same age categories, the same effect does not appear to be present when considering total length of stay for survivors of a hospital spell here. (see Table 4). Age is associated with increased likelihood of death. We tested age categories as dummy variables to look for non-monotonic relationships and found none. The parameter estimates of the model show that increased co-morbidity, age and male sex are associated with increased likelihood of dying. Spells ending in period 1 were more likely to result in death than 2 and 3.

Residing in a higher IMD decile (less deprived) was associated with a lower risk of death. Spells which were re-admissions for a COVID-19 infection, were less likely to result in death.

Air quality at either the home or provider site was not significant in the model for survival, nor were the ethnicity dummy variables

Model 1A (in Table 6) shows the impact of including local authorities as dummies within the model. Living in Bury, Wigan and Tameside was associated with increased death risk on hospitalisation compared with the reference category Manchester, the most deprived area. The measure of deprivation is significant; residing in a higher centile (less deprived area) is associated with decreased death risk.

The AIC value for model 1A is marginally lower than for Model 1. Other parameter estimates are not sensitive to the inclusion of the local authority and so we determine that there is evidence for place based effects even after controlling for deprivation.

Table 7 shows parameter estimates for the negative binomial regression model for length of stay in hospital, considering all patients (model 2). Given the results of model 1 and 1A we tested the inclusion of local authority within the analysis. Inclusion of local authority de-stabilised the model estimates and no clear pattern of association emerges from their inclusion with very small effect sizes for any which do meet the significance criteria. We have therefore excluded these variables from this part of the analysis.

Table 4: Length of stay by age category, survivors.

Age	Mean	Std	Count
Under 50	7.0	12.6	1,443
50-64	10.3	19.1	1,948
65-75	12.2	17.4	1,327
75+	13.6	13.0	2,386

Table 5: Model 1: Logistic regression model for survival. N = 10,372. * indicates significant at the $p < 0.05$ level. AIC: 11,188, pseudo $R^2 = 0.14$

Variable name	Coef.		Std.Error	[0.025	0.975]
intercept	-5.4346	*	0.1807	-5.7887	-5.0805
multiple admission	-0.2877	*	0.0883	-0.1147	-0.4607
sex	-0.3947	*	0.0472	-0.4872	-0.3022
age	0.0551	*	0.0018	0.0516	0.0587
NumDiag_Ln	0.3936	*	0.0357	0.3237	0.4635
imd_dec_2019	-0.0224	*	0.0082	-0.0386	-0.0062
period2	-0.5631	*	0.074	-0.708	-0.4181
period3	-0.5889	*	0.0657	-0.7177	-0.4601

Table 6: Model 1A : Logistic regression model for survival including local authority names, N= 10,372. * indicates significance at the $p < 0.05$ level. AIC: 11,139, pseudo $R^2 = 0.141$

Variable name	Coef.		Std.Error	[0.025	0.975]
intercept	-5.5257	*	0.1864	-5.891	-5.1604
Bolton	0.1398		0.0964	-0.0491	0.3286
Trafford	-0.1221		0.1149	-0.3472	0.103
Wigan	0.4097	*	0.0891	0.2351	0.5843
Salford	-0.0998		0.1029	-0.3015	0.1018
Tameside	0.2683	*	0.0948	0.0825	0.4541
Oldham	0.0734		0.0982	-0.1191	0.2659
Stockport	-0.1783		0.1029	-0.38	0.0233
Rochdale	0.1954		0.1009	-0.0024	0.3932
Bury	0.2677	*	0.11	0.0521	0.4832
multiple_admission	0.2932	*	0.0888	0.1192	0.4672
sex	-0.3985	*	0.0474	-0.4914	-0.3056
age	0.055	*	0.0018	0.0514	0.0587
NumDiag_Ln	0.3951	*	0.0365	0.3236	0.4667
imd_dec_2019	-0.0194	*	0.0092	-0.0375	-0.0012
period2	-0.5898	*	0.0746	-0.736	-0.4436
period3	-0.6291	*	0.0662	-0.7589	-0.4994

The key findings were:

- The death outcome is included to account for selection bias.
- Age in single years is significant in this model, older patients have longer spells in hospital. Based on prior work in the area [24] we also tested age bands for a non-monotonic association with the length of stay (Under 50, aged 50-64, aged 65-74 and aged 75 and over) and found none.
- The length of stay was longer for patients in period 2 than period 1, but not longer again for those admitted during period 3.
- Being a member of some ethnic groups was associated with longer lengths of stay, Black and Other ethnic groups experienced longer lengths of stay compared with their White and Asian heritage counterparts. However, being of Asian heritage was not associated with longer lengths of stay compared with white ethnicity patients however[1].
- Co-morbidity was predictive of longer spell length.
- Deprivation, home air quality, provider site air quality and multiple admission were not associated with length of stay. We tested for non-monotonic effects in deprivation by including dummy variables for deprivation quintile but this also did not yield significant results.
- Provider site air quality was associated with longer stays where the index measure indicates poorer average air quality.

Sensitivity to model selection was tested by fitting Ordinary Least Squares and Poisson[2] models to the data. The variables identified as significant within Model 2 remained significant in the alternative approaches.

Table 7: Model 2: Negative binomial regression model for length of hospital stay for all patients. N = 9,691. * indicates significant at the $p < 0.05$ level. α = 0.79

Variable name	Coef.		Std.Error.	[0.025	0.975]
Intercept	-0.5668	*	0.057	-0.678	-0.455
died	-0.1504	*	0.022	-0.193	-0.108
sex	-0.1273	*	0.019	-0.165	-0.09
age	0.0014	*	0.001	5.43E-05	0.003
NumDiag_Ln	0.7914	*	0.014	0.764	0.819
period2	0.5106	*	0.032	0.448	0.573
period3	0.5331	*	0.029	0.477	0.589
Asian	-0.0347		0.032	-0.097	0.028
Black	0.1706	*	0.054	0.065	0.276
Other	0.3109	*	0.064	0.185	0.437

Table 8: Model 3: Ordinary least squares model for death rate in hospitalised patients at the Local Authority aggregate level. N = 10 authorities. * indicates significant at the $p < 0.05$ level. $R^2 = 0.642$

Variable name	Coef.		Std.Error	[0.025	0.975]
Intercept	-0.4687		0.234	-1.022	0.085
imd_dec_mean	-0.0389	*	0.013	-0.07	-0.008
mean_ages_LA	-0.0247	*	0.007	0.008	0.041

Local authorities with a higher mean IMD decile of the constituent LSOAs (i.e. composed of relatively less deprived geographical units in higher deciles) experienced a lower death rate for hospitalised patients when controlling for the mean age of residents. The proportion of resident males and ethnic make up were not significant in this model. We used the same approach to modelling death rates at the MSOA level but parameter estimates were unstable using this smaller geographical unit.

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[1] For cases where ethnicity was missing, we excluded the case from the analysis reducing the number of valid cases to N=9,691 (missing Ethnicity variable = 861, 8.0%).

[2] We computed the likelihood ratio test statistic to compare Poisson and Negative Binomial models and confirmed that correcting for dispersion by using the Negative Binomial case gave a better fit to the data at the 0.001% confidence level.

5. Discussion

Our study suggests that patients who were female in Greater Manchester were at lower mortality risk and had shorter hospital stays when infected with COVID-19. Age was also another key risk factor with older age groups more likely to die from their COVID-19 infection.

The change in treatment protocols for COVID-19 was measured here by a marker for discharge or death date. In both models, period effects are significant. Although there have been clinical studies into the effectiveness of different interventions, leading to evidence for their implementation, retrospective cohort studies have not (at the time writing) sought to control for period effects in this way, so the evidence here is helpful in understanding the pandemics progression.

Death risk reduced as the pandemic progressed however length of stay in- creased. This may reflect a shift of patients who with a similar level of disease in March might well have died, but who, when presenting a few months later, survived, albeit with a longer hospital stay on account of the severity of their disease. The alternative hypothesis that it was a capacity effect in period 1 where patients may have been sent home sooner than hospital norms and as the overall levels dropped then norms re-emerged seems unlikely as in Manchester although hospitals did fill up the additional capacity Nightingale hospital was never actually used.

In this analysis, we segmented the time in hospital by key treatment change dates. Many other dates may have been relevant to treatment and disease progression. Although we can see clear period effects here associated with the dates chosen, we cannot necessarily link the specific changes in guidance to the improvement of outcomes using these data. What is clear however is that disease outcomes improved as the pandemic progressed in 2020 likely linked to a better understanding of the nature of the virus and better experience of treating patients with severe disease.

Co-morbidity is important for death risk and for length of stay. Those patients with higher co-morbidity are more likely to die, and those who survive, stay longer in hospital. Williamson et al. [29] showed an association between underlying health conditions and increased mortality risk from COVID-19, and Guo et al. [11] demonstrated a link between co-morbidity (specifically forms of kidney and liver disease) with longer lengths of stay for hospitalised COVID-19 patients. The results of our work are consistent with these previous studies and the results are consistent with patients who have underlying conditions being more likely to die, and more likely to develop severe disease requiring lengthy hospitalisation.

Multiple admissions were predictive of death, and this is to be expected - patients who have attended and been admitted to hospital multiple times for their COVID-19 infection are likely to be experiencing severe disease and they are therefore more likely to die. The multiple admission variable was not however associated with the length of stay in Model 2. It may be that the patients who are admitted multiple times present atypically and so appear well enough to be discharged but then deteriorate sufficiently for a readmission - potentially of differing lengths and severity at each time. It may also be that their home environment is not conducive to a rapid and secure recovery, leading them to be re-admitted. This ’bounce-back’ pattern may therefore be too noisy to distinguish a clear signal in the data.

In the model for death, ethnicity does not feature, however Black and Other ethnic groups stayed longer in hospital than their White and Asian counterparts. Apea et al. [4] studied length of stay and outcomes for patients in East London and reported that adjusting for risk factors, Asian and Black heritage patients were more likely to die and had greater acute disease severity resulting in longer hospital stays. The work here demonstrates the same effect in for Black patients but the link between Asian ethnicity and more sever disease within the hospitalised population was not replicated in this Greater Manchester study. The same link between Black ethnicity was demonstrated by Alnababteh et al. [3]. The authors retrospectively analysed adult patients in hospital in the same timeframe in the United States. Black patient hospital length of stay was 21% longer compared with other ethnicities, but there was no difference found be- tween ethnic groups for mortality. This paper confirms these findings for Black patients and - given the different contexts (e.g. health care systems) of the different studies - this suggests that this ethnicity effect is robust across contexts and is something that warrants further investigation.

Deprivation was not significant in the length of stay models, whereas it is significant in the model for mortality risk.

The proportion of deaths of hospitalised patients varies by local authority within the city region. For this dataset, only 61% of patients survived in Tame- side where the mean IMD decile for the LSOAs within the authority is 3.6, versus 74% in Trafford with a mean IMD of 6.8. A model at the local authority level showed that deprivation within an LA is associated with the death rate for hospitalised residents, when controlling for the age of the LA population. Male proportion and ethnic make up were not statistically significant in this analysis but it is clear that there is a deprivation effect on the risk of dying in hospital from COVID-19, and that due to the spatial inequalities within Greater Manchester, some areas suffered a greater death rate than others, even in quite close proximity. In a model at the MSOA level the same effect was observed however a much smaller proportion of the variance was explained.

Using an area based deprivation statistic for individuals has shown a link between mortality risk and deprivation and when aggregated based on geographical units, this effect persists. Purdam [22] showed spatial differences in life expectancy within the city region and in the review commissioned by the Greater Manchester Health and Social Care Partnership (GMHSCP), Marmot et al. [16] reported that there has been a significant change in life expectancy, correlated with deprivation-space in the Greater Manchester area, this is replicated in the individual level hospital data and so it seems that the acute care system is not able to cut through this unequal disease burden once hospitalised. This may be because of other risk factors we have been unable to capture (for example obesity, or specific forms of co-morbidity) or it may represent the long term embedding of adverse outcomes associated with deprivation. Deaths occurring outside of the hospital system do not feature within this dataset and so we are unable to capture deaths either within private residences in the com- munity or within the residential adult and elderly social care population. It is therefore likely that the death burden within the patients in this analysis is underestimated.

It may be the case that the predictors of the additional death burden replicates those identified in these non hospitalised populations. We did not account for hospital overcrowding within the models which may have impacted admission decisions and could potentially have exacerbated area effects, however we note that the 'Nightingale' hospital in Manchester was commissioned but remained unused, and therefore we assume that although the hospitals were very busy, they were not overwhelmed during the period of the study data.

6. Strengths and Limitations

Previous analyses of length of stay have been restricted to the COVID- 19 Hospital Episode Statistics (CHES) data, analysed in close to real-time for operational purposes. The CHES data is more limited and data quality improves with time as coding is updated and records quality checked meaning that analyses earlier in the pandemic were subject to significant truncation and missingness. The data used in this analysis include all hospitals within Greater Manchester and have the benefit of a time distance from the event which improves data quality and reduces the extent of missingness.

The data are truncated; the dataset contains only hospital spells which have completed by 24/06/21 and so any very long spells admitted before this date but not concluded are not included in the dataset. The first admission within the data is 30/12/19. We minimised this effect by selecting a defined period within the data availability, defined by sensitivity analysis to the truncation effect.

Delayed transfers of care are not accounted for in this model as the data were not available and so some longer stays may reflect a spell persisting because there is a difficulty in finding an appropriate discharge destination for a patient, rather than their ongoing care need being to stay in the acute setting.

We have no information on subsequent re-admissions after the dataset, or on deaths which occur post discharge in the community. There may also be deaths resulting from post COVID-19 infection complications which are coded as an admission for the primary presenting diagnosis and thus do not appear as a COVID-19 case in these data. For example, some patients have experienced cardiac health episodes, likely related to their prior COVID-19 infection, and these hospital episodes would not be recorded as a COVID-19 case but a death in this instance may well be related to the original COVID-19 infection.

7. Conclusion

The data present a complex picture and this is not easy to understand with- out further work. The reported link between deprivation and severe disease is detected within the death risk for hospitalised patients within Greater Manchester but not for the length of stay. On the other hand, Ethnicity is important for length of stay in the city region, but not for death risk upon hospitalisation.

A key point here is that data only concern the hospitalised population so a key component of the data generating process for these data occurs after the event (infection) that drives the primary reason for the study. We need more research into how COVID-19 has impacted different communities, with a broader range of data so we can understand how deprivation, ethnicity and space have intersected to impact on outcomes through the infection process.

7.1. Contribution

There have been many studies into the length of stay for COVID-19 patients, as medics seek to understand the patterns of disease for different patient groups and plan healthcare provision for their populations.

The current study used complete administrative data covering the whole of Greater Manchester for the period January - November 2020. The inclusion of more complete and accurate social, demographic and spell data for each stay has allowed a nuanced and detailed analysis of the factors affecting spell length and mortality in the city region for hospitalised patients.

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Statement on conflicts of interest

The authors have no conflicts of interest to declare.

Ethics statement

Data were made available to authors via secure server and were functionally anonymised [9].

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Abbreviations

CCG:	Clinical Commissioning Group
GM:	Greater Manchester
GMHSCP	Greater Manchester Health and Social Care Partnership
SUS	Secondary Users System
GP:	General Practitioner
IMD:	Index of Multiple Deprivation
LSOA:	Lower Super Output Area
NHS:	National Health Service

Chapter 7

Discussion and Conclusions

The work presented in the prior chapters is located at the the interface between health research and social science (Meckin and Elliot 2021). That interface embraces a complex nexus of topics and methods and the papers presented in this thesis are subject to all of that complexity. It is clear that health and society are inextricably linked; our health and our lived experience as humans - filtered through complex social structures - are interdependent, forming a complex multidimensional system in which differences and inequalities arise. The extent to which measurable attributes of individuals and their contexts can be determined to be causal or influential in determining variation in health outcomes is therefore of interest to policy makers and governments, providing as it does an opportunity to improve those outcomes for those who experience adverse impacts of inequality.

As discussed in Chapter 3, the precise form of this work has been heavily determined by the issues of data access and quality but the overall shape has been driven by my driving interest in inequalities. Each piece of work highlights a different aspect of the overarching topic and invites discussion of a different element of the complexity involved in researching inequality. The topic is large and complicated and so as a researcher I have approached the task by designing related questions and considering the topic from different angles, based upon the capability of data and any access restrictions.

This thesis is a contribution to the field of health inequalities research considering the relationship between deprivation and space in three facets of inequality; in access, wellbeing, and outcomes. This is a topical assessment conducted on recent and emerging policy approaches and thus adds to the literature concerning ways to reduce inequalities and ensure equitable health for all. The resources and time frame available to a doctoral researcher would never be sufficient to cover the scope and complexity of this topic and so although the quasi-facet approach (see Chapter 3) arose through necessity, it can be considered a strength of the work here, providing as it does an opportunity to consider different parts of a large and complex arena. It would in fact never be possible to produce a coherent and linear thesis investigating such a complex and intrinsically complicated phenomenon and so in this discussion, I summarise each of the papers as case studies, taking a wider vantage point and consider the perspective given by each separate exploration.

7.1 Investigating the impact of distance on the use of primary care extended hours

This study sought to determine whether distance and deprivation impact on the uptake of extended hours GP services that use a hub practice model. This work examined the issue of deprivation through the lens of primary care provision and service commissioning. The aim of such research is to determine whether people access the primary care that they need and if services are commissioned in a way that widens or reduces inequalities in access. Deprivation is place sensitive and so if distance effects persist in a system, the choice of location for any services delivered under a hub and spoke model is critical to ensuring that parts of the community are not disadvantaged in access.

The analysis showed that distance from a 'hub' location where extended hours appointments can be booked is important when predicting the use rate of the hub service by patients from a given practice. Whether or not a patient's home practice has been designated a hub in the commissioning process also has a statistically significant effect above and beyond the distance effect, with patients more likely to use the service when it is located at their registered 'home' practice. There was no evidence that deprivation (as measured by the IMD decile of the home practice) was associated with lower use of the extended access service, however it is important to remember that deprivation can be highly geographically granular and as such, the distance from a service may mask an underlying issue with deprivation. This is not purely an inner city phenomenon, rural poverty coincides with geographical dislocation from core services and by commissioning provision in population dense locations, the rural and semi-rural poor may be further excluded from accessing the care they need. Likewise, the patients of practices located in more deprived areas, may have greater needs for care through the complex impact of social, financial and spatial inequalities on their health and thus their experience of health inequality. The lack of association of deprivation with use may in fact be a null effect which indicates a bias in useage towards less deprived areas and thus an indication that the service is in fact unintentionally widening access inequalities.

The extended access service analysed for this investigation still exhibited spare capacity. This raises the possibility that the mechanism used to increase access to primary care has indeed improved access for all patients. However, as discussed in Chapter 2, access can be conceptualised as a multidimensional concept constituted of availability, affordability and acceptability. Increasing the number of appointments within the primary care service clearly increases availability, and is a supply side factor, but simply increasing the number of appointments in a larger pool of supply may not adequately address restrictions on affordability and acceptability.

Increased distance from the hub locations in this model of extended access is associated with lower uptake; with patients from practices which are further away from their nearest hub having much lower use rates of the service. This research provides evidence that distance is a factor in uptake and I suggest that this is because distance impacts the affordability dimension of good access. A greater distance from the hub implies a greater cost of attendance and so it follows that this is a barrier to using the service. The interaction of distance as a factor with deprivation is however, subject to significant complexity. Increased financial and time costs are inherently harder for more deprived households to bear and so distance effects may also imply greater access restrictions for the more deprived households in any given practice. For this reason, it is possible that the importance of distance in the models for this research are in fact masking some issues of hardship. The index of multiple deprivation was introduced stepwise into the models and it was not at any point statistically significant as an explanatory variable in the absence of distance, however this index itself contains an aspect of distance and health as part of the Geographical Barriers Services subdomain [1] although it is important to note that there was no significant correlation or multicolinearity detected in the preliminary data analysis between the two variables.

Rubin et al. (2006) showed that being able to see a preferred medical practitioner is important to patients and Schoen et al. (2007) discussed the concept of a medical home. The need for familiarity to ensure good access to care and optimal outcomes, shown by these authors in prior research is something which may also be important in determining acceptability of appointments in distant locations. Hubs that are further away may be in less familiar areas, they are not with the "usual" doctor, and so the use of appointments at a hub by patients who are not registered there may be reduced. Conversely if a patient is registered at a hub, the introduction of extended hours services simply offers a wider window in which to experience

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[1] This is a subdomain of the Housing and Services Domain within the index. (McLennan et al. 2019)

the same service and greater flexibility in timing and so it makes sense that once a patient has decided to make an appointment to see a doctor, there is no structural barrier to the flow of usage between the core hours or extended hours service.

In Chapter 2 I discussed research by Schoen et al. (2007)and Rubin et al. (2006) that shows patient experience is more positive when patients have a medical "home" which is easy to access. Accessing primary care through the extended hours service for patients of non-hub practices will necessarily involve travelling to an unfamiliar health care setting and the likelihood is that the patient will not see their usual core hours doctor. A patient may perceive there to be a risk of miscommunication between professionals and additional errors in care because it is not their usual service provider. The policy approach of using hubs to deliver services over an extended hours timetable does not give greater availability at the patient's medical 'home' for those whose practice is not designated a hub. The service provision may drive patients into using hub appointments when they would prefer not to and thus there is a risk that sending them to practices other than their 'home' can erode the quality of care as a structural feature of the service provision. I propose that this could have the unintended impact of in fact reducing effective access to health care, rather than improving it.

For marginalised communities and those of lower means, familiarity may have an even greater effect. It is easy to imagine challenges within the familiarity domain that might be of more importance for these patients and patients may experience significant feelings of uncertainly related to an unfamiliar setting, adding to any anxiety they already hold surrounding their medical condition and thus having even more of a capacity to compromise the extent to which the patient can effectively access care. Will the doctor understand my cultural needs? Is there somewhere free I can safely leave my children whilst I see a medic? Will the parking be more expensive?

Considering this issue of familiarity then, I suggest that it is certainly possible that a lack of familiarity has a disproportionately negative impact on those who are from deprived and/or marginalised communities and that therefore the structure of this commissioned service, does not in fact provide an additional supply of acceptable, affordable and available primary care to some people. There may be some transfer of provision from core (home practice) to non core (hub) hours for certain sections of the practice population, reducing demand for the core hours appointments at the home practice, and this may alleviate some unmet need within marginalised and or deprived communities, but the assumption that a hub model increases supply for all may be flawed.

Beyond these theoretical considerations this investigation was also methodological - is it possible to use purely administrative data to uncover interesting and important associations around access, use and deprivation? Certainly the work uncovered some interesting effects but it is clear that it was limited by a lack of more granular geographical data and detailed individual level information.

The lack of individual level data led to a research design which considered appointments, aggregated to the practice level as the response variable. Although these appointments are made and used by individuals, the data units are administrative entities rather than people; uses rather than users.

Individual motivations affect the underlying flow of appointments from the core provision to the extended hours, but there are also practice level effects, many of which could not be captured in this work.

Socio-demographic characteristics for each use were assigned at the practice level using geography, but clearly practices serve catchments which are much wider geographically than an LSOA unit. Even within the same LSOA, two streets of houses may well experience very different socio-economic circumstances. This use of practice postcodes as a proxy for patient location will have caused some misclassification which may have further impacted the performance of the deprivation measure (IMD score) in the models. The Modifiable Area Unit Problem is potentially relevant here and the lack of direct association with the outcome measure after controlling for other factors could simply be caused by the misclassification of the level of deprivation, rather than the lack of a deprivation effect itself.

The extent to which access to GP appointments has been improved through the extended hours service is difficult to discern from the data available but there is evidence that the service structure may well be increasing or embedding existing health inequalities of access. The aim of providing primary care appointments outside of core hours is to improve access and this is predicated on the assumption that unmet need is caused by a lack of capacity at an appropriate time. This may be due to overcrowding of services in core hours, or it may be due to the unsuitability of core hours for some primary care users. Patients want, and use, extended hours services, however distance and familiarity are two potential barriers to equal access for all and certainly this work demonstrates that these access inequalities are not necessarily adequately addressed by the service design. The study suggests that patients living further away use the service less. For patients who cannot travel, or are unwilling to accept an appointment somewhere other than their medical 'home', the extended hours service may not be an effective way of improving access and may be increasing inequity. A simple view would be that if there is spare capacity in the system, then all need must be met; however, this analysis provides evidence that spare capacity in the system does not of itself demonstrate that access issues have been eradicated. It may be that patients who are already empowered to access health care are simply being given more choice; with no increase in the provision for those whose needs are not currently met. Provision of greater service volume without consideration of the way in which people are motivated to use it, risks leaving those groups with unmet needs behind and reporting spare capacity risks hiding this unmet need in the data.

Policy makers and health care commissioners need to understand the differences in the extent and nature of uptake to inform their design and evaluation of future services. They should consider whether or not this type of model works to provide additional access and may use the findings in this study to inform the selection of hub practices – perhaps focusing on practices which minimise the average distance travelled for patients, or where there is relatively greater evidence of constrained capacity. This is particularly important in the context of closing health inequality gaps as those who are least enabled to access services may be those who need them the most.

A possible direction for this research in its next phase would be to conduct a more detailed network analysis of journeys to and from hub services.

This would require a significant data collection effort (which could be digitalised using in-hub devices or locally displayed QR codes etc.) but could provide better insight into the types of users of this service, and by omission, identify those members of the practice registration list who are not using the service. This level of granular data collection and analysis would be a large undertaking requiring the cooperation and permission of multiple practices and hubs, but it might provide greater insight into patterns of usage in a form that is useful for system design. In any case, revisiting the use of these services with whatever administrative data is currently available would be informative as so many face-to-face appointments no longer take place as a result of pandemic restrictions. It may now be that digital services are those most frequently accessed, such as e-consult and online appointments, and that these may structurally exclude different groups from care, or indeed that the shift to online has removed some of the distance barriers as consultations can be conducted from any place with an internet connection, and made those with means more able to access care thus freeing up capacity in localised services for those without. Certainly the interplay between extended hours and digital services will have changed the landscape of access for patients and the extent to which this has prevented those who are more deprived from accessing care should be assessed.

7.2 Wellbeing during the COVID-19 pandemic in the UK: a secondary data analysis

This study considered how deprivation impacted the experiences of people in England during this period. Specifically, I used a subjective measure of wellbeing to investigate an impact of the COVID-19 pandemic that was not specifically COVID-19 disease itself. This measure was sampled monthly in April to July 2020. Whereas the first study examined inequalities through the provision of primary care, this study considered how people's wellbeing was impacted when the normal mechanisms of formal and informal health care were totally disrupted. If paper 1 is a consideration of the inequalities which arise in people's ability to access services that have been commissioned to provide additional capacity, this paper is the effectively the converse. It considers the inequality of outcomes when the supply of care in multiple forms is abruptly stopped or at least severely compromised.

In this paper, I uncovered interesting and apparently counter-intuitive effects. There was in fact no association between deprivation and the recorded wellbeing scores during the course of the data collection. An overall decline in wellbeing was observed in the data for the first lock down period beginning March 2020 and extending until July 2020. This was matched with a corresponding recovery between April and July as restrictions were gradually lifted - but these changes were not directly related to the deprivation variable used.

Sex effects were present, with women recording a greater decline in wellbeing, and a subsequent greater recovery, mirroring the situation for men, but with greater severity. Loneliness and prior measures of wellbeing (a pre-pandemic baseline score) were predictive of the decline, with the same factors associated with recovery.

My prior predictions were along the lines that things are always much worse for those who are experiencing deprivation, and this is well founded, given the social gradient of health that persists at all levels of society. Times of adversity and extreme stressful events have been linked with increased risk for poor wellbeing (Galea et al. 2002; Masten and Narayan 2012) and the pandemic has presented unprecedented change and restriction to our lives. It was reasonable therefore to expect that this additional stress and adversity would have a greater impact on those who's personal situation is already difficult. The lock downs resulted in dramatic shifts in the labour markets and resulted in financial stresses for many workers. Furlough and the increase in universal credit gave some protection, but for many workers with insecure or zero hours contracts, these measures provided little protection from acute financial stress. In combination with this reduction in means, the process of providing for one's family became increasingly difficult with shortages and a near total removal of the ability to pay with cash. I hypothesised that these additional difficulties in going about our ordinary existence, may have been even more difficult to manage for those on low incomes.

Overall, I showed that the first wave was associated with an overall decline in wellbeing, but that the removal of lock down restrictions was also associated with a recovery. I expected wellbeing trajectories to differ along sex, ethnicity, deprivation and underlying health conditions, and that some of these differences would be explained by the impact of stress (specifically financial crisis), the level of community support experienced (community cohesion) and the extent of social isolation experienced by respondents (measured by loneliness).

There may be some ceiling effects within these data, however due to the very low instances of high values, the impat on the analysis is negligible. Likewise, floor effects may be present but this is a feature of all longitudinal analyses of these types of wellbeing data. In this particular case because the period effect I am observing moves the distribution of the wellbeing scores to the right (away from the floor) the impact on the analysis will again be negligible.

The models did not show the expected differences between groups. The decline was sharp, but the improvement was sustained over the first wave such that measurements of wellbeing were almost at the baseline by July 2020. This elasticity demonstrated a bounce back effect and a capacity for rapid recovery across all sections of the sample. Figure B.1 held at Appendix B shows the homogeneity of the wellbeing trajectory over imd deciles (note that the data is presented in this figure as quintiles for ease of interpretation).

The sample was skewed towards the less deprived deciles and so this may partly be a non-response issue, with those suffering the greatest deprivation, least able to engage with the survey, possibly through poor mental health as reported by Mirowsky and Reynolds (2000) who showed that the probability of dropping out of a longitudinal survey is increased with higher baseline values for depression. In this work, in contrast to the first thesis paper, I was able to assign deprivation to individuals using their home LSOA. This is still to an extent problematic, as each LSOA represents approximately 1500 individuals and thus may be heterogeneous with respect of deprivation - not everyone in an LSOA experiences identical socio-economic conditions.

One way of considering deprivation is as a state which increases a person's susceptibility to a disruption of any form and certainly deprivation could well be expected to have increased vulnerabilities to the social, economic and health impacts of the pandemic, particularly considering the evidence linking increased deprivation with poorer health outcomes (Prime, Wade, and Browne 2020). However, the expected negative association of deprivation and health is not one that has been found universally in previous studies (for example Tunstall et al. 2007; Doran, Drever, and Whitehead 2006; Cairns, Curtis, and Bambra 2012). The results of studies into health outcomes in deprived areas suffering multiple aspects of inequity can sometimes be counter-intuitive and several investigations have shown that communities record better health outcomes than might be predicted from socio-demographic factors. These communities can be said to display 'health resilience' and outperform expectations on measures such as life expectancy.

This study may be subject to these effects - the poorest communities already experience deep inequalities and thus may have been resilient to the wellbeing impacts of the pandemic, and this resilience cancelled out the expected social gradient in health. This same gradient implies that wealthier areas would experience less of a decline in wellbeing but in fact many people in these communities were subjected to a level of stress to which they would be unaccustomed given their usual level of financial comfort and position of privilege in society. The threat of furlough, home working, home schooling and removal of a normal social life, may have been a sufficiently adverse effect on the better off that the mental health impact of the crisis has in fact been felt more equally than is usually the case.

Alternatively, it is possible that this effect can be explained with reference to Homes and Rahe's work on stress (T. Holmes and Rahe 1967). Homes and Rahe proposed that life changes are the primary driver for reductions in wellbeing, and so it follows that the extent of a life change, determines the extent of the change in wellbeing. The changes experienced by the better off may have in fact been more radical, relative to their existing comfort, and thus acted as a primary driver for a greater reduction in wellbeing in the initial phase of the lock down, causing the levelling effect observed in the data.

Respondents may also have implemented some very specific coping strategies during this time, drawing upon their ability to adapt to the crisis. Indeed, some participants may have experienced a degree of post traumatic growth (Masten and Narayan 2012; Masten 2007; Lepore and Revenson 2006) whereby the imposition of adversity results in an improvement in wellbeing as those faced with the stress, draw on strengthened personal and social systems to thrive despite the situation in which they find themselves. It is impossible to determine from this work whether this effect was present and more prevalent in any particular grouping. The ability of a person to return to normal levels of wellbeing after a negative experience is also considered within the adaptation and coping literature. The adaptation framework proposes that adverse experience may result in an initial reduction in wellbeing, but over time the person affected can adapt and subjective measures of wellbeing will consequently return to prior levels (Heink 1993). Coping theory describes the development of behaviours that aim to reduce stress (although this framework does not presume that any coping mechanism will in fact be successful whereas the concept of adaptation is deemed to be inherently positive)(Lazarus and Folkman 1987). Adaptation is a plausible explanation of the findings in this work and certainly the elasticity detected in the wellbeing scores could be considered to be evidence for adaptation. In this discussion, I consider the results and experience of the panel members in terms of a decline and recovery as this provides a more parsimonious theoretical framework for the improving wellbeing scores and is consistent with the real situation dynamic as the pandemic progressed, with a lock down followed by a relaxation, both of which map on to the observed differences in wellbeing scores.

Women experienced a greater drop in wellbeing (a rise in the caseness score) than men, however at the end of the first wave there was no difference in the change in wellbeing between men and women. Self reported health is a combination of underlying health and reporting behaviour. Self reported mental health metrics are affected by misreporting, a potential impact of the continued stigma around mental health. This undereporting bias has been shown to be greater for men when considering the same GHQ-12 questions from the Understanding Society survey and its predecessor the British Household Panel Survey from 1999 to 2016 (Brown et al. 2018), and so it may be the case that the sex effect in this study is actually a factor of reporting bias. The baseline of the scores showed lower mental wellbeing for women than for men, the change was then greater for women than men, matched with a greater improvement. This uniformity of elasticity across the sexes and the lack of lasting difference would tend to support a theory that the difference seen here can be attributed to reporting but is illustrative of the complexity of trying to measure and understand complex concepts like wellbeing and inequality, and how this is further complicated by the dynamic situation in which these data were recorded.

There was a low response rate amongst ethnic minority members of the panel with only half the expected number of respondents coming from an ethnic minority background of any type (approximately 10% from ethnic minorities in this sample, compared with 20% in the underlying survey panel). This necessitated the collapse of the detailed ethnicity variable to a binary ethnic minority/white measure. This is problematic because clearly people from different ethnic minority backgrounds are not homogeneous and may well have had experiences of the pandemic which varied by ethnicity for example due to the differing experiences of and relationships to family and community within different ethnic groups. The use of a binary variable also necessitates the categorisation of people with dual heritage into either "minority" or "white" and confounds British ethnic minority respondents with immigrant populations. Use of binary variables for ethnicity is problematic where the dominant research narrative considers the white perspective as central, and the ethnic minority perspective as "other". That said, ethnicity was significant in the recovery model for men (model 2), An ethnic minority background was associated with a bigger "bounce back". This may be because ethnic minority males suffered a greater decline in wellbeing which was not detected in the modelling, or there maybe resilience factors in play. However, the effect size and the overall contribution towards the explanation of variance were small. The lower response rate of respondents from more deprived areas and those of non-white ethnicity means that people from more deprived groupings and those of non white ethnicity are likely to be systematically absent from the data. The intersection of ethnicity and deprivation is complex and we cannot know what the experience of those who did not respond could contribute to our understanding.

Age was significant for men and women in the initial decline of wellbeing, and for women in the recovery, but with a small effect size. Older people suffered a smaller decline in their wellbeing, and then a smaller recovery as the wave progressed. The impact of age on the decline in wellbeing for women was double that for men. The mean age of respondents was skewed towards the older members of the panel which may have reflected older people having more time on their hands having been relieved of their normal social lives and also perhaps the care burden for grandchildren, whereas younger adults were more likely to be juggling full time work from home whilst also caring for and schooling children. (Mirowsky and Reynolds 2000) reported attrition in longitudinal response related to poorer wellbeing and so it may be that younger groups were experiencing poorer wellbeing and that this contributed to their non-response.

Many of the coping strategies and adaptation mechanism which mediate resilience to external stress are constituted through family mechanisms, social interactions and relationships. Green et al theorise that ”Multilevel attachments” are protective against life’s stresses (Greene, Galambos, and Lee 2004) so forming and maintaining useful relationships builds a protective ’web’ around an individual, and we use our networks not only to maintain our general wellbeing, but also as a form of additional health care that substitutes for formal medical settings. Walsh et al observe that families can adapt in times of crisis, and family relationships can mitigate against poor wellbeing(Walsh 2015). Strength of the family and other social relationships can also therefore provide a path to adjusting to stressful situations and recovering from poor wellbeing and are an important part of personal and community resilience.

In communities where people are likely to speak to each other and respondents report having neighbours they can rely upon for help, I expected the negative impact of the pandemic to be reduced and for there to be differences based on how cohesive the respondent perceived their community to be, but this was not the case in the model for decline although there was an effect in the recovery. The lack of effect of the community level variables in the decline and the asymmetry of the relationship feels counter intuitive here. If social structures have been consistently shown to protect against life's stresses and even substitute for formal care, then why in a time of stress, did those who live in cohesive communities not see a protective benefit to their wellbeing from the established structures and social networks (whether family or other). One possible explanation is that the pandemic lock downs changed the fundamental nature of our families and communities and so even in communities which score low on this measure, there was a level of network which sprang into action as an adaptive reaction to the situation. It may be that the effect of the pandemic was to totally disintegrate all of our social networks in this context and the isolation effect was therefore universal - whether you live in an ordinarily socially cohesive environment with strong family and other networks, or not. It may also perhaps be indicative of the physical reality of the lock down; during the lock down phase, access to the social capital that community cohesion represents was constrained and therefore its availability for mitigation may have been limited. Once lock down restrictions were eased then that social capital may once again have become available.

People's experience is influenced by the narrative of how they should react and process the tragedy around them. Not for the first time in a British tragedy, media and politicians made reference to the "Blitz Spirit" and the rhetoric of survival, courage, fortitude and being 'in this together', using collective actions such as the "Clap for Carers" to further emphasise a message of solidarity (Jones 2020). This "resilience culture", may have been a universal protective factor at a national level, facilitating the observed elasticity of mood, moreover at a local level, the removal of traffic from streets, the necessity of restricting contact to only those who you saw on a daily permitted errand or exercise session may have emphasised the importance of living in a cohesive community for mental health, reflected here in the model for recovery - the measure of community cohesion showed no effect for decline, but it was associated with stronger recovery for both men and women. Linkov and Trump write about communication as a key factor in resilience (Linkov and Trump 2019, p 109). Effective communication from policy makers and health care systems whilst under stress is critical in encouraging behaviour from the population which does not lead to a breakdown of those mechanisms brought in to reduce risks - in this case, COVID-19 lock down restrictions and guidance on preventing disease transmission. So the outcome observed here is consistent with the relatively good communication during the early pandemic and consequential widespread compliance with pandemic restrictions observed in the first lock down.

The study showed that the experience of loneliness was predictive of a of a decrease in wellbeing in April for both men and women and was a main contributor to explaining the variance in the data. Ongoing loneliness was also statistically significant in the recovery period with people who experienced continued loneliness using this measure, recovering less well as the pandemic progressed. There may be a stigma related to admitting that you are experiencing loneliness and so there may be biases in the loneliness variable but the difference emerging between those who are lonely and those who are not is indicative of the different ways in which people experienced the progressive loosening of restrictions. Some people opted to remain isolated, out of concern for their health, or because of shielding advice, whilst others made the most of new “freedoms”.

The financial impact of lock down differed widely dependent on employment sector and to an extent caring responsibilities as school age children remained for the most part, in the home. For respondents in the sample, an acute financial crisis resulting in food bank use was predictive of a worse mental recovery and this is consistent with expectations around stress and mental health. However, for women, a negative change in income also predicted worse recovery. That this is different for men and women is of interest. The income variable is set at the household level so this may reflect a response which differs by gender to the same phenomenon. It may also reflect the unequal caring burden placed upon women and in fact be a example of increasing marginal returns. Women within the analysis were already suffering worse wellbeing and a greater decline in the pandemic. The addition of reduced income may have thus been incrementally more stressful for them, given that they were, already suffering poorer wellbeing together with increased demand on time through the unpaid work burden associated with caring - for example through home schooling. A further analysis of income distribution and domestic versus paid work during the same period would be a logical direction in which to take this particular finding and supplemented with qualitative research looking at female and male responses to the responsibilities of running the financial side of a household would provide a richer insight into how chores such as provisioning and financial planning shifted and were allocated in households with income which came under stress during the lock downs.

There was to an extent a level of novelty in the initial phases of the pandemic. The surveys taken in March through to July of 2020 were conducted in the earliest stages when the longer term impact of the pandemic's duration and severity will probably not have impacted upon the mood of those responding, and when fewer respondents may have directly experienced the impact of COVID-19 disease themselves. This may mean that differences and the impact of the social gradient of health are not detectable in this study.

This study was designed to use existing data to uncover interesting features in non-COVID-19 related wellbeing during a period when many normal aspects of care provision were absent or severely impacted. Although the outcome variable is a measure of the indirect impact of the pandemic, it cannot be separated from the experience of those who directly suffered during the lock downs directly by COVID-19 as a disease either through loss of their own physical health or bereavement. Further indirect effects of the pandemic will take some time to uncover, but will include long term unemployment, and projected adverse outcomes in other health conditions and it would seem likely that these should follow the same social gradient as has been observed for other diseases.

Subsequent to the period of this work, there have been further data collections and these data are now available to researchers. Although the data collection interval changed, and different modules were included at each collection point, the COVID-19 dataset from Understanding Society now provides a rich resource for further consideration of the impacts of the pandemic on household life and population wellbeing. In January 2021, a further very strict lock down with school closures was called overnight with school children having returned to the classroom for just one day. By this point, the vaccination program was beginning to be rolled out to the oldest members of society, and so the landscape was very different but after almost a year of restrictions and uncertainty, it would be interesting to investigate if the same resilience and mood elasticity had persisted into the pandemic's second year. Anecdotally, people seemed to feel less positive as the second year of restrictions set in and it is possible that we experienced some sort of pandemic wellbeing fatigue, which could be reflected in further studies using these data. As discussed above, it would be interesting to investigate the impact of any ”novelty” of the pandemic and how this may have waned and as more people experienced the disease and the length of time spent isolated and restricted extended whether or not this revealed more of a social gradient in outcomes. I would like to take this work further and potentially extend it into the current period which is 'post pandemic' but where there is still significant, and rising, financial strain in the UK and examine how long lasting our resilience has been, and whether there has been a downturn in wellbeing which can be linked to global events, and how this has been expressed in different groups and communities. Likewise, a deeper dive into rich individual socio-economic data and perhaps a multi-level approach to combining this with area level deprivation could provide an interesting lens to consider how inequalities have arisen or been exacerbated during the time of COVID-19 in non-covid related outcomes.

7.3 Deprivation effects on length of stay and survival of hospitalised COVID-19 patients in Greater Manchester

In the third paper, I investigated the impact of deprivation on the outcomes for hospitalised COVID-19 patients in Greater Manchester and controlled for risk factors identified within the literature. My work suggests that patients who were female in Greater Manchester were at lower mortality risk and had shorter hospital stays when infected with COVID-19. Age was also another key risk factor with older age groups more likely to die from their COVID-19 infection. This paper concludes my work, looking at outcomes for those who have accessed services, and how these might be impacted by inequalities.

Examining outcomes for a new disease during the learning phase (about it's treatment), poses some specific challenges; unpicking where inequity arises in a context of changes in outcome related to changes in treatment or the progression of the pandemic further complicates any analysis. In this work, the change in treatment protocols for COVID-19 was measured by a marker for discharge or death date leading to the discovery of significant period effects in the models for length of hospital stay and death risk. To provide further clarity, I segmented the time in hospital by key treatment change dates in an attempt to control for the rapidly developing situation which characterised the first year of COVID-19. Many other dates may have been relevant to treatment and disease progression and although we can see clear period effects here associated with the dates chosen, we cannot necessarily link the specific changes in guidance to the improvement of outcomes using these data. However, we can say that disease outcomes improved as the pandemic progressed in 2020, and it seems likely that this improvements is linked to a better understanding of the nature of the virus and better experience of treating patients with severe disease, and so it was important to strip out these effects when analysing equitability of outcomes. Although there have been clinical studies into the effectiveness of different interventions, leading to evidence for their implementation, this type of retrospective cohort study has not always sought to control for period effects in this way and so this study provides evidence that COVID-19 risk shifted over the course of 2020 and there were significant period effects which meant that later infections carried a lower death and long-stay risk. This finding is supported by the models also demonstrating that whilst the death risk reduced as the pandemic progressed, length of stay increased. This is likely to reflect a shift of patients who with a similar level of disease in March might well have died, but who, when presenting a few months later, survived, albeit with a longer hospital stay on account of the severity of their disease.

The analysis also highlighted the importance of co-morbidity in outcomes. Patients with higher co-morbidity are more likely to die; those who survive, stay longer in hospital, and this makes sense. It might be expected that a patient with an underlying condition would be more likely to die, and more likely to develop severe disease requiring lengthy hospitalisation. The intersection between disease burden and deprivation as a form of inequality is important here. Disease burden for specific types of illness, falls unequally in the population. Heart disease, obesity, lung disease and other conditions are more prevalent in lower socio-economic groups and have higher prevalence in areas of higher deprivation. This then makes the difference between pre-existing illness, and pre-existing deprivation, difficult to separate - and both are part of a complex picture of inequality. Are people more at risk from COVID-19 because of their illness, or is it because of their deprivation, or are these intertwined and interactive, that is to say that their income inequality and unequal access to general services, expressed as a deprivation statistic, is in fact causal to their underlying illness risk? The multiple facets of inequality and deprivation which cause this additional risk can be considered to be pre-existing vulnerabilities. The arrival of a global health pandemic may have simply have shown what was already there, or it may be that these vulnerabilities themselves have a multiplying effect on the risk from COVID-19.

A patient having multiple admissions to hospital was also predictive of death, and this again is to be expected - patients who have attended and been admitted to hospital multiple times for their COVID-19 infection are likely to be experiencing severe disease and they are therefore more likely to die. The multiple admission variable was not however associated with the length of stay. It may be that the patients who are admitted multiple times present atypically and so appear well enough to be discharged but then deteriorate sufficiently for a readmission - potentially of differing lengths and severity at each time. It may also be that their home environment is not conducive to a rapid and secure recovery, leading them to be re-admitted. This repeated admission pattern may therefore be too noisy to distinguish a clear signal in the data. The dataset used in this analysis is not capable of giving us the kind of in depth person based information that might allow us to understand the circumstances of re-admission but there may be some deprivation factors which apply here. These may operate, for example, through a person's reduced ability to advocate for their own health and access the care they need, linking back to the ideas of access explored in the first paper. Alternatively, limited means, amplified by the economic contraction of the pandemic, may have compromised the ability of some patients to adequately care for themselves at home after discharge.

There has been significant discussion in the media around the ethnicity risk for death and severe disease; in these data, ethnicity was not associated with death risk. However, Black and Other ethnic groups stayed longer in hospital than their White and Asian counterparts. Apea et al. (2021) studied length of stay and outcomes for patients in East London and reported that adjusting for risk factors, Asian and Black heritage patients were more likely to die and had greater acute disease severity resulting in longer hospital stays. Alnababteh et al. (2020) retrospectively analysed adult patients in hospital in the same time frame in the United States. Hospital length of stay for black patients was 21% longer compared to other ethnicities, but there was no difference found between ethnic groups for mortality. The analysis conducted here seems to confirm these findings for the Greater Manchester cohort. This research and the pre-existing literature were conducted in radically different contexts - different countries experiencing different waves of infection, with different public health measures in place and different health systems, and yet the effect appears to be consistent across all settings. This would suggest that the ethnicity effect observed in our data is robust. There are a multitude of possible theories and frameworks which might explain why this is so consistently found, of which systemic racism resulting in embedded deprivation across non-white groups is just one, and it is certainly a finding which warrants further investigation so that policy makers and those working towards social justice in health can understand why these non-white populations have been impacted in this way.

The length of time spent in hospital was not associated with the index of multiple deprivation. However, analysing mortality risk showed a statistically significant association with the place based deprivation variable for an individual. Those from more deprived areas were more likely to die from the disease demonstrating a link between the underlying inequality experienced by an individual, and unequal outcomes in hospital care.

The proportion of deaths of hospitalised patients also varies by local authority within the city region. For this dataset, only 61% of patients survived in Tameside where the mean IMD decile for the LSOAs within the authority is 3.6, versus 74% in Trafford with a mean IMD of 6.8. A model at the local authority level showed that deprivation within an LA is associated with the death rate for hospitalised residents, when controlling for the age of the LA population. The proportion of males and ethnic make up of the LAs were not statistically significant in this analysis but it is clear that there is a deprivation effect on the risk of dying in hospital from COVID-19. In a model at the MSOA level the same effect was observed although a much smaller proportion of the variance was explained.

Using an area based deprivation statistic for individuals has shown a link between mortality risk and deprivation and when aggregated based on geographical units, this effect persists. Purdam (2017) showed spatial differences in life expectancy within the city region and in the review commissioned by the Greater Manchester Health and Social Care Partnership (GMHSCP), Michael Marmot et al. (2021) reported that there has been a significant change in life expectancy, correlated with deprivation-space in the Greater Manchester area; this is replicated in the individual level hospital data.

These are interesting findings and suggest that the acute care system is not able to compensate for the unequal disease burden within Greater Manchester once patients are hospitalised. There may well be other risk factors that it is not possible to include here due to data limitations, for example obesity, or specific forms of co-morbidity and these may be impacting on mortality risk in hospitals. However, it may be that this finding shows us a long term embedding of adverse outcomes associated with deprivation and certainly prior literature in the Greater Manchester city region investigating place based life expectancy would support this as a theory for explaining the spatial difference in COVID-19 outcomes. Deaths occurring outside of the hospital system do not feature within this dataset and so these results do not consider deaths either within private residences in the community or within the residential adult and elderly social care population and so it is likely that the death burden within the areas in this analysis is underestimated.

Unpicking the cause of localised differences in mortality and hospital stays within Greater Manchester is a possible further area of research which is of great interest to those commissioning care in the city region and which could be conducted using further analysis of this secondary dataset. The findings of this work have been delivered to the Greater Manchester Health and Social Care Partnership, and their data analysts have confirmed that for one CCG at least, they have detected differences in hospital policy which may have led to outcome differences for hospitalised patients[2]. The ecosystem of care in any given location can have an impact on hospital outcomes when measured as simple administrative measures such as mortality and length of stay. This ecosystem may be a function of an area's socio-demographic characteristics and may also then amplify the effects in a complex feedback look. Delayed transfers of care due to adult social care restrictions, community infection outbreaks or other factors may influence lengths of stay, as may many other features of how the local care providers knit together to form an overall health service. A deeper dive into more localised data would provide

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[2] Note that this is operationally sensitive data and no further detail has been released at this stage. Should this research be continued and developed, this is something which would be of great interest and could provide a rich subject for more qualitative methods based research to compliment the administrative data analysis presented here.

interesting insight into how differences in Greater Manchester are arising and how best to address the challenges - whether they are arising through underlying deprivation and need in the community, or at a system level through (for example) localised policy or resource constraint. As discussed in the literature review, there is evidence of poorer primary care provision in areas of greater deprivation measured as the number of full time equivalent GPs per head. Macro level statistics suggest some geographical and demographic inequality in COVID-19 outcomes for care home populations and this will link with hospital outcomes, in particular lengths of stay as the care home transfer process can lead to delay in discharge. Care homes have been under unprecedented strain and restrictions during the pandemic, and the distribution of care home beds is not even. Nationally the distribution is even but when disaggregated, the North has a greater proportion of care homes in underprivileged areas, compared with the south. This may result in an increased vulnerability to COVID-19 amongst staff and residents (The Health Foundation 2020a) and feed into area level variation seen in Greater Manchester as care homes were a source of hospital admissions and potentially caused some barriers to discharge.

7.4 Summary and Conclusions

This thesis has thrown light onto three distinct but related 'facets' of the complex and dynamic field of health inequality; considering aspects of inequality in access, in outcomes when there is no access at all, and in outcomes when services have certainly been accessed (in a hospital setting). The results are as complex as the field itself.

In paper 1, no link between deprivation and uptake was found, however distance factors persist in the distribution of usage of the primary care extended hours service and so there are some people in some areas who are using the services more than others. These geographical differences cannot be mapped simply onto a deprivation measure, but could be a proxy for some other underlying social and economic inequality and this inequality may then cause health inequities which arise through unmet need resulting from service design which does not take this distance factor into account.

The identification of deprivation is complex, and there are many factors within all the analyses carried out as part of this work which could be impacted by (and indeed contribute to) deprivation. Disentangling the true deprivation, distance and affordability effects within the work here is difficult. Furthermore, a focus on spare capacity by policy makers may blind future service design to the needs of people in geographically distanced locations, further embedding any access based health inequities. Enquiry into patient outcomes and explicit research focused on access and whether these systems have met the care needs of the underlying population is needed as part of the service evaluation, using alternative non administrative data sources and potentially mixed methods approaches to truly understand the impact of the way services are commissioned.

The advent of the pandemic to an extent collapsed access to services in a more universal way as everyone became subject to the same restrictions of movement, and experienced the same drop in availability of services needed to maintain and improve health and wellbeing, whether these were formal health care settings, or through informal family and social groups, services and networks. In paper 2, I found no link between deprivation and the decline or recovery in wellbeing during the first pandemic lock down but again the situation may be more complex. People surveyed and analysed for this study showed a level of resilience and elasticity in their response to the stress of lock down. There was no association between deprivation and wellbeing but income and foodbank use were important, indicating that some of the factors which are typically captured in deprivation indices and which indicate underlying inequality were important, but that perhaps the instances where this was linked to poorer wellbeing was not necessarily well correlated with areas of entrenched inequality as measured by the index of multiple deprivation. The variables used in the analysis captured change in circumstance for income and foodbank use, and this could be quite different to whether or not the respondent lives in an area with a high level of deprivation as measured by the IMD. The baseline score was the biggest predictor of outcomes, suggesting that the response to the situation was to an extent embedded at an individual level. There was however a noted skew in the deprivation deciles represented in the respondents to the survey and reduced representation from ethnic minorities. Given the additional disease burden experienced by non-white and deprived communities, their relative absence from the data cannot be assumed to be random. Ensuring that those most affected by any health phenomenon are not excluded from research into it is critical to gaining a proper understanding of how different factors affect health trajectories and outcomes, and the extent to which inequities arise. Having said this, the evidence provided by this thesis suggests that the unprecedented nature of our collective experience from March to July 2020 was to an extent a leveller. Those who are less privileged in these data did not in this instance experience a worse outcome (remembering that the outcome was for non-COVID-19 related wellbeing) probably because those with the worst outcomes did not have the capacity to respond to the survey, and also because of the universal nature of the shock to our normal social existence.

The link between deprivation and outcomes was complex in paper 3, which considered people who had certainly accessed services. Deprivation predicted death risk but not the length of stay. Ethnicity was important for length of stay, but not for death risk upon hospitalisation. It is difficult to understand the impact of deprivation and pre-existing inequalities on COVID-19 outcomes from these data and we need more research into how COVID-19 has impacted different communities in order to understand how deprivation, ethnicity and space have intersected to impact on outcomes. However, this study would suggest that the hospitalised patient population may not the most informative cohort to study if seeking to understand these complex social health factors as so much of what we need to consider when looking at the complex interaction between social factors and health, occurs outside of the hospital setting in the community - whether this is in other settings such as care homes, or in private residences. The work did identify spatial differences between health authorities in the city region which did not necessarily follow an average deprivation gradient and so we must conclude that there are other factors in play here - potentially at the hospital policy level, or indeed within specific geographically defined communities. That space once again features within these findings hints that simple consideration of deprivation is insufficient to detect patterns of inequality in such a complex system and we may need to interrogate further the nature of the space inhabited by communities with adverse experience and other common factors for these patients that may better explain their outcomes than a simple census unit level deprivation measure.

Macintyre, Maciver, and Sooman (1993) reviewed the literature on the interaction between health and area and argued that the use of area level data can in fact be a flawed approach. Throughout this thesis, I use area level statistics in addition to personal characteristics and I do not in fact make reference to the actual areas themselves, but there may well be significant area features both physical and social which impact on the extent to which residents can live healthy lives; for example access to green space or the absence of air pollution. The spatial disparities identified in the work on hospitalised COVID-19 patients, and the discrepancies noted between this and the predicted gradient of outcomes based on area deprivation statistics alone, suggests that a more considered and detailed investigation of the nature of space and services within each area may give a more informative and nuanced set of findings which better address growing inequality and better serve the needs of people in more marginalised communities.

In a developed economy like the UK, the social gradient in health is complicated and difficult to investigate. Commissioning services which seek to reduce health inequities and commission and provide access to health care that is determined by need and not the ability to pay, at the same time as pursuing policies which reduce spending in a climate of widening financial inequality would seem to be a fools errand, and yet this is what the health service has to do in the current political climate. It is also important to note what a small role acute and primary care plays in early mortality, remembering from Chapter 2 that the portion of the health function which is attributable to services rather than other factors is relatively small. In 2019, researchers at the Institute for Public Policy Research estimated that an additional 130,000 preventable deaths had occurred in just 7 years as a direct result of so called 'austerity' policies which saw state provision pared back through budget cuts (Hochlaf, Quilter-Pinner, and Kibasi 2019). Progress in reducing preventable disease has stalled since 2012, and local health spending has been reduced, with impact on preventative services. The philosophy of placing responsibility for maintaining health upon the individual has prevailed, whilst policy makers have ignored the impact of living in a place that makes high levels of health difficult to achieve. The IPPR report was published in the relative calm before the storm that has been the pandemic, but further research has asserted that it is clear that the nations health was in decline prior to the events of 2020, that this decline was inequitable, and that the arrival of COVID-19 has exposed health vulnerabilities across the social spectrum whilst pushing the health services of the UK to saturation, after an extended period of funding contraction. The poor state of the nations health at the start of the pandemic, and the specific local impact of widening health inequalities in the city region was further confirmed by Marmot and Allen (2021) in their report *Build Back Fairer in Greater Manchester.* Paper 3 adds weight to these conclusions showing that prexisting deprivation laid patients open to higher mortality risk on hospitalisation but paper 2 does not add huge weight to these arguments, and in fact suggests that there was a relative level of equity in the mental health burden experienced during the first lock down, notwithstanding limitations in the data and that subsequent experience may have changed this picture.

The collection of work presented here serves to further highlight that investigating health inequality is indeed a complex and difficult task, and at the heart of this must be an understanding of what the researcher seeks to measure and how this relates in real terms to the lived experience of the study population. Although there are a multitude of data sources and methods at the disposal of a quantitative researcher in this field, understanding these data and how they relate to real lives is of utmost importance if we are to draw any meaningful conclusions, and a uniform approach using standard measures may not always be the most informative. My contribution through this work illustrates that care and attention is needed and that the answers to questions around inequality, deprivation and health are not always straightforward and may even appear counter intuitive. Supplementation and triangulation using mixed methods approaches may therefore be appropriate and this should be considered as a priority by those working in health policy such that they may develop a rich understanding of people in their context, whether that be physical, economic, social or environmental, and how this impacts on their ability to access care and adopt health promoting behaviours. We must continue our endeavours to understand the social gradient in health, and the trajectory of gaps in health, so it is of upmost moral and social importance that we are not thwarted by the complex nature of the interface between health and deprivation so that we can continue to improve wider health outcomes and increase resilience to the perhaps inevitable ongoing and future health pandemics.

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Appendix A

Length of Stay in ICU of COVID-19 Patients in England, March - May 2020.

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Contribution

This paper was produced as part of a wider interdisciplinary team within the university in response to the Rapid Access to Modelling the Pandemic initiative convened by the Royal Society to support and inform the work of the Government's scientific advisors.

My contribution included data wrangling and manipulation, advice and assistance on imputation of geographical variables onto administrative datasets, input into discussions around data provenance and reading and commenting on substantive work.

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Length of Stay in ICU of Covid-19 patients in England, March - May 2020

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Abstract

Introduction

Length of Stay (LoS) in Intensive Care Units (ICUs) is an important measure for planning beds capacity during the Covid-19 pandemic. However, as the pandemic progresses and we learn more about the disease, treatment and subsequent LoS in ICU may change.

Objectives

To investigate the LoS in ICUs in England associated with Covid-19, correcting for censoring, and to evaluate the effect of known predictors of Covid-19 outcomes on ICU LoS.

Data sources

We used retrospective data on Covid-19 patients, admitted to ICU between 6 March and 24 May, from the "Covid-19 Hospitalisation in England Surveillance System" (CHESS) database, collected daily from England's National Health Service, and collated by Public Health England.

Methods

We used Accelerated Failure Time survival models with Weibull and log-normal distributional assumptions to investigate the effect of predictors, which are known to be associated with poor Covid-19 outcomes, on the LoS in ICU.

Results

Patients admitted before 25 March had significantly longer LoS in ICU (mean = 18.4 days, median = 12), controlling for age, sex, whether the patient received Extracorporeal Membrane Oxygenation, and a co-morbid risk factors score, compared with the period after 7 April (mean = 15.4, median = 10). The periods of admission reflected the changes in the ICU admission policy in England. Patients aged 50-65 had the longest LoS, while higher co-morbid risk factors score led to shorter LoS. Sex and ethnicity were not associated with ICU LoS.

Conclusions

The skew of the predicted LoS suggests that a mean LoS, as compared with median, might be better suited as a measure used to assess and plan ICU beds capacity. This is important for the ongoing second and any future waves of Covid-19 cases and potential pressure on the ICU resources. Also, changes in the ICU admission policy are likely to be confounded with improvements in clinical knowledge of Covid-19.

Keywords

COVID-19; length of stay; intensive care; survival analysis; England

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Introduction

Background

As of 1 February 2021, more than 103 million people worldwide had tested positive for SARS-CoV-2, with over 2.2 million deaths due to Covid-19[1] 93,448 deaths within 28 days from a positive test were reported in England[2]. Numerous efforts have been undertaken by epidemiologists to study the spread of the pandemic [1, 2], fatality rates [3] and the effectiveness of non-pharmaceutical interventions such as mitigation and suppression [4]. Several medical and public health studies have highlighted the increased length of stay (LoS) in Intensive Care Units (ICUs) [5–8].

Some infected people are asymptomatic [9], others have symptoms of varying severity, with a significant minority requiring ICU admission (5% of all of those testing positive in China [10]; 12% in Italy [5]). Such rates can lead to a fast depletion of ICU capacity, especially with increasing prevalence of Covid-19 in the population (idem). This information is relevant during the decision-making process on admission to ICUs, and also for the management and planning of resource allocation in the health care system [11]. Hence, it is important to know the average of and expected variation in ICU LoS, and to determine which factors might predict that variation.

Early studies of ICU LoS for Covid-19 restricted themselves to reporting descriptive statistics. A median of nine days was reported in an Italian study of 1,591 ICU patients with an average age of sixty-three [5]. In China, a median of eight days in ICU was found based on a compilation of 46 different studies [12]. The overall median conceals a wide variation in LoS, from a median of five days for patients who had died in ICU [13, 14] to a LoS of twenty-eight days for patients aged over sixty who had not died during the study [14]. For total hospital stay (including ICU), a median of twelve days (mean 12.8) was found for 1,099 Covid-19 patients in China with an average age of fifty-two [15]. In England, a median of twelve days for survivors and ninety days for non-survivors were reported as of 3 July 2020 [7].

For all the aforementioned studies, the complete LoS was calculated only for patients who had already died or been discharged from ICU; the LoS estimates were not adjusted for censoring, i.e. for the fact that patients still in ICU may go on to have greater LoS than that observed during the data collection window of the study. For example, 94% of those reported by [15] were still in hospital and were not included in calculating LoS. ICU LoS reported by [5] included 58% of the patients still in ICU but did not correct for censoring. LoS reported by Intensive Care National Audit & Research Centre (ICNARC) [7] was based on 9,768 patients with 519 still receiving critical care. Therefore, these figures on ICU LoS for Covid-19 are likely to be underestimates.

Aims

Our aim was to provide more accurate estimates of the ICU LoS attributable to Covid-19. We analysed the LoS in ICU of patients with Covid-19 during the first wave of the SARS-CoV-2 pandemic in England using data from a national reporting system using survival analysis methods that can compensate for the censoring of LoS data. We also aimed to investigate potentially important predictors of LoS, such as sex, age and the presence of comorbidities, as well as structural factors such as changes to care guidelines that occurred during the data collection period [16, 17].

Methods

Data

This was a secondary analysis of data collected by the COVID-19 Hospitalisation in England Surveillance System (CHESS) daily reporting mechanism. CHESS collates epidemiological surveillance reports from all National Health Service (NHS) hospitals in England to provide daily patient-level and aggregate data on COVID-19-positive hospitalisations[3]. In the patient-level data, patients are followed through their hospitalisation pathway, with the dates of various events recorded, such as date of admission to hospital, date of admission to ICU and final outcome date. CHESS also provides information about demographics and comorbid conditions. We used the data that was released on 26 May 2020. The individual-level data were obtained from 103 NHS trusts, with 134 participating trusts that provided aggregate data [18]. In England, there are a total of 150 acute trusts [19][4].

Of the 103 NHS Trusts providing individual data to CHESS, we excluded twelve due to data quality issues. In these trusts, less than 50% of patient-stays in ICU had dates recorded for both entry and exit. A further ten trusts were removed as they had no cases that passed the exclusion criteria. In the remaining trusts, we analysed all cases admitted to hospital between 6 March and 24 May 2020 who had a positive, laboratory performed, polymerase chain reaction test for Covid-19, were admitted to ICU and were 18+ years old. This resulted in a sample of 4,041 cases. Sixty-one patients were admitted to ICU more than once, so the number of unique patients in this sample was 3,980. See Appendix A for full details of the sample selection criteria.

Duration in ICU or censoring

The outcome variable was LoS in ICU, measured in days. This was calculated as the date of leaving ICU (either through death, discharge, or transfer) minus the ICU admission date. In the absence of the ICU admission date we used hospital admission date ($n = 154$) as a proxy. If the ICU leaving date was missing but the case had a reported outcome, we used the date of that outcome ($n = 1{,}140$), or the date of the record update ($n = 8$) as a proxy. These proxy measurements permitted us using a substantially larger sample while not underestimating a patient's actual LoS, as records are always updated after the outcome (a median of 6 days later).

Table 1 shows the number of records by final outcome and its occurrence. 743 cases were either recorded as being

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[1] https://www.worldometers.info/coronavirus/

[2] https://coronavirus.data.gov.uk/details/deaths?areaType=nation&areaName=England

[3] https://www.england.nhs.uk/coronavirus/wp-content/uploads/sites/52/2020/03/phe-letter-to-trusts-re-daily-covid-19-hospital-surveillance-11-march-2020.pdf

[4] There are also 25 health and care trusts which include 10 ambulance trusts, and 53 mental health trusts.

Table 1: Number of records of ICU stays by final outcome and when the outcome happened

Final Outcome	While in ICU	After ICU stay	Unknown	Total
Death	1,350	83	1	1,434
Discharged	843	1,020	1	1,864
Censored	222	137	384	743
Total	2,415	1,240	386	4,041

Source: own elaboration using CHESS data until 26 May 2020. Note: the final outcome denotes the outcome that could have happened after a patient left ICU.

still in ICU at the end of the data collection period, or had an incomplete record which omitted the final outcome. For these latter cases, we assumed that the last date on which the patient's CHESS record had been updated, or if this was not available the date of the most recent SARS-Cov-2 test swab (after they had been admitted to ICU), was the last date they were definitely still in ICU ($n = 222$) as this date is the last time we actually observe the patient to be in ICU. Thus, we treated these patients as having censored ICU LoS. Those patients might, in fact, have left the ICU but the data do not contain information on such an event.

Records for which LoS could not be calculated ($n = 386$), or for which negative LoS ($n = 13$) or zero LoS ($n = 48$) were implied by the data were removed from the analysis, leaving a sample of 3,594 cases. After also removing cases with missing predictor information on health risk factors score ($n = 545$), a final sample of $n = 3,049$ was used. Table B1 presents the LoS a recorded in the final sample broken by characteristics described in further sections.

Patient-level pre-morbid predictor variables

We found no studies specifically focused on evaluating risk factors for ICU LoS due to Covid-19, although associations have been found for non Covid-19 ICU LoS (see for example [20]) and Covid-19-related hospital (not exclusively ICU) LoS [21]. Instead, we looked at studies that evaluated pre-morbid, individual level risk factors for Covid-19 severity and mortality. Of these, the most consistently reported were old age, male sex, and the presence of comorbid conditions [22–25]. We used these as the primary predictors of LoS in our analyses. In our sample, there were 920 (30.2%) females and 2,129 (69.8%) males. We grouped age into four categories: 18-49 years old ($n = 682$), 50-64 years old ($n = 1,322$), 65-74 years old ($n = 726$), 75 or over ($n = 319$). We further evaluated whether there might have been differential effects of age on LoS by sex, as well as the effects of age and sex independently.

We also explored differences in LoS by ethnicity. These analyses were exploratory because of the amount of missing ethnicity data ($n = 535$) and the consequent potential for biased findings. Ethnicity was grouped into five categories (based on those used by the UK Office for National Statistics): Black (including black African and Afro-Caribbean; $n = 134$), Asian (primarily Indian, Pakistani, and Bangladeshi; $n = 388$), Mixed ($n = 51$), Other ($n = 162$), and White ($n = 1,779$). The White group was used as a baseline category in the analysis.

Risk factor score

We used information on eleven individual health-related risk factors recorded in CHESS: asthma (requiring medication), diabetes (I and II combined), chronic heart disease, hypertension, immunosuppression due to disease, immunosuppression due to treatment, chronic liver disease, chronic neurological disease, chronic renal disease, respiratory disease, and clinician-rated obesity; all were coded as binary items ($0 = \text{no}$, $1 = \text{yes}$), apart from clinician-rated obesity which was coded on a three-point scale: ($0 = \text{no}$, $1 = \text{maybe}$, $2 = \text{yes}$). The data on risk factors was incomplete; specifically, there was often no distinction between the patient not having a condition and the information being missing due to not being recorded. To make maximum use of the available information, we used the one-parameter Rasch partial credit model to combine the information from all of the risk factors into one overall score. This model allowed us to test whether the risk factors formed a uni-dimensional scale and to account for their intercorrelations (e.g. heart disease and hypertension were highly correlated) [26]. The Rasch risk score summarised the pre-existing health-statuses and comorbid conditions of the patient, a high score indicating the presence of many health-related diseases and risk factors, and a low score indicating lower risks. Details of the Rasch model results are in Appendix A.3.

Treatment-related factors

Some studies have reported on post ICU-admission factors (e.g. mode of respiratory support, fraction of inspired oxygen, secondary infections) influencing outcome severity [5]. The secondary infections indicate that they might be acquired in general ward or intensive care (Hospital-Acquired Infection; HAI). Typically, these infections lead to longer LoS [27]. There were 580 cases with secondary bacterial pneumonia or other infections in our sample, and they had, on average, longer LoS in ICU than other patients (19.3 vs. 11.6 days for patients with an outcome recorded). However, only 125 cases had a swab for that infection after they were admitted to the ICU, which we believe suggests it was acquired in ICU. This was assessed by comparing the swab date for secondary infection with the dates of admission and leaving of the ICU. We decided not to use the treatment-related factors as predictors because they will not be available before the patient is admitted to ICU, and they likely reflect a complex interaction between unobserved patient characteristics, the severity of infection and the treatment choices made by the clinicians, which would render these predictors endogenous to the outcome.

The single exception to this decision was the inclusion of whether the patient received Extracorporeal Membrane Oxygenation (ECMO) while in ICU. Previous studies have shown that ECMO patients had longer LoS in ICU because of the severity of their condition and the nature of the treatment [28, 29]. To complicate this further, ECMO was only available in a few hospitals in England. For these reasons, we included an indicator variable for whether a patient received ECMO ($n = 73$) in our analyses.

Accounting for period effects: admission period, ICU entry guidelines and guidance on proning

We used data from a two-month period when Covid-19 infections were rising rapidly to a peak in England, approaching and nearly overwhelming critical-care capacity in some areas. During this time there was a change in official health-service guidelines on the criteria to be used in assessing Covid-19 patients for suitability of ICU admission [16][5]. The nature of the change in guidelines was to give more weight to frailty rather than age of the patient when considering whether they might benefit from treatment in ICU. As the pandemic progressed, clinicians gained experience in treating Covid-19 patients, reflected in the guidance on proning of conscious patients on 12 April 2020 [17] to improve their oxygenation and hence survivorship [30]. All of these factors are likely to have had an impact on the characteristics of patients being admitted to ICU and decisions on who and when to discharge from ICU.

To account for these period-effects on LoS we divided the data collection window into three periods, focusing on the change of the ICU entry guidelines: i) pre-change, i.e. until 24 March 2020, for ICU admissions before the guideline update ($N = 387$), ii) transition, covering ICU admissions from 25 March to 7 April 2020 ($n = 1,452$) during the transition in guidelines, and iii) post-change, for ICU admissions from 8 April to 24 May 2020 ($n = 1,210$).

We hypothesised that the changes over time might have had a differential effect on patients based upon their age and frailty. We did not have a direct measure of frailty, so we used the health-related risk factor score as a proxy variable, which is likely to be positively correlated with frailty (i.e. a patient with many risk factors is unlikely to have a low frailty score).

Statistical analysis

We used parametric, continuous-time survival models, also known as Accelerated Failure Time (AFT) models, to evaluate the LoS from ICU admission until the patient left ICU (by death, discharge, or transfer). We used the AFT models to evaluate how the above-described predictor variables lengthen or shorten LoS. These models can also allow for patients who were still in ICU and who had therefore not yet reached their full LoS (i.e. censored observations). This is achieved by making an assumption about the distributional form of the underlying hazard. The hazard is the probability that leaving ICU will occur at a particular time, given that it has not already occurred. In our models, we evaluated two commonly used parametric hazard distributions: the *Weibull* and the *log-normal*. The Weibull distribution can allow for hazards that are either stable, or monotonically increasing or decreasing over time. The log-normal can allow for hazards that are non-monotonic, i.e. the risk of observing an event for a patient first increases until a peak, then decays. We fitted these AFT models by maximum likelihood estimation. We used the Stata 16 command streg [31]. Code for the method is available at https://github.com/a-wis/CHESS-covid19-los.

We divided our analyses into two sets. In Set 1 we evaluated models of LoS that did not include ethnicity as a predictor. In this set we compared models of the main effects of the predictor variables above, with models that also included the three interaction effects: (admission period)*age, (admission period)*(risk factor score), and sex*age. We also evaluated the choice of baseline hazard function, i.e. Weibull or log-normal. The goodness-of-fit of these models were compared using Akaike's Information Criterion (AIC), which is a penalised likelihood suitable for comparing complex multivariate models because it adjusts for model complexity and the likely fit of the model in alternative samples of data [32].

In Set 2 we evaluated the effect of including ethnicity as a predictor variable into the preferred model from Set 1. The large amount of missing data for the ethnicity variable meant that the sample size was smaller for Set 2 models compared to Set 1 models, which might lead to biased estimates of LoS. To evaluate if this smaller sample biased our LoS estimates from Set 1, we also fitted the preferred Set 1 model (without ethnicity as a predictor) on the Set 2 sample (i.e. just those patients who did have their ethnicity recorded).

Results

Descriptive statistics

Table B1 and Figures B1 and B2 in Appendix B present the descriptive statistics of the LoS in ICU broken down by the predictors used in the model. In these figures we also break down the results by either of the outcomes (death or discharge/transfer) and censoring.

Among the patients with censored LoS, long ICU stays were more common, with a mean of around twice that of those who died or were discharged. The later the admission to ICU date, the more censored cases we observed (Table B1: $n = 28$ before 25 March; $n = 265$ afterwards).

For patients younger than seventy-five years old with known outcomes, we observed a mean ICU LoS of approximately thirteen days, whereas for those seventy-five or over this was around nine days. We observed a decreasing mean LoS for patients with known outcomes with the three periods of ICU admission. Non-White patients had slightly longer LoS in ICU; whereas those needing ECMO stayed around four days longer in the ICU. There was also a considerable variation in the observed LoS for all subgroups; overall the standard deviation (SD) was ten days for those with known outcomes and sixteen for those without.

AFT models

We found that the assumption of a log-normal baseline hazard function, which allows for a non-monotonic, peaked hazard, gave the best (lowest) AIC (7,937.42, compared to 8,021.42

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[5] Information about updates to the guidelines can be found at https://www.nice.org.uk/guidance/ng159/chapter/Update-information

for the equivalent Weibull model; see Tables C1 and C2). The interaction effects (between admission period with age and health-risk score, and between age and sex) did not improve the AIC (7,949.64 and 7,953.82 for the log-normal models with interactions; see Tables C3 and C4, respectively), so we report the results from the log-normal model with main-effects only in Table 2. Results for the other tested models, including Weibull and models with interactions, are shown in Appendix C.

Table 2 shows the model coefficients, which represent the effects on mean log LoS associated with the predictors. Patients admitted during the early admission period had a significantly higher average LoS compared to those admitted after 7 April (at a significance level $\alpha = 5\%$). There was weak evidence (p value = 0.055) that admissions during the middle period (25 March to 7 April) had longer LoS. The 50-65 age group had the longest LoS, with all other age groups having shorter estimated LoS in comparison. Treatment with ECMO was strongly associated with longer LoS ($e^{0.40} = 1.49$, i.e. around 49% longer than non-ECMO patients, after controlling for the other predictors). We also found a negative association between the co-morbid risk factors score and ICU LoS. Patients with the lowest score (i.e. least number of co-morbid risk factors, weighted for their co-occurrence in the Rasch model) had LoS around 6% longer than average; those with the highest score had LoS shorter by around 14%. There was only very weak evidence of an association between sex and the LoS.

We used the results from the model shown in Table 2 to predict LoS for each patient (Table 3). The overall mean predicted LoS for the sample was 16.5 days (SD 3.0). The variation in model predicted LoS associated with the two main significant predictors, admission period and age, are shown in Figures 1a and 1b.

Figure 1a shows that the age group with the shortest predicted mean LoS, 10.7 days (SD 1.0), was the oldest group (75 and older). Inspection of the final outcomes for this group showed that it was the one with the highest proportion of deaths (over 70% of the 304 non-censored cases). The next-shortest average LoS, of 15.4 days (SD 2.3) was for the youngest group (less than 50 years old). This younger group had the lowest proportion of deaths (18% of non-censored cases). The group with the longest predicted LoS was the 50-64 year old group, with a mean of 18.4 days (SD 1.9).

Figure 1b shows that the later the admission period, the shorter the LoS on average, with the early period having a mean predicted LoS of 18.4 days (SD 3.4) and the latest admission period, after April 7th, having a mean predicted LoS of 15.4 days (SD 2.6). The LoS distributions by admission period were notably bi-modal, with a small peak with relatively short LoS for each period. This was associated with the patients in the oldest age group, which, as shown in Figure 1a, had the shortest average predicted LoS by some margin.

The inclusion of ethnicity (based on a smaller sample size $n = 2,514$) did not improve the model fit (AIC = 6,572.26 without ethnicity vs AIC = 6,574.48 with ethnicity). Moreover, the pattern of findings from the model without ethnicity as a predictor was virtually the same as in the model without ethnicity but with the full sample size $n = 3,049$ (see Table C5 and Figure C1).

Discussion

Our estimated mean LoS for ICU patients was over sixteen days. The median, at nearly eleven days, was similar to the values reported by ICNARC [7] for England (twelve days for survivors, nine for non-survivors; or 10.8 for either of the outcomes on 3 July; 10.1 on 5 June). Our estimates adjust for the censored cases, who have longer than average LoS in the sample (Table B1).

Comparisons with other countries are less informative, because of differences in the populations and health-care systems, but our estimated LoS were longer than [5] for Italy, (2020; median nine days), and [12] for China (median of eight days based on a compilation of forty-six different studies);

Table 2: Log-normal Accelerated Failure Time model with main effects results

Variable	**Coefficient**	**Robust SE**	***p***
female	−0.05	0.04	0.193
admission period	(reference: after 07/04)		
before 25/03	0.21	0.07	0.002
25/03-07/04	0.09	0.05	0.055
age group	(reference: 50-64)		
<50	−0.22	0.06	< 0.001
65-74	−0.12	0.05	0.021
75+	−0.55	0.06	< 0.001
risk score	−0.06	0.03	0.047
ecmo	0.40	0.14	0.004
intercept	2.42	0.05	< 0.001
$\log(\sigma)$	−0.07	0.02	< 0.001
n	3,049		
AIC	7,937.42		

Source: own elaboration using CHESS data.

Table 3: Predicted length-of-stay in days based on the log-normal model with main effects

Age	**Measure**	**Admission period**			**Total**
		<25/03	**25/03-07/04**	**>07/04**	
18-50	mean	17.3	15.5	14.8	15.4
	median	11.2	10.1	9.6	10.0
	SD	1.9	1.8	2.5	2.3
	N	79	306	297	682
50-64	mean	21.3	18.8	17.2	18.4
	median	13.8	12.2	11.2	12.0
	SD	2.0	1.4	1.2	1.9
	N	141	646	535	1,322
65-74	mean	18.9	16.7	15.1	16.5
	median	12.3	10.9	9.8	10.7
	SD	1.3	0.8	0.8	1.5
	N	106	360	260	726
75+	mean	12.3	10.9	9.7	10.7
	median	8.0	7.1	6.3	7.0
	SD	0.5	0.5	0.4	1.0
	N	61	140	118	319
Total	mean	18.4	16.8	15.4	16.5
	median	12.0	10.9	10.0	10.7
	SD	3.4	2.7	2.6	3.0
	N	387	1,452	1,210	3,049

Note: "mean" denotes a mean of the predicted mean LoS for all individual patients; "median" denotes a mean of the predicted median LoS for all patients. Source: own elaboration using CHESS data.

some studies reported median LoS in ICU as short as five days [13, 14].

We found that ICU LoS was decreasing over our study period, with patients admitted before 25 March having LoS five days longer on average than those admitted after 7 April. There was no evidence of any differentiation of this effect between patients in various age groups, or with pre-existing risk factors.

Unfortunately, the reasons for this change cannot be determined from the CHESS data, as several different and likely influential processes were confounded (except patient age, which we adjusted for): changes in the characteristics of patients contracting Covid-19 because of the stage of the epidemic, changes in who was admitted to ICU because of guideline changes and shielding introduced by the UK Government [33] around 21 March 2020 (i.e., during the first wave of the pandemic), and changes in the treatment and management of Covid-19 patients [17]. The first of the above possible explanations is further obscured by the non-uniform spread of the Covid-19 across the regions of England, with London and the Midlands being affected first. The changes to the guidelines are likely to have a modest effect as the final decisions on whether to elevate care to intensive are ultimately taken by clinicians. Also, general compliance with advice on shielding of vulnerable groups might have influenced the composition of patients admitted to specific hospitals and ICUs [34]. Further, at no point was the capacity of the ICUs in England overwhelmed by the number of patients, according to the NHS data on bed availability and occupancy [35]. However, some of the hospitals (e.g. in London) were close to the limit.

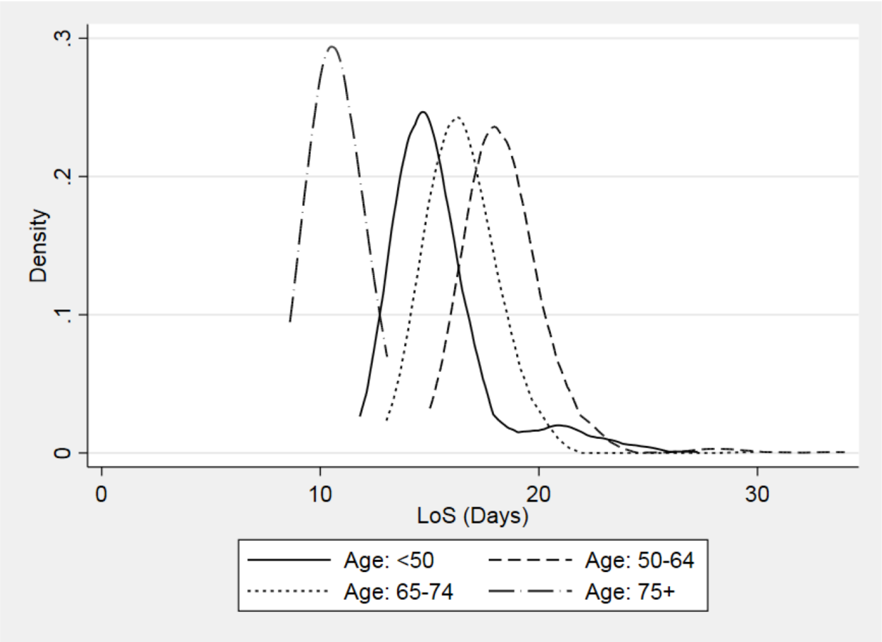
It is not clear from the CHESS data whether this trend in shortening ICU LoS for Covid-19 patients was approaching an asymptote, but the balance among the influences on LoS may shift as the pandemic moves on from the first peak, possibly lengthening the LoS again in future waves of the pandemic.

We found that LoS was not monotonic with age (i.e. either increasing or decreasing), unlike the relationship between age and Covid-19 severity and mortality [7]. While the group with the shortest LoS was the oldest one, the group with the longest LoS was the "younger" middle-aged group between 50 and 64 years. The middle-aged groups in our sample had roughly equal proportions of those who died and those who were discharged from ICU (for the patients with non-censored outcomes), i.e. the final outcome for these patients was likely the most uncertain on admission to ICU. Our sample was highly selective (i.e. patients ill enough to be in ICU with Covid-19) and this has the potential to bias our results, particularly with regard to age. For example, for patients with the same level of severe symptoms of Covid-19, younger patients were more likely to be hospitalized than older, frailer patients [36].

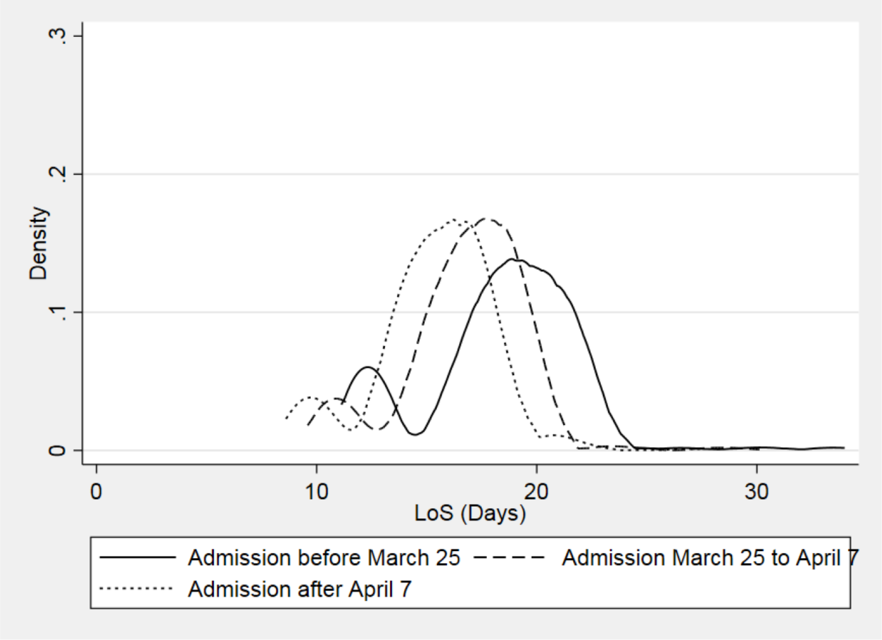
We found no evidence in the CHESS data that LoS in ICU is related to sex or ethnicity of the patient, and this was consistent across all tested models. Also, the shorter LoS found in more recent periods was not selectively affecting e.g. non-White patients only nor patients with certain pre-existing conditions score.

We argue that the median LoS better describes the central tendency of LoS, but mean LoS might be better to be used in planning of ICU capacity. In our case, mean LoS was five days longer than the median (Table 3); this reveals a tail of the distribution of mean predicted LoS with very long LoS, as

Figure 1: Distribution of mean predicted LoS in ICU



(a) Model-predicted LoS, by age group



(b) Model-predicted LoS, by admission period.

Source: own elaboration using CHESS data and log-normal AFT model.

also shown in Figure 1. This ought to be taken into account in situations when the infections are increasing exponentially during early phases of the pandemic or potential further waves.

Limitations

The individual-level CHESS data, while in principle being a census of all patients with Covid-19 in England, had severe missingness issues. For example, when compared with the NHS Situation Reports (SitRep) deaths, they captured only around 13% of deaths in hospitals. Those reported cases suffered from missingness of predictors and other key information, especially dates of admission to ICU and final outcome, as well as ethnicity. The missingness patterns varied by NHS trust and geography; London and the Midlands had the highest percentages of missingness, which might have been due to these regions experiencing the peak of the pandemic earlier than elsewhere. Further, each NHS trust operates their IT system autonomously, which may lead to discrepancies in coverage and quality of collecting non-routine data, such as individual-level CHESS data. These data-collection systems might have been under various levels of pressure during the peak of the pandemic.

Although our statistical models were suitable for adjusting the observed overall LoS for censoring, they did not provide LoS estimates separately for those in ICU who eventually died and those who were discharged. The models only capture the "net" effect of predictors on LoS, and these effects may be countervailing for different outcomes, e.g. old age may be associated with a shorter LoS for eventual death but a longer LoS for eventual recovery. To overcome this limitation, more sophisticated models can be used. These methods include AFT models for "competing" outcomes [37] and multi-state models [38], that allow for finer-grained analysis of the influences on ICU LoS and the different effects of predictors on death vs. discharge. However, these approaches would require data with nearly perfect coverage of all events, which was not the case with the CHESS data.

Conclusion

Covid-19 Hospitalisation in England Surveillance System (CHESS) data are limited due to case and variable missingness. Future planning should enable more automated data collection for clinical staff, e.g. based on existing patient data, with a common standard of a minimum set of patient characteristics that would permit national comparisons. Also, more detailed information about inclusion and exclusion criteria for the NHS trusts participating in the data collection [18] would help alleviate potential biases resulting from the selective samples.

Our analyses of the CHESS data suggest that using the mean LoS, as compared with median, might be better suited as a measure for assessing and planning ICU bed capacity, because the median neglects the severe skew of the distribution of LoS. This is important when considering subsequent waves of Covid-19 cases and potential pressure on ICU resources. We found that the most informative pre-admission predictors of LoS were not necessarily the same ones that predict severity of Covid-19 outcomes, with the exception of age. The weak effect of comorbidities and the likely potential for them to be influenced by clinical practice suggests that using them to make predictions may also require using more recent data and improved models. When considering the utility of such predictors in planning ICU bed capacity, we note that changes in ICU admission policy are likely to be confounded with improvements in clinical knowledge of Covid-19, rendering their utility labile over time.

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Statement on conflicts of interest

All authors declare that they have no conflicts of interest.

Ethics statement

Public Health England gathers data from National Health Service microbiology laboratories, storing it in the SGSS database for epidemiological analysis, an activity permitted under Section 251 of the National Health Service Act 2006, which allows processing of patient data for defined purposes, including public health surveillance such as CHESS data. This work was prepared for the Scientific Pandemic Influenza Group on Modelling (SPI-M) that advises the UK's Department for Health and Social Care on its COVID-19 response.

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Abbreviations

AIC: Akaike Information Criterion
CHESS: Covid-19 Hospitalisation in England Surveillance System
ECMO: Extracorporeal Membrane Oxygenation
HAI: Hospital-Acquired Infection
ICU: Intensive Care Unit LoS Length of Stay
NHS: National Health Service SD Standard deviation

Appendix B

Paper 2: Additional figure

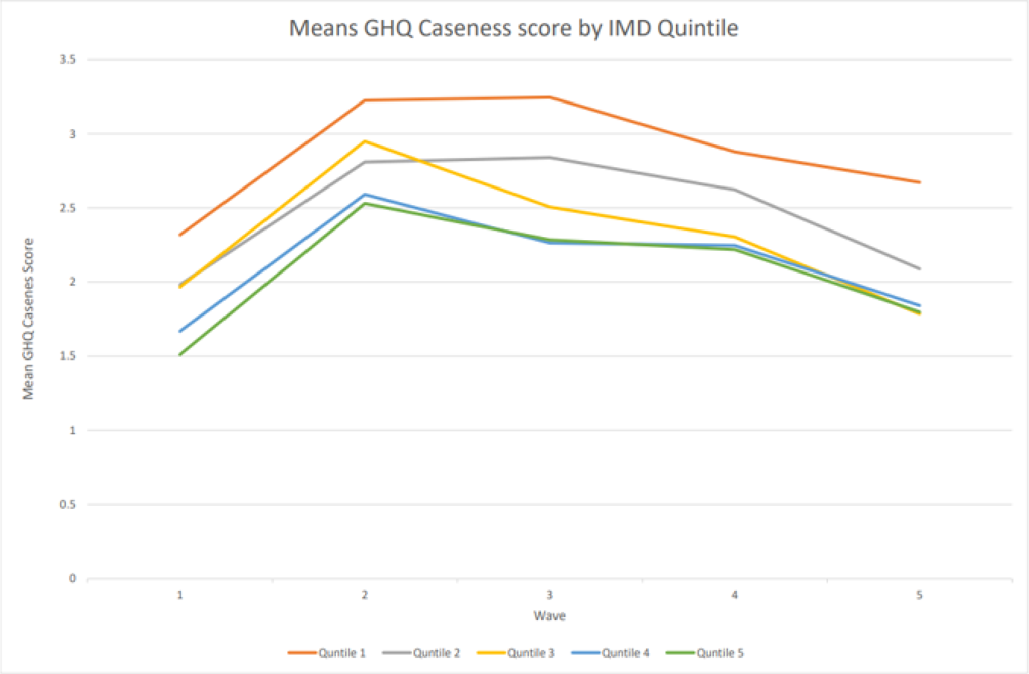

Figure B.1: Trajectory of wellbeing presented by IMD quintile. In this graphic, wave 1 represents the baseline and wave 2-5 represent monthly data collection from April to July.