The Vibrancy and Resilience of British High Streets

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Declaration

I, Abigail Hill, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work.

Signed

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Abstract

British high streets have endured significant economic and cultural challenges both in the leadup to and as a consequence of the COVID-19 pandemic. The volatile and challenging socio-economic environment has been brought about by the lingering effects of the 2008 recession, high business rates, competition from online retailers, and the impact and implications of the global pandemic. The changes to the high street retail landscape have been recorded using new sources of data that can supplement traditional data sources such as local government retail surveys. New sources of data such as consumer data, property portal data and mobility data are more spatially and temporally granular. As a result, local governments, the retail sector and stakeholders can use these emerging forms of data to create more easily updateable measures of high street composition and performance. This thesis utilises the Local Data Company's Britain-wide database on retail location, type and vacancy. The data ranges between the start of 2017 and June of 2021, containing around 800,000 records of occupiers. The analysis within this thesis starts by describing the composition and vibrancy of British high streets in the lead-up to the pandemic. Next, the thesis provides an evaluation of the impact of the COVID-19 pandemic and the subsequent shift towards remote working on the viable resilience of commuter towns. This section is followed by an exploration of the short-term impacts of the COVID-19 lockdown restrictions on the resilience of Britain’s high streets. Finally, the application of new forms of data in informing local government high street regeneration policy is studied as part of a knowledge exchange with the London Borough of Camden. This thesis contributes to our understanding of how the circumstances of different British high streets can be monitored and mapped, with the goal of improving understanding of vibrancy, resilience, and potential for regeneration.
Impact Statement

British high streets have been subject to many different challenges, including the rise of e-commerce, high business rates, economic recession, political uncertainty, and government enforced restrictions during the COVID-19 pandemic. Yet, there are still substantial gaps in the evidence-base for comparing all the high streets in Britain and identifying those which are struggling the most. Existing literature suggests that commercial data might be beneficial in creating granular and easily updated measures of high street performance. However, the potential benefits of using large commercial datasets to inform high street intervention strategies and other actions by local authorities remains under-researched. This thesis seeks to understand how commercial data can best be utilised to measure the vibrancy and resilience of Britain’s high streets, including the roles played by local authorities in local regeneration projects and decision-making.

The findings challenge how high street success can be viewed and ranked. This thesis proposes that commercial data can be used to successfully produce measures of high street vibrancy and resilience using new applications of existing methods. The methodological aspect of this research has impacted a wide variety of audiences and has been disseminated through presentation to academic conferences, academic and commercial societies, local government organisations, and commercial stakeholders.

Academic impact

This research has impacted Geographic Information Studies through publications and conference presentations. Three academic conference abstracts have been published directly as a result of this PhD work, resulting in one ‘best paper presentation’ award for an Early Career Researcher at the GISRUK conference 2022 (08-04-22) for material included in Chapter 6. My research has been disseminated to wider academic audiences via academic blogs and news outlets including the Consumer Data Research Centre’s Data Stories, the UBEL-DTP Research Blog and UCL News. I used my expertise on the vibrancy and resilience of British High Streets to lead a geography field trip as part of the ‘Geography in the Field 1’ module at UCL’s Geography Department. My knowledge aided my explanations of key concepts and literature in discussions with students. To continue the impact of this research within academia, I plan to write an additional peer-reviewed paper in addition to those already submitted, building on Chapter 7.
Non-academic impact

The greatest impact achieved during my research was through the Knowledge Exchange conducted with Camden Council outlined in Chapter 7. My research and insights informed the decision-making of their high street regeneration team regarding the data sources and geographic boundaries they use to inform policy. My research also strengthened the relationship between UCL and Camden Council. My research has also been presented to other government organisations including the Greater London Authority (20-04-22). My research has also resulted in engagement with commercial stakeholders; media coverage led to invitations to present my research at the Society for Location Analysis (18-05-21) and Pets At Home (23-09-21). The research in Chapter 5 was used to inform a report written for Retail Economics as part of a UKRI project, where my research was used to brief their stakeholders on investment decisions. This thesis and my public engagement add to the debate surrounding data-driven regeneration projects for high streets.
Acknowledgements

First of all, I would like to thank my primary supervisor, Professor James Cheshire, for his essential role in managing my research project and enabling unique opportunities to research topics that I am passionate about. I would also like to express gratitude to my secondary supervisor, Professor Paul Longley, who provided me with important advice throughout my PhD and maintains such a supportive research group. This thesis would not have been possible without the ESRC, which provided the funding, and the Local Data Company, which granted me access to their data. I would also like to thank my colleagues and friends in the CDRC for all their support and for making my PhD such a memorable experience. I would like to thank my parents, brother and grandma for constant support throughout my academic experience. Finally, I would like to thank Lewis for proofreading all my work and for your support.
Thesis Outputs

Peer-Reviewed Conference Papers


Papers in Peer-Reviewed Journals


Other Conference Presentations

- The Society for Location Analysis. 2021. How Resilient are Commuter Town High Streets to the Impact and Implications of COVID-19?

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<td>BID</td>
<td>Business Improvement District</td>
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<tr>
<td>BRC</td>
<td>British Retail Consortium</td>
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<tr>
<td>CAZ</td>
<td>Central Activities Zone</td>
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<tr>
<td>CDRC</td>
<td>Consumer Data Research Centre</td>
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<tr>
<td>COVID-19</td>
<td>Corona SARS-CoV-2</td>
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<tr>
<td>DBSCAN</td>
<td>Density-based spatial clustering of applications with noise</td>
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<td>DSH</td>
<td>Data Safe Haven</td>
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<td>ESRC</td>
<td>Economic and Social Research Council</td>
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<td>EU</td>
<td>European Union</td>
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<td>FHRS</td>
<td>Food Hygiene Ratings Scheme</td>
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<td>FSA</td>
<td>Food Standards Agency</td>
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<td>GDHI</td>
<td>Gross Domestic Household Income</td>
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<td>GLA</td>
<td>Greater London Authority</td>
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<td>H3</td>
<td>Hexagonal Hierarchical Spatial Index</td>
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<td>High Street UK 2020 project</td>
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<td>Key Performance Indicator</td>
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<td>LDC</td>
<td>Local Data Company</td>
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<td>Location Quotient</td>
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<td>Lower Layer Super Output Area</td>
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<td>Median Absolute Deviation</td>
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<td>New Economics Foundation</td>
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<td>United Kingdom Research and Innovation</td>
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<td>Variance Inflation Factor</td>
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<td>Valuation Office Agency</td>
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Chapter 1

Introduction

British high streets face a volatile and challenging socio-economic environment brought about by the 2008 recession, high business rates, competition from online retailers and now the impact and implications of the COVID-19 pandemic. Local high streets are therefore impacted by wider global trends as well as socio-economic and market forces. In fact, Wrigley and Lambiri (2014) have argued that the economic shockwave caused by the 2007-2008 financial crash exposed Britain’s high streets to numerous challenges that triggered major forces of change. With the COVID-19 pandemic once again having pushed Britain into a recession, this is a crucial time to quantify the changing composition of retail areas.

Whilst the high streets are in decline, the volume of data available for capturing information about those who shop there has never been greater (Hall, 2011). Previous studies that have focused on the demographic composition of high streets and their catchment areas have analysed businesses composition and clusters or resources available to specific demographic groups (Vaughan et al. 2018; Ruggs et al. 2015; Wrigley and Lambiri 2015). Yet, vibrancy as a measurement or tool for development, combining both store composition and demographics, remains under-researched. Nevertheless, wider research has presented evidence of correlation between creative community driven methods and economic growth (Pedroni and Sheppard, 2013). Additionally, increased cultural activity can positively impact on the revitalisation of local residential areas and bring commercial activity to high streets (Silver and Miller, 2013; Woronkowicz, 2015). While high street spaces and purposes were in the process of being reimagined through creative development, the COVID-19 lockdowns have arguably shown how community and wellbeing, and their integration into the centre of towns and cities, can provide a broader purpose to the surrounding populations.

This thesis is particularly timely given that there are multiple local government schemes and initiatives focusing on creative place making, improved vibrancy, and regeneration to help reverse the fortunes of the high street in Britain (Forman and Creighton, 2012). The vague interpretations of ‘vibrancy’ leave the term open to debate, with different disciplines offering an insight into how the concept can be conceived.

One additional and increasingly popularised measure of high street success used within the literature and current policy is ‘resilience’. High street resilience can be defined as the ability of an area to return to its pre-existing state following an economic or social shock, or to adapt to new conditions (Fernandes and Chamusca, 2014; Hudson, 2010). The adaptive aspect of resilience can therefore be used to measure whether a high street can sustain long-term development and adapt to the needs of its local population. Since the COVID-19 pandemic there has been an increased shift from measuring high street success in terms of vitality and vibrancy, to considering their resilience. The pandemic-
induced lockdowns have prompted studies that measured the resilience of retail to the disruptions caused by stay-at-home orders (Quinio, 2021).

This raises an important point on the change in focus from concepts such as ‘vibrancy’ to increasingly common narratives of ‘resilience’. Further research is needed into the qualities associated with both terms and the potential trade-offs in achieving them. For example, while some literature considers the presence of large national chains to be a symbol of investment and potential resilience it, it inevitably displaces smaller independent stores, with the resulting homogenisation of local places leading to a reduced diversity in what high streets offer (Duignan, 2018). These threats to the urban landscape are of particular concern in communities made up of vibrant projects and where small businesses play an essential role in the area’s economic and social vibrancy, identity, and market competition (Everett, 2016).

This research predominantly explores the measurement of vibrancy and resilience through the use of ‘big data’, specifically store location data. Commercial data providing granular information on shops is a prime example of a new ‘big data’ source, that allows for Britain-wide retail analysis that can derive trends on the success and characteristics of specific store categories, both spatially and temporally. Additional information alongside shop location (such as occupier name, occupier description, and vacancy status) also provides invaluable insights that can be used to derive performance metrics such as occupier turnover rate and vacancy rate.

Access to a large store location database provided by the Local Data Company (LDC) was brokered through the Consumer Data Research Centre (CDRC), a big data initiative funded by the Economic and Social Research Council (ESRC). This dataset has not previously been applied to a measure of high street vibrancy across the whole of Britain, and presented a unique opportunity to study how commercial data can be applied to measure high street success and to inform policy.

The overarching aim of this thesis is to provide a considerable contribution to an understanding of how commercial data can be used to measure the vibrancy and resilience of British high streets. Measures of vibrancy and creative placemaking have traditionally been measured through qualitative sources that are predominantly generated at a local level, making national cross-comparisons difficult. This thesis aims to examine quantitative measures and conceptualisations in which high street successes can be viewed, and to evaluate whether new commercial datasets can be used to support existing practices. However, before such commercial data can be repacked to produce measurement tools and inform policy, it is crucial to scrutinise the data’s accuracy, validity, and any potential errors. Due to commercial data not being openly accessible, there is minimal research into the validity and accuracy of such data and its applicability to social research. Consequently, this thesis also provides explicit detail of the data cleaning processes required and the limitations of the LDC data when used to create measure of success.
An important note regarding the aims of this thesis is that they are somewhat specific to the LDC dataset. Therefore, this work does not endeavour to develop a framework for applying commercial data to high street success measurements, but rather provides unique insights on the impact of economic and social shock on British high streets. A priority of this work was to make the most of this unique opportunity to have access to such a granular spatial-temporal dataset of store locations - specifically by using it to validate open sources available to policymakers who use data-driven methods to inform intervention strategies.

1.1 Aims

As indicated in the first section of this chapter, the purpose of this thesis is to develop a comprehensive understanding of the vibrancy and resilience of British high streets from 2017-2021 by using novel sources of commercial data. The more specific aims of this thesis can be categorised into three main themes. Firstly, to develop a measurement of vibrancy within Britain’s high streets during the time period of 2017-2019, when the main narrative of high street success was framed in terms of vibrancy and vitality. This required extensive cleaning of the LDC store location data in order to devise new variables and measures of vibrancy. This process demonstrated the potential of commercial data for comparing high streets across Britain in terms of their vacancy and occupier churn.

During the development of this thesis, the COVID-19 pandemic hit. This caused a change in the primary narrative used within policy to describe high street success. Consequently, the analysis between 2020-2021 is focused on addressing the second key aim of understanding and measuring the resilience of British high streets. It was recognised that a measure of high street success should incorporate an understanding of how they respond to economic and social shock, and the impact of the government enforced restrictions in response to the pandemic.

The third aim of this thesis was to establish how new forms of data could be used by local councils to help inform high street intervention strategies. While this thesis primarily adopts quantitative geo-spatial analysis to measure the success of high streets, it was acknowledged that a mixed-methods approach using engaged scholarship was needed in order to gain a first-hand understanding of how local councils use data and quantitative analysis to inform high street policy.

Considering these three broad research areas, the thesis has four main aims:

1. To appraise current indicators of high street success including measures of ‘vibrancy’ and ‘resilience’, and then identify opportunities for improvement, using a unique commercial dataset.
2. To assess the quality and validity of a commercially-produced shop location dataset when proposing improved indicators of high street success.
3. To explore the operational potential of such data to develop new measures of British high street ‘vibrancy’ and ‘resilience’.
4. To develop recommendations as to how new sources and forms of data might be used to inform retail revitalisation policies and council-led intervention strategies.

While this thesis predominantly focuses on the applications of a commercial data source, the resultant objective of this work is to identify data sources that are already openly available to local councils that can be used to inform policy. These open data sources are then compared to the more granular and frequently updated commercial data source to evaluate their validity. This outcome is considerably different to the aims and motivations of the commercial sector, which are focused on selling new data sources to create high street success metrics rather than utilising existing resources. It was hypothesised that open data sources in combination with periodic updates from commercial datasets may be sufficient to produce regular measures of high street vibrancy and resilience.

The predominant focus of this thesis (Aim 3) is reported in Chapters 4 to 6. These chapters are focused on firstly measuring the vibrancy of British high streets then shifting to a resilience-based measurement of success. The second main focus (Aim 4) is reported in Chapter 7, which presents the results and outcomes from a knowledge exchange conducted with the London Borough of Camden. Overall, these chapters seek a politically neutral measure of high street success throughout 2017-2021 and assess the viability of measures implemented into local policy.

1.2 Thesis Structure

This next section provides a detailed outline of the thesis’ structure.

1.2.1. Chapter 2 – Literature Review
Chapter 2 provides an overview of the concepts of vibrancy and resilience in literature relating to the analysis within this thesis, highlighting their value as an addition to existing studies. The literature includes, firstly, an overview of the current threats to high streets in Britain. Secondly, an overview is provided on intervention strategies aimed at overcoming these challenges, including creative place-making solutions. Finally, this chapter provides an overview of previous studies that have aimed to measure high street success in relation to their vitality, vibrancy, resilience, and sustainability.

1.2.2. Chapter 3 – Data Description and Quality Considerations
Chapter 3 introduces the data sources and the main dataset that will be used for analysis in the successive chapters. The chapter provides a detailed explanation of the Local Data Company’s dataset on retail type, vacancy, and address, and its attributes. Subsequently, initial descriptive analysis is conducted on the composition of British high street retail and how it has appeared to change over the last five years. The main aim of this chapter is to record the substantial data cleaning process applied to the LDC data and to select a quantifiable definition of a high street. Both the cleaned data and high street boundaries are important for the analysis in the successive Chapters 4 to 7.
1.2.3. Chapter 4 – The Composition of British High Streets (2017-19)
Chapter 4 uses the LDC dataset and develops a measure of high street ‘vibrancy’ and a high street classification based on the proportion of ‘essential stores’ and chain stores. The chapter also delves into the political backdrop during 2017-19 to contextualise the changes. The chapter develops a new classification system which incorporates the main legally defined consumption practices during the multiple COVID-19 lockdowns. Local authority differences in the vibrancy of high streets in the years leading up to the pandemic are then mapped. Finally, the case study of the London Borough of Camden was selected to demonstrate the high street classification system devised within this chapter alongside high street vibrancy. The use of Camden as a case study is consistent across the following chapters to follow the performance of high streets within the borough across different forms of success measurement.

1.2.4. Chapter 5 – The Impact of the COVID-19 Pandemic on Commuter Town High Streets
Chapter 5 focuses on the impact of the COVID-19 pandemic with specific relation to commuter town high streets. The chapter focuses on how the pandemic has changed economic behaviour and working patterns, with a particular impact on commuter towns. The aim of the chapter is to create a resilience index for commuter towns surrounding London, Manchester, Birmingham and Leeds. This chapter’s shift to a focus on measuring high street success in terms of resilience fits within the change in narrative that was accelerated due to the pandemic. Finally, the chapter concludes with a selection of case studies of commuter towns with varying levels of resilience, which have been used to show how areas within high streets can differ in their levels of stability and vacancy.

1.2.5. Chapter 6 – Measuring High Street Resilience in Great Britain
While Chapter 5 focuses on the short-term impact of the COVID-19 pandemic on British high streets for a specific subset of towns, Chapter 6 aims to report the geographical disparities in high street resilience across the whole of Britain. Specifically, this chapter aims to inform discussion related to policy tools for town centre recovery and revitalisation following the lockdowns. The analysis in this chapter develops a comprehensive and Britain-wide measurement of the resilience of high streets and the impact of the government-enforced lockdown restrictions.

1.2.6. Chapter 7 – Current Use of Data in High Street Policy
Chapter 7 aims to build upon the quantitative measures of high street success developed in Chapters 4 to 6 and explore possibilities for the practical implementation of such uses of data in local council policy strategies. In particular, the chapter discusses the use of an engaged scholarship approach to conduct a knowledge exchange with the London Borough of Camden. Specifically, the knowledge exchange aims to explore the breadth of data that can be used to inform Camden’s Future High Streets programme. The chapter explores whether using a multi-faced data approach provides more opportunities to monitor the factors that influence people’s interactions with high streets as well as to capture patterns of retail and area change.
Chapter 8 – Discussion, Applications and Research Prospects

Chapter 8 reinforces the main findings and arguments made throughout this thesis. The key contributions of this thesis to existing research and policy are discussed in terms of the methodological approaches and knowledge generated regarding new ways of measuring high street success. The implications of using commercially generated data to develop measures of high street success in terms of ‘vibrancy’ and ‘resilience’ are discussed through both an academic and local policy lens. The chapter concludes by identifying areas of future research and collaboration.

1.3 Note on Software and Code

Most of the analysis undertaken within this thesis was conducted using R Software for Statistical Computing (R Core Team, 2022). R is an open-source program freely downloadable from www.r-project.org. The data scraping conducted in Chapter 7 from the online property portal was conducted using Jupyter, which is another free software that is compatible with the coding language Python and is downloadable using the instructions from https://jupyter.org/ (Jupyter, 2022). Associated scripts in both R and Python are available upon request. The software which was used to make all the maps within this thesis was QGIS, an open-source Geographic Information System which is available to download from https://www.qgis.org/en/site/ (QGIS, 2022).

1.4 Ethics

This research was approved by the UCL Research Ethics committee (Project ID: 504)
Chapter 2

Literature review

This chapter provides an in-depth introduction to the literature and terminology relating to the high street analysis conducted within this thesis. Sections 2.1 and 2.2 provide background information on the British retail system and changes to its structure over the past decade. Sections 2.3 and 2.4 then explore the current threats, responses, and evidence of decline in the upkeep of British high streets before going on to provide an overview of some trialled intervention strategies. Sections 2.5 and 2.6 compare the composition, local demographics and success of high streets alongside their associated characteristics. These sections include engagement with literature that measures high street success in terms of vibrancy, vitality and resilience – specifically, the ways in which data encapsulating factors such as vacancy rates can be used to compare high streets and inform national and local policy intervention strategies. Finally, Section 2.7 provides an overview of previous research that aims to measure the success of high streets.

2.1 The British Retail System

2.1.1 The definition of a high street

Literature in the disciplines of business and geography are yet to produce a cohesive and accepted definition of a ‘high street’. In a broader sense, Britain’s high streets have been the traditional setting for retail activities, with other retail formats such as shopping centres and out-of-town retail parks only becoming popularised in the last few decades (Hackett and Foxall, 1994). They have played a vital role in maintaining the economic and social health of the cities, towns and local communities that surround them (Cassidy and Resnick, 2022) and often contain sights and buildings of local historical significance, resulting in a state heritage definition of high streets as “a major thoroughfare of the late nineteenth century” (Penrith Heritage Inventory, 2008). The buildings within a high street can often be of local aesthetic significance and contribute to important streetscape elements. In addition, British high streets have historically been at the centre of public sector property portfolios. Nevertheless, some towns that have been built since the 1950s do not contain what could be classified as a ‘traditional high street’. A more up-to-date interpretation of British high streets should therefore encapsulate their status as a phenomenon that evolves over time to meet wider and continuous changes in retailing culture (Jones, 2010).

While there is no agreed definition of a high street, Ordnance Survey (OS) (2019) has been able to devise a street-level quantitative definition through classification of retail clusters and street names. The OS state that high streets are “defined by a cluster of 15 or more retail addresses within 150 metres, linked to roads” (ONS, 2019: 3). Whilst the bounded retail clusters purposefully exclude industrial estates, standalone shopping centres and retail parks, the classification system has still been used to categorise and identify 6,969 individual shopping streets in Great Britain.
Nevertheless, a comprehensive definition of a high street should consider both the socio-economic structures and the more intangible aspects of what high streets can provide to their local communities (Griffiths et al., 2008). As a morphological construct, high streets have been characterised by their dual role as both symbols of communal identity and as economic centres. In the realm of planning, urban high streets are often considered as sharing similar qualities – for example, being geographically close to a city centre (Hall, 2011). The discipline of geography also has a longstanding tradition of producing in-depth studies of the high street, dating back to Dickinson (1947), Smails (1953), and Freeman (1958). All of these influential studies on British towns utilised land-use patterns and structures to uncover the outlined trends. Moreover, geographers including Dawson (1988) and Alexander (1974) have built upon Horwood and Boyce’s (1959) ‘Central Business District Core and Frame’ – a framework that can be used to clearly define the edge of a core high street in relation to its form. The high street core has additionally been defined as bordering a lattice of properties which are not currently economically viable to refurbish.

2.1.2 Characteristics of a high street
Within Britain the term ‘high street’ has traditionally carried connotations of small-town community hubs. The history of high streets bares strong roots within the urban renaissance of the 18th century. During this period, there was acceleration in the improvements being made to the built environment resulting in a more consumer orientated society. During the 18th century, areas within town centres associated with consumption became an important part of everyday life with these areas beginning to compete with markets and fairs. In many instances, high streets were built around areas previously known as sites of markets so continued to be the centre of communities. Since the emergence of high streets in the 18th century, these areas of retail have exemplified their ability to adapt to economic and social changes. Such retail changes include the arrival of the department store in the 19th century, the rise in out-of-town shopping and ever-increasing use of e-commerce (Griffiths et al., 2008).

Some researchers within the field of geography have broadened their scope beyond traditional definitions to recognise the cultural connotations that the term ‘high street” carries. Griffiths et al. (2008) note some of the factors that encompass these associations, such as being a fundamental part of a small towns’ identity, especially in socially cohesive areas. Griffiths et al.’s (2008) review also touches upon other physical elements used to characterise a high street, such as easy pedestrian access to everyday goods and services. Nevertheless, the study focused on exploring how these traditional pre-conceived ideals are perhaps an outdated interpretation of what a high street is, especially in the wake of suburban retail growth and larger town-centre development strategies. It is therefore important to acknowledge the distinction between high streets and suburban retailing including out-of-town shopping centres; a division that Ordnance Survey (2019) decided to draw in their definition.

The rise of out-of-town retailing and the different characteristics that these new areas possess has been subject to extensive coverage in academic literature and policy documents (URBED, 1994; Gwilliam et al., 1999; Jones et al., 2007). Heightened
decentralisation pressures have resulted in new forms of retail that have challenged the longstanding historic stability of high streets (Jones, 2010). Yet there are still some apparent differences between what can be classified as a ‘high street’ and other retail areas. For example, Guy (1988) suggests that out-of-town retail areas predominantly comprise convenience retail stores, while high streets are more heavily dominated by stores selling specific consumer goods and offer a unique shopping experience. Despite the restructuring of retail areas, Jones (2010) has argued that city centres have remained the primary location for comparison shopping due to their large quantity of high street shops resulting from minimal immediate development opportunities.

High street experience is perhaps central to the characteristics of a high street, particularly in terms of rivalling the convenience of online shopping. The uptake of online shopping is particularly high in Britain, which has the largest segment of online retail shares in Europe. The rise in online shopping practices can be attributed to British consumers’ desire to seek lower prices, greater choice, and convenience (Centre for Retail Research, 2020; Dolega, 2012). As consumers increasingly choose to shop online, there has been numerous implications for high streets leading them to adapt and change with market conditions. Knight Frank (2000) suggest that retailing technologies have had substantial implications for how consumers shop. Yet they also suggest that online shopping will only challenge high streets as appose to eradicating them completely. Similarly, Chesterton (2000) suggests that online retailing will remain as a channel of distribution for retailing but will never replace the in-person experience that a high street can provide. Understanding both the characteristics and where high streets fit within the retail market is important to ensure their survival.

2.1.3 High street boundaries
When creating high street boundaries, Batty and Longley (1994) have stated that such boundaries are unlikely to be smooth, as their physical form is irregular and transitions between old and new developments are difficult to definitively map out. Despite these challenges, the Ordnance Survey (2019) have developed a series of smooth polygons outlining Britain’s high street boundaries. The boundaries have been developed using spatial cluster analysis combined with street names to create linear clusters. Density-based spatial clustering of applications with noise (DBSCAN) spatial clustering was conducted on over 750,000 retail addresses from the OS ‘AddressBase Plus' database resulting in the identification of 6,969 high streets. Each high street boundary can be joined to land-use profiles by using OS data to identify additional associated buildings within 50m of the high street boundaries. While definitions of high streets outlined in the literature have suggested the importance of retailing, the address-based OS methodology only detects 31% of locations within its boundaries as being ‘retail’. In addition, despite the methodology used to create the OS high street boundaries being openly available, the boundaries and address data used to delineate them are not, creating reproducibility issues.

In the wider realm of retail boundaries, Geolytix (2017) have created a spatial dataset of ‘Retail Places' which cover the whole of the UK. The boundaries have been developed using an internal database of UK businesses. The retail addresses have been classified
using variables such as size and type, then a weighting has been applied based on attractiveness. The methodology used to develop the boundaries consists of spatial clustering based on proximity and contiguity, which transforms the polygons of building outlines into boundaries of retail places. The retail places range from stretches of three or more units, such as small parades of shops, to larger major urban centres containing up to 5,000 retailers. Although the Geolytix retail centre boundaries do not exclusively focus on high streets, they are arguably more comprehensive boundaries than those produced by OS and have been periodically updated to provide methodological improvements. However, the Geolytix boundaries have the limitation of being a commercial product meaning they are not available for research or policymaking purposes.

The CDRC’s (2017) retail centre boundaries offer another approach to developing high street boundaries. The areas have been created using the LDC’s 2015 retail units location dataset and built using the Graph-DBSCAN clustering method (Pavlis et al., 2018). Despite the dataset encompassing all types of retail areas, including out of town retail parks, the boundaries can be filtered to only contain main town or city centre retail clusters. The CDRC has also developed corresponding convenience retail catchments for the retail centres in Great Britain. The catchment boundaries represent the maximum likely catchment area for the retail centres, based on their size. These boundaries were developed by calculating the shortest road network distance between a convenience retail unit and the centre of the Output Areas of Great Britain. Convenience catchment boundaries are useful for high street research as it is necessary to identify the characteristics of a high street’s surrounding population.

When exploring the conceptualisation of a high street, it can be suggested that the collaborative work between Ordnance Survey and the Office for National Statistics (ONS) has provided a straightforward quantifiable definition of a high street. The CDRC has also provided functional and easily obtainable town and city centre retail area boundaries. Meanwhile, wider literature can be used to provide a more in-depth description of British high streets. Such holistic interpretations include area boundaries with residential areas, distinctions between stores, and consumer experience.

2.1.4 Summary

The definition, characteristics and uses of high streets are variable over time. Consequently, research exploring the British high street landscape should account for the restructuring and repurposing caused the decentralisation of retail and the rise in online shopping. Previous studies have stressed the importance not only of high streets’ economic importance in job creation and retailing, but also the role high streets play in developing and supporting local communities. While an all-encompassing definition of a high street is difficult to quantify, sources such as OS and ONS have developed a quantitative definition of a high street with corresponding Britain-wide boundaries. Nevertheless, the boundaries developed by OS and the ONS raise issues surrounding access. These boundaries are not openly available and finding boundaries that are open access to enable the research of all high streets across Britain is difficult.
2.2 Changes to the British High Street

2.2.1 Global changes

High streets, retail centres and town centres are dynamic phenomena (Peel, 2010) that have complex urban ecosystems resulting in an ability to continuously evolve to meet changing consumer needs (Bettencourt et al., 2007). The retail sector cultivates a continuing flow of transformations shaped by innovation, consumer needs and policy influence, intertwined with the actions of developers, investors and occupiers (Bryson, 1997). Hughes and Jackson (2015) have suggested that these transformations occur in a series of waves of opposing and complementary states of de- and re-centralization. This supposed pattern results in businesses simultaneously flourishing and failing as they either develop or downscale.

Changes to local high streets are also impacted by global trends and market forces. Global trends are often adopted by mass retailers, in effect bringing those trends to local high streets (Majima, 2008). Such transnational channels can be aided by business, technological and political innovation. Consequently, high streets are reliant on the actions of developers, investors and occupiers; these, in turn, are all constrained and influenced by the economic and regulatory context (Bryson, 1997).

More specifically, Hall (2011) has suggested that there are two main forces that impact the retail profile of high streets. First, the influence of economic volatility on the expansion of affiliated and independent stores. Second, the political influence on high streets at both a national and local level, which can for example create a focus on local high streets and small independent businesses. The latter can be exemplified with the case of the Mayor of London’s Draft Replacement London Plan in 2010 that promoted the support of Small and Medium-sized Enterprises (SMEs) through shopping locally. Hall’s (2011) research also touched upon a third global force which can influence changes in high street composition, namely the levels of immigration and ethnic diversity in an area which, in the case of London, have led to a growth in ethnic retail.

One economic force that particularly impacted British high streets was the 2008 recession, when the challenges associated with the economic shock triggered a rise of convenience culture, changes in migration patterns, and accelerated the growth of online sales (Wrigley and Lambiri, 2014). The short-term impact of the 2008 recession was a sharp rise in vacancy followed by a change in composition of high streets. Infact, in the first half of the 2000s there was over 20% increase in the number of convenience stores which was also accompanied by an increase in ethnic retail stores, particularly concentrated in London and the south of England. This rise in ethnic stores led Guy (2008) to name the rise, the ‘Polish grocer’ effect.

Nevertheless, the high street’s function extends far beyond retailing as it can act as an encouraging environment for social interaction and that plays a large role in the lives of local people. A successful high street can also provide support and resources to individuals at risk of marginalisation, such as the aging population and low-income groups. However, the heavy dependence of certain groups on high street services
increases the risk of an economic crisis disrupting or removing important support networks from people’s lives if they were to be closed (Yuill, 2009).

Increased car ownership and changes to consumer lifestyle have also had an impact on whether local high streets are still a viable concept. One major shift in consumer behaviour has been influenced by changes to working patterns. The last few decades have seen a steady rise in working from home or remote working. Felstead et al.’s (2001) study using data collected by The Labour Force Survey suggested that even as far back as the early 2000s approximately 25% of the working population worked from home at least partially (Griffiths et al., 2008). This steady increase was drastically accelerated by the COVID-19 pandemic where people were forced to work at home unless it was unfeasible. Even in a post-restriction era hybrid working the preferred system of working within large firms where employees only come into the office 2-3 days a week (Triyason, et al., 2020). This growing trend is arguably transforming high streets from places of work that have for years been filled with offices and worker populations, to places that rely more heavily on residents than workers or commuters.

2.2.2 Clone towns and individuality
The intersection of retailing and the internet alongside the relentless presence of globalisation has led to the ubiquity of the term ‘clone town’ within geographical literature. The term is used to denote the replacement of a high street’s individuality by uniform replications of national and global chains (Powe, 2006). The clone town effect that consists of a rise in large national chains can cause the inevitable displacement of smaller independent stores with homogenisation of local places leading to a reduced diversity in what high streets offer (Duignan, 2018). Such transformations of high streets can create new challenges for the urban economy. Threats to urban landscapes are of particular concern as communities made up of vibrant projects and small businesses play an essential role in the wider economic and social vibrancy of urban economies, local identity and business competition (Everett, 2016). Such communities including country towns often have consumers who are more likely to desire shops which embody individual character and a local element than larger towns (Powe, 2006). Consequently, there is often debate within the literature between community led development and retail-led regeneration, with studies varying greatly in terms of the scale of regeneration scheme and sizes of high street (Findlay and Sparks, 2009).

Dobson (2015) offers a critique of retail-led regeneration programmes which is often the cause of clown town development and the privatisation of public spaces. The critique suggests that regeneration should be based on re-learning how to value and apply resources that are already present within high streets rather than rely on other sources of trickle-down economics. The book then goes on to suggest that there should be a heightened solidarity when regenerating a high street where the future of the area is developed with shared ambitions. However, Dobson (2015) suggests that as individuals we lack the motivation and time to become invested in the regeneration of our local high streets. Furthermore, McGuinness (2016) suggested that society would need a massive economic shock followed by a large enough societal shift such as described by Jackson’s (2009) book ‘Prosperity without Growth’ in order to gain large enough traction for
widespread solidarity. Such a radical shift in consumption could be exampled by the COVID-19 induced lockdowns where individuals were forced to shop locally and there was a collective effort to support small businesses. However, the COVID-19 pandemic also exacerbated the rise in online shopping, and it is debateable whether the social solidarity and co-operation to support local high streets has been sustained as restrictions were lifted. In particular, Florida et al. (2021) has suggested that the impact of the pandemic may lead high streets to lose their commercial role but rather become amenity centres and places to window shop to advertise buying online. Nevertheless, the impact of online shopping ultimately depends on factors such as financial markets.

2.2.3 Health of high streets
Further distinctions can be drawn in the way individual high streets experience change, specifically in regards to an area’s deprivation level. An important examination of the future of high streets, The Portas Review (2011), was commissioned by David Cameron’s former coalition government (2010-15) to analyse rising vacancy rates and the economic challenges faced by retail areas. One of the report’s suggestions was that having a high concentration of fried chicken and betting shops can prevent an area from thriving and decrease vibrancy. Townshend (2017) continued the exploration of the changing conditions of high streets in poorer areas, acknowledging the increasing vacancy rates of retail spaces, and based their research around the rapid replacement of empty plots with unhealthy and ‘toxic’ uses. The ‘unhealthy’ shops that were opened to revive ‘ghost towns’ were outlined as: fast food takeaways, all-you-can-eat buffet restaurants, betting shops, tanning salons and convenience stores selling discounted alcohol and tobacco.

While the relationship between low-level nutritious food, consumption, and health implications are complex, there is considerable research to suggest a link between areas of poverty and processed food consumption. On the one hand, it has been found that fast food restaurants are predominantly concentrated in poorer areas (Macdonald, Cummins and Macintyre, 2007). On the other hand, studies also show that the food that surrounds us – the food environment – heavily influences an individual’s diet (Caspi et al., 2012; Charriere et al., 2010). Therefore, it is important to consider possible circular supply and demand relationships in which retail placement could negatively impact community health.

Another store type which often sparks debate within the literature is the impact of charity shops on high streets. Bramall (2020) has suggested that the recolonisation of previously vibrant high streets by stores such as charity shops is considered to be the ‘wrong’ sort of retail activity. Following the 2008 recession, charity shops are often seen to replace vacant premisses. The pattern of charity store openings is perhaps also attributed to their exemption from full business rates. The Charity Retail Association (2018) argues that charity shops can increase vibrancy of high streets by providing affordable goods to low-income individuals while also being sustainable. The success of charity shops in improving vitality and replacing vacant stores perhaps relies upon the tailoring of charity retail stores to suit the local demographic – for example, placing boutique versions of charity shops in more affluent areas.
The type of stores denoted as ‘healthy’ for the vibrancy and resilience of high streets can also change over time. Outlets that are heavily frequented by office workers, such as cafés and sandwich shops, used to be seen as key elements in supporting the success of high streets. However, following the change in working habits since the COVID-19 pandemic, cafés and shops near transport links saw a large rise in vacancy (Cofe, 2020). This raises the question as to whether a ‘healthy’ high street is one that serves the local community’s needs, rather than the needs of commuters.

Arguably the most important measure of high street health is vacancy rates. Even before the COVID-19 pandemic, high streets had already been facing numerous challenges, including loss of attractiveness to investors (Jones, 2010). One cause of the decline of high street health is due to landlords being reluctant to fill vacant spaces in downward markets, exampled during the 2008 recession (Grenadier, 1995). Landlords can be seen to make these decisions as it is more cost-effective for them to retain the current environment of vacancy with the cost of vacancy being enough to offset the possible benefits of filling the vacant space. Consequently, for those high streets already struggling with high vacancy rates, the economic shock caused by the pandemic may have exacerbated their inability to fill vacant premises and led to a further decline in high street health.

2.2.4 Summary
High streets are subject to continual economic and social changes. These changes and pressures include economic crises, the restructuring of retail spaces, technological innovation, and social shifts such as those brought about by the COVID-19 pandemic. Global pressures and changes in consumer trends have also changed and shaped high street composition. Continued debates surrounding what constitutes a ‘healthy’ high street have often been shown to be fragmented. On one hand there is often consensus that an increase in takeaways might have negative impacts on community health. On the other hand, the role of other stores including charity shops in maintaining vibrancy is still open to debate.

2.3 Current threats, impact and evidence of decline
2.3.1 Current threats
The 2008 recession exposed multiple fragilities in Britain’s high streets, resulting in substantially increased vacancy rates that were further exacerbated by multiple large national retailers falling into insolvency (Jones, 2010). In fact, the Local Data Company (LDC, 2009) reported that in the year after the recession hit, 10.8% of the UK’s high streets amounted to empty floor space. Nevertheless, the LDC also reported that this rate was twice as high in certain towns, suggesting that some areas are more susceptible to economic shocks.

The recession also demonstrated that different types of shops were impacted to different degrees. While food and household stores had the lowest ratios of closure to new store openings, clothing and footwear were most hard hit, followed by personal goods and services (Thomas and Shah, 2009). Studies such as that of the CBRE (2009) also indicate
that particular store closures and locations result in a similar pattern of new occupants. The study reports that following the collapse of Woolworths, 37% of the new occupiers were discount stores and 31% were grocers. The change in occupiers may display a shift within high streets to a centralised focus on convenience goods. Specifically, Jones (2010) argues that such changes have perhaps led to the withdrawal of fashion stores from town centres and their relocation to purpose-built shopping centres as the number of desirable central retail locations has dwindled.

While there have been numerous changes in the retail real estate market and in high street composition over the last decade due to technological developments and urbanisation, the COVID-19 pandemic has brought new challenges. The various lockdowns imposed across Britain drastically reduced spending within high streets, with different age groups changing their spending at differential rates. For example, Anderson et al. (2020) found that those aged under 29 decreased their spending by around 10%, despite being the age group at the lowest risk of mortality. Consequently, different high streets might be impacted to different degrees depending on their local demographic. Younger consumers might also be more likely to have contributed to the increase in online retail sales during the pandemic.

There was a rise in online purchasing during the second quarter of 2020, when fear of market disruptions caused by the pandemic resulted in abnormal purchasing behaviour such as panic-buying. However, Budd et al.’s (2020) study found that although consumers conduct extensive product research online, they still tend to make purchases in physical shops. Consumers continue to come into stores to purchase goods and view and engage with products before purchase. For this reason, customers still continued to shop in person even when government restrictions such as social distancing requirements were in place. The pandemic has therefore resulted in an increased trend in both pure online shopping but also in online product research and offline purchasing. It could therefore be suggested that high streets might adapt to the changed circumstances by embracing digital platforms and the role of multi-channel retail businesses (Nanda et al., 2021).

2.3.2 Impact
The shifting patterns in vacancy rates within high streets can be used to identify underlying cultural shifts, such as a growth in value-oriented customers (Dolega and Lord, 2020). Consumers are increasingly motivated by declining disposable income and living standards, making discounted stores such as Home Bargains and Poundland more desirable (Reynolds et al., 2007). In line with the rise in online shopping, traditional stores are attempting to keep up with consumers’ technology expectations. As a result, hybrid shopping experiences have emerged, such as click-and-collect models that entice the customer to save on delivery costs or receive a reward voucher (Davies et al., 2019). More specifically, online shopping has had a substantial impact on the structure of real estate. Jones and Livingstone (2018) have suggested that the desirability of retail premises within high streets will decline because their study found that online shopping and click-and-collect has prompted many high street retailers to relocate to retail parks. However, innovations such as click-and-collect still struggle to keep up with the round-the-clock convenience that online shopping offers, as well as the lower fixed costs of
online retail which can be passed onto customers via lower prices and offers (Singleton et al., 2016). In particular, Wrigley and Lambiri (2015) have suggested that all retailers are now subject to online price comparison. The Grimsey Review 2 (2018) displays this trend, highlighting that retail insolvencies are once again rising. Specifically, 31,600 stores have closed in the last decade due to business insolvency and portfolio reductions (Grimsey et al., 2018).

Regarding the impact of the 2008 recession on British high streets, Tselio et al.’s (2018) study, found that retail centres which had lower vacancy rates before the recession were more negatively impacted. However, this effect was influenced by the location and size of a retail centre. Yet, as (Enoch et al., 2022) points out, the specific ways in which high street activity correlates to their resilience against economic shock and their resulting ability to recover remain understudied.

When considering the impact of economic shock on high streets, Wrigley and Dolega (2011) argue that there are two main aspects of addressing research and policy gaps. First and foremost is the task of developing new empirical evidence that measures the impact in a way that extends beyond descriptive analysis; and secondly, the theorising of the complex processes taking place. Regarding the first task, commercial companies including the LDC have met the demand for Britain-wide analysis measuring fluctuations in store categories within high streets. Commercial companies such as the LDC have been able to provide frequently updated granular data which is viable for in-depth academic analysis. The second task of theorising the complex impacts of economic shock is particularly important due to the varying resilience of different British high streets. Nevertheless, terms such as ‘resilience’ that are used to evaluate the impact of economic and social shocks on high streets are themselves subject to debate (Martin, 2011), a factor which this thesis endeavours to explore.

2.3.3 Evidence of decline
Following the 2008 recession, a narrative of high street decline became more common within literature and wider policy which could be seen physically through an abundance of vacant stores across Britain (Distressed Town Centre Taskforce, 2013). While vacancy rates across Britain are unevenly distributed, with some high streets recovering from economic shock, the narrative of high street decline has prevailed (Sparks, 2021). In response to intensifying concerns over rising vacancy rates, Hughes and Jackson (2015) have turned to the identification of factors which indicate retail locational obsolescence. The researchers define obsolescence as a loss of value related to the extraneous elements of a building, economic functionality, the surrounding area, and accessibility. Their conceptual model of retail locational obsolescence is an important addition to the literature as it begins to unpick the complex and dynamic retail market consisting of market, regulatory, and socio-economic functions (Cowan et al., 1970). The principles included within the study provide a useful framework for future research.

Whilst the paper focuses on an absolutist interpretation of 'obsolescence' (meaning that a space offers no viable retail possibilities for users, investors and developer markets), the same principles may be applicable to the study of retail store turnover. As included in
Hughes and Jackson’s (2015) conceptual model, individual retail stores have a strong reciprocal relationship with the surrounding environment. The ‘broken tooth effect’ can be used to describe how a single closure can result in a rapid reduction in surrounding business footfall which spreads across an area of a high street (LDC, 2009). Vacancy throughout a high street can create an impression of neglect and decline, often leading to a sequence of exponential deterioration (Berwyn, 2012). For this reason, Maliene et al’s (2022) work on developing a sustainability assessment framework for the high streets includes a category on ‘safety and security’, encompassing perceptions of crime and ways of making consumers feel safe, such as CCTV and street lighting. In addition, the study stresses the importance of unified management of high streets to help to address decline.

Consequently, from the literature it is apparent that high streets, and their management by local councils, play a major role in their success of decline. The Mayor of London’s (2017) report ‘High Streets for All’ suggested that the perception of high street decline can further threaten their survival due to housing pressures. Within London specifically, there is an ever-increasing pressure to find space for housing developments which poses a threat to retail and employment space. It is important not to undervalue the importance of a high street’s ability to generate employment opportunities when faced with a demand for growth in housing. The report suggests that non-designated high streets are most at risk, while high streets with a diversity in ownership can be more resilient to blanket development. Ball et al. (2021) have suggested that blanket redevelopments tend to trigger reactive responses rather than evolve to changing customer demands, and take pre-emptive actions to prevent a fall in high street performance.

2.3.4 Summary
High streets are continually subjected to new challenges, particularly in relation to economic, social, technological and policy changes. These constant changes have shaped and reformed Britain’s high streets leading to changes in the way consumers value and purchase high street goods and services. Commerical companies have been at the forefront of producing frequent and timely granular data on retail type and vacancies within British high streets. Such data can be used to conduct analysis on high street decline and identify geographic disparities.

2.4 Intervention strategies
2.4.1 Creative planning approaches
Words such as ‘liveability’ and ‘vibrancy’ have become prominent in the retail industry literature and policy documents (Mayor of London, 2020; London First, 2020). Traditional economic thinking stipulates that the ends necessarily justify the means, and that inward investment is more important than community progression and resilience. In contrast, creative planning aims to position the needs of residents as central to urban planning (Krueger and Buckingham, 2012). More creative approaches to town planning often involve promoting economic and community development by making changes to both physical and social elements of an area. However, when broad concepts such as ‘vibrancy’ are used as a measure or indicator for proposed place making, issues can arise
regarding their ontology, goals, and operationalisation complexities. While it is less common to see these intangible concepts used as overall measures of the impact of creative interventions, researchers are beginning to utilise vibrancy as a factor in their projects.

A project aiming to devise a measure of high street vitality is the High Streets Task Force (2020), which was commissioned by the UK government in 2019. It brings together members of the public and private and community sectors which provide knowledge, advice, training and data. However, the task force only offers advice and analysis for high streets in England. Other previous attempts to promote the regeneration of an area have led researchers such as Hart (2003) to criticise intervention strategies that have resulted in gentrification.

The challenges in coming up with a successful intervention strategy are predominantly centred around creating opportunity for gains in social enterprise which can benefit all members of the community. One example of a local council-proposed high street regeneration project is the Night Time Enterprise Zone in the London Borough of Waltham Forest, which aims for increased, sustained vibrancy, and inclusivity – with culture being a central consideration. The multidimensional plans aim to provide low-cost business spaces to encourage late-night high street activities for all ages. The council's strategies are also heavily shaped by the community, with residents encouraged to actively participate by submitting suggestions (Waltham Forest, 2019). However, with all regeneration projects that take place in a consumer setting there is always concern that commitment to making an area attractive to shoppers excludes those who do not have the economic means to participate.

2.4.2 Meanwhile use and pop-up stores
High street transformation is not solely limited to physical appearance and trading hour expansion – facilities such as free WiFi have also been introduced to encourage regeneration. This double-headed approach not only increases access to all but also promotes the publicising of an area on social media. Access to free Wi-Fi also enables easy access to a wide variety of information, such as store format resources, public transport routes and local events (Wu et al., 2017). Other high streets across the country have adopted more temporary yet arguably equally effective solutions to transforming un-vibrant spaces. Feneri (2016) has documented the rise in pop-up shop use as a temporary interruption to vacant stores. The literature has associated pop-up shops' success with the increased popularity of unplanned approaches to urbanisation and use of space (Overmeyer et al., 2013). Deslandes (2013) has suggested that pop-up shops are a more flexible approach to inner city space use than traditional, top-down interventions and takes a more tactical approach. The temporary uses of space can encompass a multitude of small-scale urban interventions, whether they are unsanctioned, 'insurgent' or community-led (Hou, 2010; Mould, 2014). Berwyn (2012) describes these activities as 'meanwhile use', whereby vacant lots are temporarily used for economic or social gain until they are ready for commercial use. The benefits of 'meanwhile use' extend beyond monetary considerations, and can improve vibrancy and contribute to an improved quality of life for the community. Henceforth, Berwyn's (2012) work has led to the development
of the Meanwhile Foundation (2019), a charity designed to give practical and legal information to owners of vacant property or interested external stakeholders regarding meanwhile use. The Meanwhile Foundation exemplifies the successes that result from partnership working, which allows for grassroots development in which the local needs of the community are addressed. The projects that the charity have been involved in so far include the 504 and 505 arches at Loughborough Junction, renovated railway archways now used as a shared workspace and host to cultural, artistic and sporting events.

Collaborative projects such as these also have the added benefit of encouraging local volunteers to participate in the renovation of their community, while simultaneously providing them with valuable skills and experience. Perhaps the biggest asset of pop-ups as a contributor to increased vibrancy is the flexibility of the settlements. Pop-ups are arguably only confined by the project participant’s spatiotemporal imagination as they can be in a continuous state of transformation, being erected and dismantled as needed to inject a sustainable source of stimulation and vibrancy into an area (Harris, 2015). The use of shipping containers to house pop-ups is a prime example of how structures can be easily moved and personalised to suit a space and its usage requirements. Successful shipping container projects include the ‘Boxpark’ pop-up mall in Shoreditch, the ‘Norjske’ bar in Birmingham, and the Troubadour theatre in White City (Jones et al., 2017; Ljeh, 2019). However, when assessing the impact of non-permanent structures on an area’s vibrancy, the challenge of mapping their geography at both a national and local scale arises due to their ephemeral qualities (Jones et al., 2017).

Perhaps the biggest challenge when devising a temporal regeneration project is creating the perfect balance between utilisation of pre-existing resources and the ability to mutually benefit surrounding urban areas. Other examples of non-permanent experiences are ‘Survive the Nightmare’ (2019) an immersive horror experience run by a pop-up theatre company in Manchester that offers an escape into a ‘dilapidated old Victorian house’. Immersive pop-ups such as these can redirect consumer flows around a city and be mutually beneficial to surrounding businesses – for example, the horror experience is surrounded by a number of pubs and restaurants. The literature on urban regeneration makes clear that pop-up planning should take into consideration the relationships between the commercial and the community. Careful selections of areas and activities can benefit surrounding businesses through increased consumer flow, and in turn can lead to increased investment.

2.4.3 Place-based policy
Over the last few years, place-based policies have become more prevalent in British policymaking. A report developed by United Kingdom Research and Innovation (UKRI) entitled ‘A place-based shift’ suggests that levels of productivity are unevenly distributed across Britain which leads to stark interregional differences in other factors such as wellbeing and town-centre viability (McCann, 2019). In response to regional inequalities, policies aimed at ‘levelling up’ attempt to regenerate forgotten high streets, towns and cities (Davenport and Zaranko, 2020).
While the concept of levelling up is not new, the UK government under Prime Minister Boris Johnson (2019-2022) has endeavoured to grant funds to struggling town centres and attempt to address the deep-rooted north/south divide within England (HM Treasury, 2021). The levelling-up funds are split into six different streams and are managed by three different government departments resulting in a complex funding allocation process. The funding process sits within a decentralised framework aiming to empower local areas (Connolly, 2021). The devolution of power takes the form of local areas bidding for centralised funds.

The actions of local authorities to regenerate high streets take various forms. One avenue is to work alongside property owners of declining or vacant stores to incorporate their premises into wider investment projects. For example, Stockton-on-Tees' local authority bought two shopping centres within its high street and plans to demolish one to remodel the area. The council were efficient in raising the funds from multiple sources as local authorities face the challenge of budget deficits and reduced income from business rates. Other local councils such as Wigan are focusing on the development of multi-purpose spaces within high streets including provisions for both leisure activities such as bowling alleys but also new residential properties.

Nevertheless, redevelopment of large properties within high streets can be challenging with plans often falling through – for example, the transformation of the Whitgift shopping centre in Croydon, which ceased as a result of the COVID-19 pandemic (Hammond and Cook, 2022). In contrast, it could be argued that in some instances creative place making interventions are not the most appropriate methods of ensuring resilience. Other more traditional economic based interventions during the pandemic were possibly more effective in attempting to protect small and medium-sized enterprises on the high street. Such interventions included the government furlough scheme where the government paid up to 80% of furloughed employee’s salaries. In addition, SMEs could apply for business rate relief, deferral of tax payments, loans and request protection from eviction (Albonico et al., 2020).

The levelling up agenda and its application of decentralised policy has multiple drawbacks. Firstly, while the bidding system for funds does include local involvement, all the power is still in the control of the government. MPs consider the weighting given to bids with their priorities being highly political, possibly restricting which MPs are best able to state their case to central government. As part of the process areas are categorised on a scale of 1 (highest priority) to 3 (lowest priority). An analysis conducted by the Financial Times found that in England 14 places had been placed in category 1 despite having above average levels of wealth, arguably a result of the predominance of Conservative MPs in these areas (Bounds, 2021). Another major critique of the government’s strategy to level up is the methodology used to rank area by their funding needs (Newman, 2021; Jennings et al., 2021). Levels of deprivation within an area have been excluded from the measures, thereby completely ignoring the systemic relationship between health and deprivation (Holmes, 2021).
2.4.4 Summary
Recent years have seen the rising popularity of creative planning approaches which focus on making policymaking a more community-centred process. In relation to high street regeneration, a focus on local culture, skills and pre-existing capacities can help with the generation of employment, investment capture, and all-round success. Local regeneration initiatives can take the form of pop-up and interim premises, which can reduce vacancy and in some cases nurture community-led projects. Nevertheless, the current levelling up strategy is highly politicised, which may lead to some of the most deprived areas not gaining high street regeneration funding. Such funding is vital for maintaining the viability of high streets, job creation and serving the local community.

2.5 Differences between high streets

2.5.1 Geographic distinctions and ‘health’ of high streets
Britain has a broad spectrum of high street sizes, locations, attractions and populations. It is therefore important to incorporate these characteristics into an interpretation of vibrancy and resilience, as despite their differences, they all share the common capacity to act as a local hub for services, trade and employment (Powe, 2006). Another distinction that can be drawn between towns and cities is their extent of individuality. The New Economics Foundation (2005) explores the distinction between ‘home towns’ as places with individual recognisable character, and what it terms ‘clone towns’ consisting of national and global chains. Powe (2006), further expresses how the shopping experience varies in these different town categories. Rural high streets with high individuality and character were found to attract urban visitors, with their primary activities being consumption of meals or refreshments alongside visiting historical or cultural activities. The role of high street classification on vibrancy is perhaps, as Pinkerton et al., (1995) suggested, based on the demographic factors of the surrounding population linked to outshopping.

High street configuration is subject to geographical differentiation, which can be a reflection of long-term structural imbalances between local economies, producing regional variation in high street characteristics. Nevertheless, some attributes may indicate a distinction between high-end and low-end high streets, not in terms of gentrification but with regard to their ability to meet the needs of the local population by providing positive services and contributing to the local economy. For example, deprivation can have a twofold relationship for high streets and surrounding populations, as the multitude of underlying factors including income, crime and education can be seen to be interlaced with the central structures.

Where high streets face stages of decline and decay, great costs to the economy begin to emerge, including indirect costs such as increased obesity within a community (All-Party Parliamentary Small Shops Group, 2015). Therefore, it can be said that high streets can play a critical role in reducing deprivation and health inequalities (Carmona, 2015). Consumers can also be seen to have different priorities based on their level of social
deprivation, and therefore require varying qualities from their local retail areas (Clarke et al., 2012). A high-end high street may also be characterised in terms of what the literature considers ‘healthy’ (Griffiths, 2010; Townshend, 2017). Specifically, Townshend (2017) outlines evidence to suggest that there is a substantial relationship between accessibility, distance, availability and consumption of unhealthy shops and services. The problematic issue of co-location is important to consider in regards to a measure of retail vibrancy, as certain issues such as poor mental health and addiction are disproportionately high in deprived areas (Griffiths, 2010).

One quantifiable measure of the ‘health’ of an area is The Access to Healthy Assets and Hazards Index (2019), a multi-dimensional index consisting of different indicators and developed by the CDRC. The index covers Great Britain and aims to measure whether ‘healthy’ individual neighbourhoods can be allotted to corresponding high streets (Green et al., 2018). The indicators for the index fall under four domains of accessibility: retail environment, health services, physical environment, and air quality.

The literature is beginning to stress the importance of a good high street incorporating mental and physical wellbeing services. Xu (2019:5) defines such resources as ‘active places’ which combine ‘high potentials of walking activity and social interaction’. Fusion of high streets and active places are showing to be a success, with a 15% increase in the opening of health and fitness facilities in high street locations between 2017 and 2019 (Kirton and Edwards, 2019). Low-cost fitness operators have increasingly begun to occupy a large array of premises including former retail spaces. These centrally-located gyms can promote footfall to deteriorating retail spaces. In addition, quasi-retail has led to the development of a fusion between retail and health/fitness. One example is the retail store chain Sweaty Betty (2020), which offers free and paid classes in Pilates, HIIT and Barrecore in store. Peloton (2020) also offers virtual classes aimed at generating interests in products that are available in-store. The increased trend in high street located fitness activities is an important factor to consider in relation to its links to high street health and vibrancy.

2.5.2 High street composition

When exploring the retail landscape of town-centre high streets, it is important to factor in individual premises type as well as wider clusters of goods or services. Growth of different retail types occur at different rates, with different areas plateauing and expanding simultaneously in the same high street (Dolega and Lord, 2020). The overall structure of high streets measured using composition rates can often display significant change. Wrigley and Dolega (2011) have found a national recorded decline in retail occupants, a trend prevalent since the 2008 economic crisis. However, consumer behaviour towards leisure and convenience has changed, resulting in positive growth in both sectors (Coca-Stefaniak, 2013). Understanding a town centre’s high street composition and how or whether it changes can aid adaptive resilience analysis. As Rousseau (2009) suggests, high streets that are resilient to external socioeconomic shocks (including increased online purchasing) are more likely to redefine their broader roles. High street re-imagination can fit in with overarching strategies to fulfil existing consumers or attract new ones (de Noronha et al., 2017).
Consequently, within the high street literature it has been important to develop typologies which can be used to draw distinctions between high streets, their composition, and resilience. While early studies including Reynolds and Schillers’ (1992) retail hierarchy were predominantly based on the number of retailers within a town centre, later studies have gone on to include an array of additional variables. Dolega et al.’s (2016) retail hierarchy uses centre size, a diversity index, proportion of leisure and anchor stores, and vacancy rates to differentiate areas. Nevertheless, the study is focused on town centres as opposed to high streets so does not incorporate long-term changes in retail area structures and roles (Jones and Livingstone’s, 2018).

Additional distinctions that have been drawn between town centres include Mumford et al.'s (2021) study which uses footfall signatures and volumes as a measure of town centre attractiveness. Yet it is questionable whether footfall signatures can be used as a direct measure of town centre success. Singular indicative measures such as this often require local knowledge and qualitative data to validate distinctions between areas (Crols and Malleson, 2019). One more advanced typology which provides more information on the composition of consumption spaces is that produced by Dolega et al. (2021), which differentiates shopping areas based on characteristics including vacancy rate, type of retail, and diversity.

2.5.3 High street community
British high street are no longer solely focused on retail, but are increasingly reoriented towards being an integral part of the community (Dickinson, 2020). While high street functions were already in the process of being reimagined, the COVID-19 lockdowns have underlined the importance of community and wellbeing and their integration into the centres of towns and cities, providing a broader purpose to the surrounding populations. Therefore, to fully create a picture of vibrancy and resilience it is important to consider the services that draw local communities into town centres.

One technique that can be used to identify and build upon the current strengths of an area is Community Asset Mapping (Beaulieu, 2002). This technique highlights existing resources within a community, covering all types of populations including those who face economic hardship and poverty. Every high street has pre-existing assets such as libraries, community spaces, businesses and parks, as well as the skills and capabilities of individuals living and working in the area (Preston City Council, 2019). An accurate depiction of vibrancy should therefore take into account the community capacity of high streets and their future potential.

Geddes (2006) has suggested that engagement with established town partnerships including local government can lead to inclusive and efficient pluralistic local governance. This can help to identify local community needs and find solutions to what local residents consider the most urgent priorities. One example of a research project which explores different communities and their high streets is the High Street UK 2020 project (Ntounis and Parker, 2017). The project included the ten geographically dispersed British retail
centres of Alsager, Altrincham, Ballymena, Barnsley, Bristol (Church Road, St George), Congleton, Holmfirth, Market Rasen, Morley, and Wrexham. The outcome of the project was the identification of the top 25 priorities for high street recovery, the development of a framework for high street recovery, and the identification of problems such as policymakers needing to develop their management and decision-making skills. However, despite being a ground-up piece of research, ultimately the project ended up merging the needs of arguably very different areas, obscuring local community needs.

2.5.4 Summary
Britain's high streets vary geographically in terms of their urban/rural character, their 'health', composition and the characteristics of the local community. In recent years and especially during the COVID-19 pandemic a new spotlight has been shone on the important role of high streets and their contribution to the health of local communities. High streets can influence the local community’s health in a number of ways. This can be negative, such as when an area has a dense concentration of 'unhealthy' stores such as fast food and takeaway stores. Alternatively it can be positive, via the availability of community assets and healthcare provisions, and by granting the local population influence over policy in their area.

2.6 What is a ‘successful’ high street?
2.6.1 High street vibrancy
In recent years, the language of arts and culture has gained a distinctive presence in place making intervention and development (Delconte, 2017). Words such as ‘liveability’ and ‘vibrancy’ have become prominent in the retail industry literature and policy documents. A more creative approach to town planning is often viewed as a holistic way to promote economic and community development by making changes to the physical and social characteristics of an area. However, when broad concepts such as vibrancy are used as a measure or indicator for proposed place making, issues can arise regarding their ontology, disagreements over suitable outcomes, and operationalisation complexities. While it is less common to see these intangible concepts used as overall indicators to measure the impact of creative interventions, researchers are beginning to utilise vibrancy as a factor in their projects.

Yet vibrancy as a measurement and instrumental tool for development is still classified under a multitude of different definitions. There is therefore a need for a well-defined measurement tool and long-term studies on these attributes to accurately assess their impact on economic regeneration (Markusen et al., 2013). Previous studies using the term vibrancy to capture their vision have ranged from urban planning to retail development. Urban planning research including Merlino (2014) and Sung et al. (2015) explores the links between architectural design and urban vibrancy. Other studies such as Gross & Campbell (2015) and Holian & Kahn (2012) have taken a more sociological interpretation of vibrancy and use variables such as crime rates, student population, and cultural institutions. The vague interpretations of vibrancy arguably leave the term open to debate, with different disciplines offering an insight into how the concept can be conceived. Consequently, this thesis takes a quantitative approach and conceptualises
retail vibrancy as encompassing the economic, social and community developed health of British high streets.

Currently, there are multiple local government schemes and initiatives focusing on creative place making, improved vibrancy and regeneration (Forman and Creighton, 2012). However, vibrancy-led development schemes could be construed as attempts to gentrify areas and raise social equity (Stern and Seifert, 1998). The indirect effects of changes to an area’s composition can include rising property value, displacement, and diminished access to affordable products and services. Chapple and Jackson (2010) even go as far as suggesting that such projects are more likely to benefit wealthy, highly educated white individuals.

Therefore, upon assessment of high street success and suggestions for regeneration it is important for initiatives to consider all the potential service users and consumers. More specifically, schemes should incorporate adjustments for demographic and socio-economic characteristics of surrounding areas. Factors that the literature often uses to characterise the population served by high streets are house prices, age, and ethnicity. Firstly, there is substantial evidence provided by geographical data outlining links between retail prices, consumer behaviour, and house prices (Aoki et al., 2004). Stroebel and Vavra (2019) found that increasing house prices lead to a shift in demand and reduced price-sensitivity which consequently results in firms raising prices. However, the relationship that they describe is different for homeowners and renters, with retail price hikes more pronounced in areas of high ownership. Geographical variation in housing demand has also been found to be connected with consumption levels. Where there is increased demand for houses, homeowners’ net worth rises; this heightened demand then rolls over into consumption demand (Aoki et al., 2004). Furthermore, the literature also suggests that the effect of house prices on consumption behaviour has varying elasticities depending on other factors such as wealth and age, making it an important segment of potential local consumption behaviour in corresponding retail areas (Stroebel and Vavra, 2019).

2.6.2 High street resilience
One additional measure of high street success used within the literature is resilience. High street resilience can be defined as the ability of the area to return to its pre-existing state before an economic or social shock or to adapt to new conditions (Fernandes and Chamusca, 2014; Hudson, 2010). The adaptive aspect of resilience can therefore be used to measure whether a high street can sustain long-term development and adapt to its local population’s needs. Since the COVID-19 pandemic there has been an increased shift from measuring high street success in terms of vitality and vibrancy to considering their resilience. The pandemic-induced lockdowns prompted studies that measured the resilience of retail to the disruptions caused by stay-at-home orders.

In an illuminating study, Appel and Hardaker (2021) divided retailer resilience into two categories. One group of retailers planned to return to their former state of success utilising their pre-pandemic methods. The second group of retailers viewed the pandemic as an opportunity for fundamental change, such as pursuing an online approach in search
of sustainable growth. The study summarises the two different aspects of high street resilience. On one hand, it is important to consider the rate at which a high street can return to its original performance. This type of resilience can also be considered as stable, when high streets have a low retail turnover and slow responsiveness to change but a high capacity to absorb economic shock (Dolega and Celińska-Janowicz, 2015). On the other hand, it is also important to conceptualise the ability of a high street to transform and adapt in line with wider social and cultural changes (Fernandes and Chamusca, 2014; Hudson, 2010). This type can be termed as ‘adaptive resilience’, whereby a high street is in a continual state of adaptation and redesign in pursuit of a core goal (Robinson, 2010). Therefore, the interpretation of resilience for each high street is important, as each different area will have specific goals which relate to either creating stability or redevelopment.

High street vacancy is an important aspect of resilience, especially when discussing the impact of the pandemic. If high streets were already having trouble with high vacancy rates before the pandemic, the economic and social shock may have intensified landlords’ difficulties in filling vacant lots. This is especially prevalent because landlords are often reluctant to fill vacant spaces in downward markets, as seen during the 2008 recession (Grenadier’s, 1995). Landlords are more likely to keep a premises vacant during economic shock because it is a more cost-effective option for them to hold onto a vacant premises rather than gamble with the possible benefits and risks of filling that space.

2.6.3 Local demographics
Furthermore, high street characteristics often reflect the macro-scale demographics of their surrounding areas. Examining changes in the average age of local residents is vital in providing demographic context for the trends in high street change. Despite growing life expectancy at the national level over the last half-century, there are strong geographical variations in population age. Aging populations have a tendency to cluster around coastal areas and urban peripheries (Wrigley and Lambiri, 2015).

According to the British Council of Shopping Centres (2006), the aging population is of particular interest to high streets. They estimated that over half of total retail expenditure came from individuals aged 45 and above. However, due to uneven access to private pensions and assets, this demographic cohort does not have a universal abundance of disposable capital. At the other end of the spectrum, younger cohorts can also provide an injection of cash flow into high streets through spending on culture and recreation, as well as sustaining micro-economies around institutions such as universities (Maurrasse, 2002). Thus, it is worth exploring how high streets cater for the needs and income levels of their surrounding age demographic when measuring retail and service success.

Ethnicity is another important consideration when building a picture of who uses, or is possibly excluded by, high street facilities. Barrett et al. (1996) detail how the global trend towards economic restructuring since the 1980s has resulted in a large increase in self-employed minority groups in Britain. Where Barrett et al. explore the structural challenges minorities face, including limited opportunities, Hall (2011) has researched why ethnic minority retailers often cluster together in areas of a high street. The work builds upon that of Kloosterman et al. (1999) to suggest that the spatial clustering of ethnic minority
entrepreneurialism can be understood through cultural and social networks alongside an economic framework of urban local dimensions.

The entrepreneurialism amongst minority ethnic groups has been valuable in terms of providing niche specialty market items and services (Iyer and Shapiro, 1999) and minimizing risk through subdividing and subletting retail spaces. Therefore, the literature construes that high streets with higher levels of ethnic diversity often result in greater variation in land use and available goods, a quality which allows for greater adaptability and economic stability. However, initiatives should also recognise the links between heightened deprivation and areas of greater ethnic minority proportion, alongside the social exclusion ethnic minorities face when engaging with community activities and services (Becares, 2012; Roach, 1992).

Vibrancy-led regeneration schemes also face challenges in developing quantifiable and robust measurements of likely outcomes, with little empirical research exploring its effectiveness to date (Markusen, 2013). For example, endogeneity could create methodological issues for some approaches where there are backwards or circular relationships with independent variables and variables used for vibrancy measures. One instance outlined by Lucas et al. (2019) is the increase of household income leading to better quality of shops and improvement of an area, while also attracting households with greater income. However, wider research has presented evidence of correlation between creative well-rounded methods and economic growth (Pedroni and Sheppard, 2013). Additionally, increased cultural activity can positively impact the revitalisation of local residential areas and bring commercial activity to high streets (Silver and Miller, 2013; Woronkowicz, 2015). Nonetheless, there is a growing need for a defined measurement tool and long-term studies on these techniques in order to accurately assess their impact on economic regeneration (Markusen et al., 2013).

2.6.4 Summary
Over recent years, high streets’ success has increasingly been measured in relation to their vitality, vibrancy and resilience. Vibrancy of an area focuses on the economic, social and community-developed health of high streets. Following the COVID-19 pandemic there was increasingly a shift in emphasis towards high street resilience. The resilience of high streets is more focused upon how an area adapts or stabilises when faced with external shock. The characteristics of high streets are usually influenced by the local demographics of the surrounding community. Therefore, when developing vibrancy-led or resilience-led regeneration schemes it is important to consider the ideal measurement and goals for the local users of high streets.

2.7 Measures of high street ‘success’

2.7.1 Retail success
Statistical analysis is not only essential for research purposes, but also for informing policy and making planning decisions that influence the retail offerings in high streets. Within the literature there are multiple studies focused on the exchange of knowledge between academia and local stakeholders to provide evidence for retail-based policy.
One example is Coca-Stefaniak's (2013) research aimed at increasing the success of six town centres that were selected as case studies. The study used statistics from the British Retail Consortium (BRC) which outlined the number and type of stores present within Britain’s high streets. In addition, Wrigley & Lambiri (2014) conducted a study to measure how British high streets were performing and evolving. The research used multiple performance measures to compare different regions and retail sectors across Britain. Commercial organisations also provide reports on retail success within high streets. The LDC produces frequent reports that outline key statistics such as vacancy rates and expansion or decline of retail sectors within high streets (LDC; 2019).

While traditional sources of data for the retail industry predominantly consist of market research, there has been a rise in the use of customer interaction data sourced from loyalty cards, footfall and in-app data (Lovelace et al., 2016). Hood et al. (2021) state that academics can build relationships with commercial organisations to enable large research challenges to be tackled through shared opportunities where commercial organisations can be encouraged to accept the social responsibilities relating to their data assets.

One specific example of how automated and manually collected retail performance data can be utilised is the SmartStreetSensor Project, a collaboration between the ESRC Consumer Data Research Centre and the LDC to monitor footfall in retail areas across the UK (Murcio et al., 2018). The project saw the instillation of Wi-Fi sensors in over 500 retail properties, collecting probe requests from surrounding devices at five-minute intervals. With the continuous generation of data, the project aimed to estimate the fluctuations in passing footfall and subsequent relations to retail profitability. Another recent application of innovative data applications to the retail sector includes Trasberg and Cheshire’s (2020) use of smartphone location data during the COVID-19 pandemic, monitoring changes in human mobility and interactions. The study highlights a method of identifying differing rates of recovery following a period of disruption – in this case, the lockdowns. Yue et al. (2017) also used mobile phone data in their research to identify the number of mobile phone users over a 24-hour period to devise a measure of neighbourhood vibrancy.

Notwithstanding the significant contribution these research projects have made to the literature on retail analysis, there still remains scope for a measure of retail vibrancy which combines multiple sources of data. In fact, the literature has identified the need for the development of a tool to identify retail areas at risk of decline. While Dolega and Lords’ (2020) research has begun to explore spatial variation in performance indicators of retail centres, they predominantly rely upon vacancy rate as an indicator. Therefore, there is an unmet need to develop a measure of high street success with multiple key performance indicators.

2.7.2 Socio-economic success

Back in 2005, the British government released ‘Planning Policy Statement 6: Planning for Town Centres’ (PPS 6), which outlined guidance on design and implementation tools for town centre planning. The document stated that the diversity of town centres is related to their levels of vitality and viability. However, despite reactive literature focusing on the
vitality and retail aspect of the document, studies rarely focus on the diversity element. Therefore, a bias towards the retail aspect of high streets is present in many studies, which is often accentuated when it comes to developing policy. Academic studies often rank high streets based on the presence or absence of certain retail aspects, such as the ratio of chains to independent stores, when adding more socio-economic elements to indexes could provide more in-depth comparisons (Hall et al. 2001; Reynolds and Schiller 1992). The focus on retail within planning and regeneration policy can be explained by two separate factors. Firstly, there is a greater abundance of large-scale granular retail data, which can be used to assess retail demand and gaps in the market. Secondly, British planning policy predominantly focuses on ensuring a balance between the size of town centres and proportion of new retail developments (Griffiths, 2008).

Hierarchical ranking of town centres arguably dates back to Christaller’s (1933) ‘Central Place Theory’. However, Christaller’s theory took a broader view of goods and services than much subsequent research, which tends to emphasise retail. It could be argued that retail-focused hierarchies reinforce a pattern in which larger town centres are more attractive for investors, while smaller high streets get left behind. Therefore, the retail-centric approach of high street intervention strategies can create situations where smaller high streets are ignored in policy due to their relative invisibility and lack of investment. This snowball effect is likely to disproportionately impact the success of smaller or suburban high streets (Griffiths, 2008).

Ravenscroft (2000) was critical of hierarchical ranking systems of urban centres that focus on retail, arguing that they fail to capture the communal, leisure and catering aspects which can often be linked to increased footfall. To overcome the dominant economic measures within high street policies, Hall (2012) has suggested that planning protection should be coordinated between streets through a unified framework or operational stewardship mechanism. Through coordination between streets and centres, a deeper understanding of a high street’s relation to its local area can be developed, thereby improving intervention strategies. Without this level of coordination that respects the cultural role of the high street, it is possible that economic measures of success will be prioritised over social and community values.

2.7.3 Sustainable high street
A high street which is sustainable and adaptable could be considered as possessing socio-spatial factors that promote long-term economic and social health. The literature often refers to the fact that diverse urban centres and high streets have the potential to contribute to the wider sustainability of an area, for example by creating local employment opportunities (Maguire et al., 2004). The New Economics Foundation (NEF) has suggested that the sustainable development of smaller high streets and smaller town centres can be reliant on the diversity of small, independent and local shops. These types of stores can provide economic, environmental and social benefits that help fuse communities together (NEF, 2006).

Organisations such as the NEF often describe smaller centres as vulnerable to corporate supermarket and retailer development. However, diversity can also be beneficial to
smaller high streets, often protecting them from economic shock (Wrigley and Dolega, 2011). There is also a large body of academic research that has suggested the importance of corporate food stores in sustainable development plans. Chain food stores can both act as a catalyst for future investment into a high street and increase linked trips, increasing footfall for surrounding stores (Wrigley et al, 2010; Storper and Venables, 2004). Achieving high street sustainability through simultaneously retaining independent stores and while also introducing chain food stores pose contradictory arguments. However, Wrigley and Dolega (2011) found that having both types of store is associated with better performance within high streets, when success is defined as a measure of smaller increases or reductions in vacancy rate.

In recent years there has been heightened consumer awareness of how consumer choices can lead to a more sustainable environment for local high streets. Shopping locally can develop a more stable market for retailers, retaining funds within a local area and boosting high street vitality (Chalmers et al., 2012). Shopping locally is also more important to certain demographics such as elderly people who might struggle to access large out-of-town shopping centres (Demko-Rihter and Ter Halle, 2015). More recent studies measuring high street success refer to the smart city concept (DBIS, 2013). Smart city proposals suggest that competitive advantage can be gained by using ICT-driven systems to improve sustainability, efficiency and quality of life (Graham and Peleg, 2017). In fact, Mosannenzadeh and Vettorato (2014) go as far to predict that innovation in ICT will be able to anticipate behavioural patterns that can be applied to high streets. Nevertheless, Fletcher et al. (2016) argue that a struggling high street cannot be the starting point for development of a coherent smart city.

For private, commercial and individual stakeholders a struggling high street can be seen as a risk to the development of a fully integrated smart city, with unsuccessful high streets already fragmenting commercial and social activities. Hernández-Muñoz et al. (2011) go on to suggest that the problem of competing systems within a smart city is important to address since cities are ‘systems of systems’. This begs the question of whether smart cities research takes the best approach to measuring high street success, as it ranks high streets based on their capacity for technological integration rather than exploring the root causes of the challenges they face.

2.7.4 Summary
High street success research can be categorised into three major areas, either measuring retail success; focusing on socio-economic phenomena; or analysing sustainability. Measures of retail success are predominantly based on indicators such as number of stores, store types, and vacancy rates. Nevertheless, new forms of retail data are becoming more prevalent in research, such as footfall data, mobile phone data, and big data on store locations. A separate body of research which acknowledges the limitations in solely focusing on retail aspects of high street success aims to evaluate how high streets meet the needs of the local community. Finally, some literature focuses on the viability and sustainability of high streets over time, sometimes using the 'smart city' concept to predict whether more technologically intertwined high streets are the future.
2.8 Chapter summary and research implications

High streets across Britain have struggled in recent years to attract enough consumers to remain economically viable. They face challenges including rising vacancy rates, higher operating costs, and market uncertainty. Additional reasons for the apparent decline in high streets are the 2008 economic recession, the overexpansion in the retail market in the 2010s, changes in consumer taste, the rise in out-of-town shopping, and the rapid growth of online purchasing. The COVID-19 pandemic which began in early 2020 resulted in numerous additional challenges for high streets, including economic recession, government-enforced lockdowns that saw footfall plummet, and the forced closure of ‘non-essential’ stores.

In response to the challenges British high street face, a large body of research has been dedicated to measuring their success in relation to their vitality, vibrancy, resilience, viability, and sustainability. Policymakers have also reacted by focusing on regeneration and redevelopment through the use of ‘meanwhile spaces’ for community-led projects. In addition, the current levelling up agenda has reinforced the decentralisation of intervention strategies by implementing bid-based systems for high street funding. However, such methods of allocating funding to struggling high streets are highly politicised and do not employ a transparent methodology that measures high street success, leading to some of the most deprived areas of Britain missing out on funding.

Consequently, an important next step in high-street research is the development of a quantifiable measurement of high street vibrancy and resilience which can compare all the high streets in Britain. Current funding allocation approaches are heavily influenced by MPs who may be motivated by political, rather than evidence-based, priorities. However, developments in new forms of data may enable a research-led policy in which high streets are quantitatively identified as being successful or in need of regeneration strategies. Furthermore, there is also the opportunity for a mixed methods approach to measuring the vibrancy and resilience of British high streets which combines data-driven approaches with the local knowledge of stakeholders such as local councils and communities. Therefore, the application of large nationwide commercial data provides the opportunity to conduct spatial analysis that can provide both macro and micro insights when measuring the success of British high streets.
Chapter 3

Data Description and Quality Considerations

This third chapter consists of three parts. Firstly, the British high street database developed as part of this thesis will be introduced alongside relevant literature and analysis and an examination of how each dataset can be used to contribute to a holistic representation of British high streets. Secondly, a detailed introduction to the LDC’s retail type, address, and vacancy dataset is given including its contribution to mapping the high street landscape. Finally, a particular part of the British high street database is explored which covers the various boundary definitions of high streets, their metadata and the boundaries used within this thesis.

The main commercial dataset used here has been created and maintained by the Local Data Company (LDC). Usually, large commercial datasets with such breadth and granularity are not made available outside of the commercial domain. Therefore, access to such a large amount of data which can be directly linked to high streets has created the opportunity for a distinctive study to understand their composition and performance across the whole of Britain.

The LDC describes itself as the UK’s most accurate retail location data company, which visits over 680,000 consumer-facing businesses multiple times a year in order to collect data on openings and closures of stores. A team of over 200 field researchers collect the data, which includes geographic coordinates of stores, creating the most accurate real-time and spatial view of the structural changes taking place across the British market. Outside of a commercial setting, access to the LDC’s data within a research context enables study of both the changes to British high streets from 2017-2021 and an assessment of the applications of commercial data in research and local policy context.

Access to the LDC data was obtained from the Economic Social Research Council-funded Consumer Data Research Centre (CDRC). As a condition of using the data, a series of organisational policies had to be adhered to in order to prevent the disclosure of commercially sensitive information, particularly in relation to the geographic location and names of stores. The CDRC classifies the data as ‘secure’, meaning that it is only permitted to be held within a secure environment with strict access restrictions. This thesis is part of a limited collection of research which uses this commercial dataset for academic purposes, consequently a number of challenges had to be overcome in relation to presentation of analysis and the aggregation of the data.

Access to the LDC data was via UCL’s Data Safe Haven (DSH), meaning all data is stored, processed and managed within the security of a system that has been certified to ISO270001 information security standards. In order to gain access to the DSH, the
Information Governance assurance process must be completed to ensure accountability for the risk of disclosure.

To output data from the DSH, the outputs have to be checked by two data scientists to ensure that the data has been aggregated to a sufficient geographical area; disclosive data has been suppressed; percentages do not lead to deduction of disclosive data; and a threshold of 10 is applied to raw data counts (see Figure10.1 in the Appendices for full CDRC Data Service User Guide). Finally, members of the CDRC’s senior management team ensure that the outputs are the same as proposed in the approved project proposal. Once approved, the output data is transferred to the user via the secure UCL DSH file transfer system where the download link and password are sent separately from the primary data scientist. Once the data has been transferred users are required to alert the CDRC when the outputs are used in any working papers, peer-reviewed journal articles, logs of impact and any other publications.

In adherence to these outlined data protection procedures the presentation of the LDC data has been approved by the data provider and constraints and aggregation have been implemented in compliance with statistical and commercial disclosure controls. The specific statistical disclosure controls have been reported alongside any descriptions of analysis within this thesis.

3.1 British High Street Database

In recent years there has been an ever-expanding quantity of available datasets for academic research, which are either in the form of open source or privately/commercially owned. Both sources have contributed to the possibility of researching the active processes that influence the changing composition and function of British high streets. Accordingly, a variety of different sources can be used to explore retailing trends. New and emerging forms of consumer data include mobility and transport data, in-app data and other forms collected either by the government or private companies. While traditional sources of data for the retail industry predominantly consist of market research, there has been a rise in the use of customer interaction data including footfall and in-app data. With specific relation to high streets, it should be acknowledged that individual experience is made up of where people shop, what they purchase, and what services they use. While the data generated from these consumer activities does not create a complete depiction of society it can still be used to gain insight into what influences consumer behaviour and how this impacts wider society as well as innovative solutions at a local level (Vij, 2016).

An extensive search for high street related data was based on the previous chapter’s in-depth literature review. Data sources relating to the factors impacting high streets’ success, vibrancy and resilience has been displayed in Table 3.1. All of the datasets are spatially referenced and cover a range of geographic scales, sources and availability. The data has been broken down into 6 categories: high street boundaries; mobility; economic; retail; and social & demographic. The variety of different data sources aim to encapsulate the retail and service structures within Britain’s high streets, the characteristics of
consumers who use them, and how high streets are changing or adapting in response to economic shocks – in particular, the COVID-19 pandemic.

<table>
<thead>
<tr>
<th>Type of data</th>
<th>Data Source</th>
<th>Aggregation Level</th>
<th>Information</th>
<th>Link</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Boundaries</strong></td>
<td>Consumer Data Research Centre retail centre boundaries</td>
<td>Retail centre boundaries as defined by the Consumer Data Research Centre (2021).</td>
<td>The CDRC boundaries are delineated using openly available data products which represent the location, extent and function of retail agglomeration areas across Britain. A hierarchical classification based on retail count, density and ranking within the respective local area serves to identify the prominence of each retail centre and captures variation between regional centres, market towns, small local centres, shopping centres, and retail outlets.</td>
<td><a href="https://data.cdrc.ac.uk/dataset/retail-centre-boundaries">https://data.cdrc.ac.uk/dataset/retail-centre-boundaries</a></td>
</tr>
<tr>
<td></td>
<td>Ordnance Survey high street boundaries</td>
<td>High street as defined by the Ordnance Survey (2019).</td>
<td>Ordnance Survey use all of their addresses classified under retail within their AddressBasePlus dataset. They cluster retail locations with a minimum of 15 retail addresses within 150 metres of each other. By using this spatial cluster analysis in conjunction with street names they create linear (straight line) clusters along a high street rather than sprawling clusters.</td>
<td><a href="https://www.ordnancesurvey.co.uk/business-government/sectors/public-sector/high-streets">https://www.ordnancesurvey.co.uk/business-government/sectors/public-sector/high-streets</a></td>
</tr>
<tr>
<td></td>
<td>ONS ‘Earnings and hours worked’</td>
<td>Local Authority</td>
<td>Annual estimates of paid hours worked and earnings for UK employees by sex, by full-time and part-time workers, and by home-based region to local and unitary authority level.</td>
<td><a href="https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/datasets/placeofresidencebylocal">https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/datasets/placeofresidencebylocal</a></td>
</tr>
<tr>
<td>Ministry of Housing, Communities &amp; Local Government</td>
<td>Local authority average weekly rents, by district and region, from 1991</td>
<td>The live tables provide the latest, most useful or most popular data, presented by type and other variables, including by geographical area or on a temporal basis.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>-----------------------------------------------------</td>
<td>---------------------------------------------------------------------</td>
<td>-----------------------------------------------------------------------------------------------------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Business Register &amp; Employment Survey</td>
<td>LSOA</td>
<td>Workplace-based employment by industry.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Office for National Statistics Regional household expenditure</td>
<td>Region</td>
<td>Data includes regional household expenditure by age, income group, economic status, socio-economic class, housing tenure, output area classification, urban and rural areas, place of purchase, and household composition.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Retail</td>
<td>Local Data Company 'Retail type, vacancy and store location</td>
<td>Retail Type and Vacancy data tables include: Shop name, Shop use, Classification, Category, Subcategory (inc. Retail Type/Vacancy).</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Local authority**

Local authority average weekly rents, by district and region, from 1991.

The live tables provide the latest, most useful or most popular data, presented by type and other variables, including by geographical area or on a temporal basis.

**Office for National Statistics Regional household expenditure**

Data includes regional household expenditure by age, income group, economic status, socio-economic class, housing tenure, output area classification, urban and rural areas, place of purchase, and household composition.

**Retail**

Retail Type and Vacancy data tables include: Shop name, Shop use, Classification, Category, Subcategory (inc. Retail Type/Vacancy).
### Table 3.1 British high street database outlining available data sources, aggregation level, additional information and links.

<table>
<thead>
<tr>
<th>Data Source</th>
<th>Aggregation Level</th>
<th>Description</th>
<th>Link</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retail Address data table includes: Unit, Building, Street No, Street, Town, Postcode, Latitude, Longitude.</td>
<td>Store location</td>
<td>The data provides the food hygiene rating or inspection result given to a business and reflects the standards of food hygiene found on the date of inspection or visit by the local authority. Businesses include restaurants, pubs, cafés, takeaways, hotels and other places consumers eat, as well as supermarkets and other food shops.</td>
<td><a href="https://data.cdr.ac.uk/dataset/food-hygiene-rating-scheme-fhrs-ratings">retail-type-vacancy-and-address-data</a></td>
</tr>
<tr>
<td>Police Crime data</td>
<td>Crime location</td>
<td>These CSV files provide data on street-level crime, outcome, and stop and search information, broken down by police force and 2011 lower layer super output area (LSOA).</td>
<td><a href="https://data.police.uk/data/">https://data.police.uk/data/</a></td>
</tr>
<tr>
<td>Modelled ethnicity estimates</td>
<td>Output Area</td>
<td>Ethnicity data (modelled)</td>
<td><a href="https://data.cdr.ac.uk/dataset/cdrc-modelled-ethnicity-proportions-lsoa-geography">https://data.cdr.ac.uk/dataset/cdrc-modelled-ethnicity-proportions-lsoa-geography</a></td>
</tr>
</tbody>
</table>

Aside from the LDC’s dataset on retail type, address and vacancy, all the data sources in Table 3.1 which are used within this thesis are open. The outlined datasets have been selected due to having coverage across the whole of Britain. For some of these datasets they have been collected at the discretion of local authorities, making it often difficult to compare the validity of the data across the whole of Britain.

Additionally, many open data sources, particularly those relating to transport and mobility, are London or large city centric, making comparisons with smaller rural high streets difficult. Where these datasets have been used throughout the thesis, more explicit discussion surrounding quality considerations has been given in detail.

Challenges in using open data to conduct high street level analysis can vary depending on the aggregation level. For the two most granular open-source datasets from the Food Standards Agency and police.uk, which provide longitude and latitude coordinates for locations, there are geographical recording issues and loss of spatial information caused by the use of snap points (by which recordings are connected to a certain address, resulting in multiple recordings in one specific location or point of interest). Additionally, the grouping and categorisation systems used can obscure the data in some cases, resulting, for example, in the grouping together of violent and sexual offences in the police.uk data.
For the other datasets in Table 3.1- which are aggregated from Output Area (OA) level up to regional level - they carry the risk of creating inconsistencies with the theoretical framework when studying high streets at the geographical level. For data aggregated to larger areas (such as local authority level) this risks generalising the attributes allocated to all high streets within a given local authority when there might be substantial variation. Data covering smaller areas, including Output Area and Lower Super Output Area (LSOA), raise the issue of determining which boundary should be associated with which high street and how these values should be aggregated.

### 3.2 Local Data Company: Retail type, address and vacancy

In this thesis, LDC data from between 2017 and 2021 is used to analyse the resilience and vibrancy of British high streets. The available data contain 851,651 records of occupiers and the latest update at the time of this thesis’ analysis was from the 30th June 2021, containing 778,816 records. The 2021 update contains the data of 688,719 premises in Britain which are classified as ‘retail’ - excluding, for example, underground stations, parks, squares, and monuments. The dataset is an example of a structured form of big data as it is made up of clearly defined variables. The data consists of information regarding occupier names, associated time period, coordinates of premises, and category information of group occupier type. A more in-depth explanation of the variables within the LDC’s 2021 store location data can be seen in Table 3.2. Within Table 3.2 there are two variables that need to be defined for the proceeding chapters. A Premises which is identified by a unique premises ID can be defined as a building that is occupied by a business or considered in an official context. In addition, an occupier is identified by its unique occupier ID and is defined as an individual or company residing in or using a premises as its owner or tenant.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Variable name</th>
<th>Data Type</th>
<th>Notes</th>
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<td>Can be used to identify premises over time</td>
</tr>
<tr>
<td>Occupier ID</td>
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</tr>
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</tr>
<tr>
<td>Chain ownership ID</td>
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</tr>
<tr>
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<td></td>
</tr>
<tr>
<td>Occupier category</td>
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<td>11 categories</td>
</tr>
<tr>
<td>Occupier subcategory</td>
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</tr>
<tr>
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</tr>
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</tr>
<tr>
<td>Building name</td>
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<td></td>
</tr>
<tr>
<td>Street Number</td>
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</tr>
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<td>Street</td>
<td>Street</td>
<td>Nominal</td>
<td></td>
</tr>
<tr>
<td>Town</td>
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<td></td>
</tr>
<tr>
<td>Post code</td>
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<td>Nominal</td>
<td></td>
</tr>
<tr>
<td>County</td>
<td>County</td>
<td>Nominal</td>
<td></td>
</tr>
<tr>
<td>Region</td>
<td>Region</td>
<td>Nominal</td>
<td></td>
</tr>
<tr>
<td>Telephone</td>
<td>Telephone</td>
<td>Nominal</td>
<td></td>
</tr>
<tr>
<td>Website</td>
<td>Website</td>
<td>Nominal</td>
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</tr>
<tr>
<td>Latitude</td>
<td>Latitude</td>
<td>Numeric/continuous</td>
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</tr>
<tr>
<td>Longitude</td>
<td>Longitude</td>
<td>Numeric/continuous</td>
<td></td>
</tr>
<tr>
<td>Occupier status</td>
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<td>Nominal</td>
<td></td>
</tr>
<tr>
<td>Premise status</td>
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</tr>
<tr>
<td>Date occupier opened</td>
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<td>Date</td>
<td></td>
</tr>
<tr>
<td>Date occupier closed</td>
<td>ClosedDate</td>
<td>Date</td>
<td></td>
</tr>
<tr>
<td>Date premise created</td>
<td>PremiseCreateDate</td>
<td>Date</td>
<td></td>
</tr>
<tr>
<td>Voa</td>
<td>Voa</td>
<td>Numeric/continuous</td>
<td></td>
</tr>
<tr>
<td>Voa business rate</td>
<td>Voa_BusinessRate</td>
<td>Numeric/continuous</td>
<td></td>
</tr>
<tr>
<td>Date occupier last verified</td>
<td>FrLastVerified</td>
<td>Date</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.2 Metadata for the Local Data Company retail type, vacancy and address data, 2021.

During the government-enforced COVID-19 lockdowns between 26th March 2020 and 12th April 2021, which forced non-essential retail stores to close, there was disruption to the frequency of data collection from the LDC’s researchers. In addition, the temporary
closure of stores created difficulties in gauging vacancy rates. Consequently, an additional dataset from the LDC was acquired which was in the same format, but which identified stores that closed temporarily due to lockdowns. The temporary closure file can be joined with the full records, and the column which outlines the date the occupier was last verified can be used to filter the premises visited since all shops were allowed to reopen on 12th April 2021. Consequently, premises with a reopening date would have opened, those which are blank would have closed, and those with 'N/A' would have either never closed during the lockdowns or opened after March 2020 when the pandemic started. The additional dataset enabled the tracking of stores’ reopening, an important addition due to many stores remaining closed after the lifting of lockdown restrictions but not being vacated.

3.2.1 Cleaning of the Local Data Company’s dataset
The occupier recordings included a premise ID, occupier ID, and the dates on which the occupier opened and closed (in the format of DD-MM-YYYY). Therefore, for each premises there were often multiple recordings for the different occupiers over time. However, for most of the analysis conducted in this thesis the tracking of occupier and subcategory information was required per premise and high street over time. Consequently, in order to use the LDC’s retail type, vacancy and address dataset, the data cleaning process set out to develop a consistent standardised dataframe that enables spatial and temporal comparisons across the period of 2017 to 2021.

As part of the data cleaning process a table was devised to report the premises’ occupier ID and subcategory at a given location, per quarter. The table was made to enable quick and easy access of statistics at varying time periods. As outlined in Table 3.2, the original data was formatted as time series data and contained an additional file with the latest updates as of June 2021. The updated data had to be merged with the historic data to account for the shops which had closed or changed occupier status during 2021. Table 3.3 displays the format of the new table which consisted of mutating the time series data into economic quarters (Q1=January-March; Q2=April-June; Q3=July-September; Q4=October-December) starting from 2017. A premises was determined to be occupied or vacant if it maintained that status for two out of three months in a quarter. The resulting table consists of columns for each quarter per year outlining whether it was occupied, vacant, or lacked data, as well as the corresponding occupier ID. The consecutive columns indicate the shop category and the multiple ID if the store was part of a chain.
Table 3. 3 Example data in the same format as the Local Data Company retail location dataset, transformed into a quarterly table.

Following the creation of the premises table and data cleaning, there were a resultant 773,334 premises across Britain where the occupier and subcategory is tracked from Q1 2017 to Q2 2021. Table 3.4 displays the volume of data available in each year across the time period.

The information for each occupier is highly specific. There are 404,559 different occupier names, placed into 11 different categories and 427 different subcategories. The subcategories are as precise as stating the type of cuisine a restaurant is (eg. Restaurant – Japanese). Table 3.5 provides a summary of the categories and example subcategories within each level. Some subcategories have been placed in multiple categories. No specific occupier names have been included within this thesis to prevent the disclosure of commercially sensitive material.
<table>
<thead>
<tr>
<th>Category</th>
<th>Number of subcategories</th>
<th>Example subcategories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clothes &amp; Fashion</td>
<td>27</td>
<td>Fashion Shops&lt;br&gt;Kilt Shops&lt;br&gt;Hat Shops&lt;br&gt;Dresswear Hire</td>
</tr>
<tr>
<td>Events &amp; Attractions</td>
<td>22</td>
<td>Golf Courses&lt;br&gt;Ice Rinks&lt;br&gt;Theatres &amp; Concerts&lt;br&gt;Bowling Alleys</td>
</tr>
<tr>
<td>Food &amp; Drink</td>
<td>32</td>
<td>Coffee Shops&lt;br&gt;Ice Cream Parlours&lt;br&gt;Juice Bars&lt;br&gt;Fishmongers</td>
</tr>
<tr>
<td>Health &amp; Beauty</td>
<td>32</td>
<td>Herbalists&lt;br&gt;Nail Salons&lt;br&gt;Dentists&lt;br&gt;Beauty Salon</td>
</tr>
<tr>
<td>Home &amp; Garden</td>
<td>59</td>
<td>D.I.Y&lt;br&gt;Furnishers&lt;br&gt;Estate Agents&lt;br&gt;Builders</td>
</tr>
<tr>
<td>Hotels</td>
<td>10</td>
<td>Bed &amp; Breakfast&lt;br&gt;Guesthouses&lt;br&gt;Holiday Flats&lt;br&gt;Hotels- 5 stars</td>
</tr>
<tr>
<td>Non Retail</td>
<td>12</td>
<td>Vacant Properties&lt;br&gt;Offices&lt;br&gt;Council Services&lt;br&gt;Warehouse</td>
</tr>
<tr>
<td>Pubs, Bars &amp; Clubs</td>
<td>9</td>
<td>Bars&lt;br&gt;Night Clubs&lt;br&gt;Public Houses &amp; Inns&lt;br&gt;XXX- Adult Venues</td>
</tr>
<tr>
<td>Restaurants</td>
<td>73</td>
<td>Restaurant &amp; Bar&lt;br&gt;Restaurant- Welsh&lt;br&gt;Restaurant- Vegan&lt;br&gt;Restaurant-Polish</td>
</tr>
<tr>
<td>Shops &amp; Amenities</td>
<td>139</td>
<td>Boat Shops&lt;br&gt;Gift Shops&lt;br&gt;Wedding Companies&lt;br&gt;Pawnbrokers</td>
</tr>
<tr>
<td>Taxis &amp; Transport</td>
<td>14</td>
<td>Car Body Repairs&lt;br&gt;Car &amp; Van Hire&lt;br&gt;Taxis &amp; Private Hire&lt;br&gt;Car Accessories &amp; Parts</td>
</tr>
</tbody>
</table>

Table 3.5 Example of the LDC occupier category and subcategory structure.

Due to some of the categories being vague, in particular ‘Non-Retail’ (which includes vacant properties), subcategories have been used primarily for the analysis throughout this thesis. However, some subcategories were excluded where no interpretable information was given on the store type (e.g. null, miscellaneous). In addition, transport-
related premises (e.g. train or underground stations) were excluded from this study as mobility elements of high streets were explored using other datasets (see chapter 7). The data also contained 6,072 recordings of different chain names, referred to as multiple names. Of these chain names, 4,648 had five or more recordings – a common definition of a chain which incorporates local chains and chains with similarities in ambience and goods or service offerings (Boston, 2014). The premises’ creation date ranges from 31-12-1979 to 28-06-2021 and the occupier creation dates also range across the same timeframe. The store location data was provided in the form of a street number, street name, postcode, and longitude and latitude coordinates. Longitude and latitude were used to infer the geographic location of the premises as it was the smallest geographical unit available.

3.2.1 Challenges when cleaning Local Data Company’s dataset
When combining the full LDC records with the updated version from 30th June 2021, the stores that closed between the updates had to be determined. Cases were selected where the historical file had ‘N/A’ for store closure. The premises’ IDs were cross-checked between the full version and the update to determine if the premises had changed ownership or become vacant. Occupier ID was used to search for occupiers that were in the original historical data but not in the update. For those premises where a new occupier had taken over but the closure date for the old occupier was N/A, the closure date was filled in as 1st January 2021. This date was used because in some cases it was known when the new occupier opened, but the closure date of the previous occupier was between updates. Where there were duplicates between the historical data and the update for Occupier ID the correct dates were selected as the earliest recorded opening date and the latest closure date.

One of the major challenges when cleaning the data was dealing with shopping centres and department stores. These type of retail locations have one Premises ID and do not have Premises IDs for each store within them. As the aim of the data cleaning process was to track occupier change in the same premises to devise a measure of occupier change, shopping centres or department stores would skew the occupier change rate for a given high street. Therefore the ‘Care of’ variable was used to determine if a shop was located within a larger complex, and such stores were given a new Premises ID of their own in order to track the occupiers over time.

Another common issue with the data was timescale overlap (where there appeared to be two occupiers on the same premises at the same period due to split or dual use locations). These types of locations have been treated as two separate locations to maintain consistency over time. When dealing with missing data a certain set of assumptions were made. Firstly, if an occupier was recorded in Q1 and Q3, it was presumed the same occupier was also present in Q2. Secondly, if there were data gaps between periods of vacancy with no new occupier and the building had not been demolished, these premises were presumed to still be vacant.
3.3 High Street and Retail Boundaries

While most of the analysis conducted within this thesis has been conducted at premises level, spatial aggregation was needed to prevent disclosure of individual store information when generating outputs. Since the focus of this thesis is Britain’s high streets, the spatial aggregation was performed at a high street boundary level. While high streets are one of the main core retail centres in Britain alongside retail parks and shopping centres, research into the geographies of high street boundaries at a national level is scarce. High street boundaries are often drawn up as part of local planning strategies, often only capturing singular geographical aspects.

One high street boundary dataset which extends across the whole of Britain was produced as a collaboration between the Ordnance Survey (OS), the Ministry of Housing, Communities and Local Government, and the Office for National Statistics (ONS). The high streets were identified as clusters of 15 retail addresses within 150 metres, linked to roads. The threshold was used to avoid labelling small rows of shops as high streets. The OS used spatial cluster analysis combined with street names to create linear clusters as appose to sprawling clusters. An example of what the OS deems to be the longest high street in Britain is London Road in Southend-On-Sea, displayed in Figure 3.1. The figure has been taken from the OS high streets demo dashboard.

![Figure 3.1: London Road, Southend-On-Sea high street boundaries (blue) as defined by Ordnance Survey (2019).](image)

The clustering methodology outlined in the ONS (2019) report ‘High streets in Great Britain’ produces 6,969 high streets in 2019, with 1,204 of those in London. Due to the method’s use of addresses as the basis for the clustering, only 31% of the addresses within the boundaries were retail addresses. Although the methodology used to create the OS high street boundaries is openly available, the boundaries themselves are not.
Therefore, this thesis combines the definition of a high street from the OS boundaries with the openly accessible Consumer Data Research Centre’s (CDRC) (2021) Retail Centre Boundaries, which span the whole of the UK.

The CDRC retail boundaries use H3 spatial indexing to take retail places, their building footprints and land-use polygons from OpenStreetMap and aggregate them into a grid of H3 hexagons. The retail boundaries are then delineated through a series of contiguous tracts of hexagons that are assembled based on their direct adjacencies. Due to the interoperable and computationally inexpensive methodology, the output is uniform across the whole of Britain – characteristic essential to the analysis in this thesis. The CDRC retail boundaries are also part of a hierarchical classification system based on retail count, density and ranking within the respective local area. The final CDRC retail classification system results in 9 different categories: district centre, small local centre, local centre, major town centre, regional centre, market town, town centre, retail park, and out-of-town shopping centre. Figure 3.2 displays the CDRC (2021a) retail centre boundaries in the Southend-On-Sea area alongside the CDRC retail classifications.

![CDRC Retail Centre Boundaries, 2021](image)

Figure 3.2: Southend-On-Sea retail centre boundaries as defined by the Consumer Data Research Centre (2021).

One distinct benefit of using the CDRC boundaries that is visible by comparing Figure 3.1 and Figure 3.2 is how the exclusion of residential addresses during the CDRC delineation leads to 7 retail centres along London Road, Southend-On-Sea (one district centre, one town centre, and five small local centres). While the OS high street boundaries consider
the whole of London Road to be part of the high street, the CDRC boundaries are more accurate at locating and differentiating between retail clusters within Southend-On-Sea. Due to this thesis focusing specifically on high streets, retail parks and out-of-town shopping centres have been excluded.

Consequently, this thesis combines both the CDRC (2021a) boundaries and the OS (2019) definition of a high street. CDRC retail boundaries have been taken from within the six selected retail categories (district centre, small local centre, local centre, major town centre, regional centre, market town, town centre) and considered a high street if they have 15 or more retail locations within them. To work out which of the boundaries contained the threshold number of retail locations, the CDRC boundaries were spatially joined with the LDC retail address dataset. By ensuring that there are at least 15 store locations within each high street boundary, this method ensures that the commercially sensitive LDC data is not disclosive and also ensures a substantial sample of data points in each high street to develop an accurate representation of the retail characteristics within.

### 3.4 Characteristics of high streets in Britain

The premises that are present in Q2 2021 have been spatially joined with the CDRC boundaries. By using the most up-to-date data at the time of research, this thesis aims to analyse the changes to high streets in Britain from 2017 to 2021. The original CDRC retail boundaries contain 6,423 different retail areas in the UK. After omitting retail parks, out of town shopping centres, retail centres in Northern Ireland and removing boundaries with less than 15 LDC store location points, there are a resultant 3,828 high streets. The distribution of high streets across the three nations in Britain is heavily weighted towards England, where there are 3,480 boundaries, compared with 202 in Scotland and 146 in Wales. Table 3.6 displays the proportion of high street boundaries within each CDRC retail boundary classification.

<table>
<thead>
<tr>
<th>High street classification</th>
<th>Count</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regional Centre</td>
<td>13</td>
<td>0.34</td>
</tr>
<tr>
<td>Major Town Centre</td>
<td>82</td>
<td>2.14</td>
</tr>
<tr>
<td>Market Town</td>
<td>112</td>
<td>2.93</td>
</tr>
<tr>
<td>District Centre</td>
<td>227</td>
<td>5.93</td>
</tr>
<tr>
<td>Town Centre</td>
<td>270</td>
<td>7.05</td>
</tr>
<tr>
<td>Local Centre</td>
<td>374</td>
<td>9.77</td>
</tr>
<tr>
<td>Small Local Centre</td>
<td>2750</td>
<td>71.8</td>
</tr>
</tbody>
</table>

Table 3.6 Proportion of high street boundaries within each Consumer Data Research Centre retail boundary classification.

While the high street boundaries are heavily skewed towards what the CDRC defines as ‘small local centres’, their inclusion is paramount to understanding the possible success and resilience of smaller local high streets when compared to larger town or city high
streets under forces such as economic pressure and the rise of convenience culture (Wrigley and Lambiri, 2014). The majority of high street boundaries are situated in London (883, or 23.1%), followed by the Northwest of England (519, 13.6%). Figure 3.3 displays the spatial distribution of the high street boundaries relevant to this analysis. See Table 10.1 in the Appendices for the number of high streets in each region in Britain.

Figure 3.3: Relative regional shares of high streets in Great Britain, 2021. Source: CDRC definition of a high street.
When considering regional differences, 90.9% of the high streets being located in England. Consequently, despite Scotland having 10% of the population, the data implies less than 5% of high streets are in Scotland. The definition of high street used within this thesis shapes these results as high streets fall below the threshold of representation in the schema. Nevertheless, the most densely populated towns and cities in Scotland and Wales are covered. In Scotland these include Glasgow, Edinburgh, Aberdeen, Dundee, and Paisley. For Wales, large towns and cities include Cardiff, Newport, Swansea, Wrexham, and Bridgend.

3.4.1 Composition of high streets in Great Britain
This next subsection will expand upon the description of British high streets between 2017 and 2021 by outlining their retail composition. To investigate the composition of high streets, the LDC categories have been used and the subcategory of vacant properties has been taken from the ‘non-retail’ subcategory. The proportion of stores in the top 4 most common categories have been taken for the first quarter of each year between 2017 and 2021 and displayed in Figure 3.4.

![Figure 3.4: The composition of high streets in Great Britain in 2017-21 (top 4 more common categories).](image)

Firstly, in relation to the retail structure of high streets, there has been a gradual decline in shops and amenities. These were the most common store type within high streets in 2017, making up 28.4% of all categories, but dropped to 23.5% in 2021. In contrast, the occurrence of vacant properties has risen steadily between 2017 to 2021, with the most prominent increase between 2020 and 2021 (15.4% to 17.8%). Specifically, between
2017 and 2021 there was a rise in vacant properties within high streets from 10.73% to 17.83%. Following the COVID-19 pandemic lockdown restrictions, vacant premissses were seen to surpass food and drink and health and beauty stores. Table 10.2 in the Appendices presents the full breakdown of the composition of British high streets between 2017 and 2021.

Furthermore, if we represent the 10 most frequently observed subcategories by order of frequency for 2017 and 2021 (Figures 3.5 and 3.6) there are some considerable differences.

Figure 3.5: The ten most frequently observed retail subcategories across British high streets, 2017.
The main difference between 2017 and 2021 is the increase in vacant properties, which reduces the overall proportions of all other subcategories. In addition, there are some interesting changes in the most common retail subcategories including the rise in barber shops moving from rank 10 (1.84%) to rank 3 (2.85%). Fast food takeaways also increased their proportion on British high streets moving from rank 9 (1.98%) to rank 6 (2.13%). In contrast, fashion shops had a steep decline in their presence on the high streets dropping off the top 10 completely in 2021 from their previous rank of 6th position (2.34%) in 2017.

3.5 Representation and Uncertainty

Due to this thesis’ use of a commercial data source for the majority of the analysis there are a considerable number of methodological considerations which need to be acknowledged. As the data source was secondary in nature, the exact data collection methods used by the LDC field researchers are unknown. Consequently, it is important to assess the quality of the LDC data – particularly in terms of uncertainties and whether it fits the purpose of this research.

One of the most important considerations when exploring representation and uncertainty of the data is the possible plausibility of the observed geo-spatial trends. Due to the nature of the LDC data, especially in terms of the frequency of updates, data generation, and granularity, it is difficult to find an available source that can be used for validation purposes. One Britain-wide source of store locations is from the Valuation Office Agency (VOA), which publishes official statistics on non-domestic rating and council tax. The
Property Details dataset includes address variables, property type, total floor area, effective date of survey, and broad VOA classifications for retail types. However, the VOA restricts access to the Property Details dataset as it is treated as personal data. The VOA also falls under the 2005 Commissioners for Revenue and Customs Act, which restricts access to the data and preventing it from being readily available for this thesis. Therefore, this next section explores a more aggregated dataset providing an insight into the distribution of retail across British high streets – the ‘High street employment, use and resident population dataset’, developed by the ONS (2020).

The dataset originates from OS and ONS sources as it uses the OS’s definition and boundaries of high streets, and the ONS employment survey. The high street definition used within the dataset is a named street predominantly consisting of retailing, defined by a cluster of 15 or more retail addresses within 150 metres. As a result, unlike the CDRC retail boundaries used to derive high street boundaries for this thesis, the ONS data does not capture rural and isolated areas, where there are smaller high streets. Nevertheless, within this thesis high streets within the Scottish local authority of Na h-Eileanan Siar did not have sufficient data to draw conclusions about their characteristics, while the ONS data did. Although, as the ONS high street definition uses a minimum retail address threshold, some locally important and traditional high streets have not been captured.

The ONS dataset includes the breakdown of addresses on the high street by land use category, aggregating the results to local authority level. The five different percentage categories include: retailing, offices, community, leisure, and residential. Three of these categories – retail, offices, and leisure – are comparable to the LDC data, which could act as a source of data validation. The categories are based on the land use type as defined by the Ministry of Housing, Communities and Local Government.

Therefore, ‘retail’ is defined as: shops, financial and professional services, restaurants and cafes, public houses and bars. Leisure premises are defined as amenity, amusement and show places; libraries, museums and galleries, and land sport facilities; water sport facilities; and holiday camps. Using the dataset, the ONS found for the “distribution of retail addresses on the high street there is no clear pattern across the country” (ONS, 2020:6). However, they did find that “hub towns” which can be characterised as free-standing settlements (often with market town heritage) had high streets with 36% retail addresses, compared to 29% overall in Britain.

The ONS data is based on the Land Use Address Classification from March 2020, therefore it has been compared to quarter 1 of 2020 in the LDC data. The 427 LDC occupier subcategories have been recategorised to match the ONS categories of offices, retail, and leisure. The proportion of each category in every high street in Britain has then been calculated. The results show an average of 53% retail, compared to the ONS’s 29%. Due to the ONS finding that “hub towns” have a higher proportion of leisure it might be suggested that the higher proportion of retail found in high streets by the LDC data could be due to the inclusion of smaller local high streets excluded by the ONS; these often have a higher proportion of premises providing necessity goods and services which would
be defined as ‘shops’. The results have been aggregated up to local authority level so they can be spatially compared (Figure, 3.7).

Figure 3. 7: A comparison between the proportion of retail addresses on high streets per local authority in Britain, 2020 as calculated by the Office for National Statistics (left) and Local Data Company datasets (right).

The ONS classifications for offices and leisure have also been used to calculate the local authority level of each (using the LDC data) and are presented in Figures 3.8 and 3.9.
Figure 3.8: A comparison between the proportion of office addresses on high streets per local authority in Britain, 2020 as calculated by the Office for National Statistics (left) and Local Data Company datasets (right).

Figure 3.9: A comparison between the proportion of leisure addresses on high streets per local authority in Britain, 2020 as calculated by the Office for National Statistics (left) and Local Data Company datasets (right).

The data in Figures 3.7-3.9 have been plotted as equal count quantiles with 4 classes. Although different high street boundaries were used for the ONS data and for this thesis,
comparisons and observations can be drawn based on the distribution of the individual datasets. For example, both datasets found a higher proportion of leisure premises in the north of England; a high density of offices in the southeast of England; and a high proportion of retail in Scotland. Meanwhile, there are stark differences in proportions of leisure and retail premises when comparing London local authorities with the rest of Britain. For example, City of Westminster has a low proportion of retail within its high streets, despite having large shopping areas such as Oxford Street and Bond Street. This is most likely due to discrepancies between the land use categories used by the ONS and the more specific occupier subcategories used within the LDC data. In addition, within the ONS data there are a number of non-high street geographies, which have been included in the analysis.

One way to validate discrepancies arising from the different boundary classification methods is to cross-reference them with another commercial source. In this case we can look to Geolytix, a company that specialises in building tools and data aimed at aiding location-planning. They have developed a Retail Places (Geolytix, 2022) dataset that contains around 20,000 polygons outlining where people shop across the whole of the UK. An extract of the area surrounding the London Borough of Camden has been taken from the Geolytix dashboard and presented in Figure 3.10. The retail boundaries included in the sample are categorised into: Urban centres (brown), Parades (Green), Leisure Parks (yellow), Trade Parks (grey), and Rail Stations (navy).

![Image of retail places in Camden](image)

**Figure 3.10**: Retail Places in part of the London Borough of Camden as defined by Geolytix (2015).

The Retail Places coloured in brown and classified as ‘Urban Centres’ in the Geolytix extract can be cross-referenced with the high street boundaries used within this thesis.
Figure 3.11: London Borough of Camden (part) high street boundaries as defined by the Consumer Data Research Centre’s (2021) Retail Centre Boundaries and the Local Data Company dataset on store location (2021).

When comparing Figures 3.10 and 3.11 there appear to be far fewer discrepancies between the two types of boundaries. The majority of the high streets included within this thesis are similar to those classified by Geolytix as ‘Urban Centres’ with some inclusion of large ‘Parades’. Some differences in the distribution of the polygons may be because the open-source version of the Geolytix data was licenced in 2015; the company’s new commercially sensitive 2021 product may reflect changes in retail structures which are captured in the boundaries derived from the more current CDRC and LDC data. Nevertheless, one reason for their similarities is that while the methodologies for both sets of boundaries slightly differ, the same data source was used to delineate both sets of boundaries through sourcing VOA data and clustering based on proximity and contiguity.
3.6 Chapter summary

This chapter has introduced the core datasets used for analysis in the chapters that follow: the retail resilience database and the Local Data Company dataset on retail type, vacancy, and address data. Both the open data sources within the resilience database and the LDC dataset encompass the whole of Britain, yet their spatial-temporal coverage is varied. While the majority of the open data sources are aggregated to levels such as Lower Super Output Area and Local Authority level, the commercial LDC data provides higher granularity and a more up to date depiction of the composition of British high streets.

From initial descriptive analysis the composition of British high street retail has appeared to change throughout the last five years. The categorisation and sub-categorisation of retail units was used to gain initial insights into the dominant location types that make up the composition of high streets. The main structural difference to high streets is the gradual and consistent rise in vacant properties from 2017 to 2021. In addition, fashion stores had a rapid decline while barbers and takeaways increased their presence.

Before using the LDC data to measure the composition of British high streets, substantial time was allocated to data cleaning. Manual checking was undertaken to deal with missing data and measurement errors caused by overlap in recorded occupiers in the same premises. In addition, high street boundaries were selected based on the Ordnance Survey’s definition in combination with the CDRC’s retail boundaries, due to their delineation method and openly available access.

The Ordnance Survey high street boundaries and the resulting local authority level analysis of composition were compared to the boundaries used within this thesis and an additional commercial dataset produced by Geolytix. Preliminary analysis on the difference between the three sources of high street boundaries exposed the limitations of using government collected land use data to derive an assessment of composition. Access to the granular dataset provided by the LDC enabled the inclusion of small and isolated high streets within this piece of analysis, which would not have been possible using solely the ONS dataset. The LDC data also provided more specific information on the stores which lie within the boundaries, unlike the dataset produced by Geolytix.

This chapter has explored the benefits of using a commercially derived dataset to produce high street boundaries and composition classifications which can be regularly updated. Yet whilst such datasets provide granular and interesting findings with widespread applications, vigilant data cleaning and interpretation is required before conducting analysis. To summarise, dealing with large commercial datasets provides great possibilities for granular retail analysis, yet also presents challenges when ensuring the reliability of the data.
Chapter 4

The composition of British high streets (2017-19)

Classifying and ranking urban centres based on their function and performance is a well-established practice within geographic literature. Such retail typologies are used for a multitude of reasons including the monitoring of change to urban landscapes, advising investment decisions and to inform economic and social policy (Reynolds and Schiller, 1992). While early attempts to draw distinctions between urban centres utilised simple techniques, there have been developments driven by access to more reliable data. For example there has been more research that ranks centres hierarchically to account for the assumption that retail centres are nested within a hierarchical network of local centres (NPPF, 2012). In addition, there is a continued consensus that there are different orders of retail and non-retail activities that can be connected to each centre’s expected level of vibrancy and vitality (Dolega et al., 2021; Jansen et al., 2014; Wrigley and Dolega, 2011). However, there is no agreed method to establish such a retail hierarchy or any strong empirical proof that retail structures are hierarchically ordered in the UK (Brown, 1991; Christaller, 1966; Parr, 2017).

A comprehensive retail centre classification system can aid the development of more insightful recommendations for regeneration projects that focus on transforming urban centres (Guy, 1998). With heightened challenges facing British high streets, such classifications are a requisite to informing policy, where new sources of granular data have made the prospect of these more complex classification systems possible. In particular, comprehensive classifications are necessary due to the underlying challenges facing high streets including changes in consumer behaviour, increased use of new technologies and competition from online shopping alongside financial and economic struggles that have been exacerbated by the COVID-19 pandemic (Grewal et al., 2018; Wrigley and Lambiri, 2015). In the pre-pandemic era, there was already a gradual shift in the traditional functions of high streets leading to concerns from the retail industry and local governments (Jones and Livingstone, 2018). The pandemic then led to additional challenges prompting a re-evaluation of how consumers viewed and interacted with their local high streets. On one hand some sectors struggled to compete with online sales that accounted for 33.3% of all retailing during the height of the first lockdown. More specifically, sectors such as fashion retail exampled how internet businesses can adapt quickly and opportunistically to replace physical stores as online fashion retailing reached 49.4% of all fashion sales (Deloitte, 2022). On the other hand, different high street stores saw a rise in sales such as local convenience stores. Local convenience stores had a 32% rise in the number of baskets of items bought between March and July 2020 compared to the four months leading up to the pandemic (Retail Gazette, 2020). Nevertheless, the overall impact of the pandemic has had significant implications for high
streets with 62% of people visiting their local high streets less often than before the pandemic and 69% of people visiting their local city centres than in pre-pandemic times (PWC, 2022).

This chapter explores the nature of high streets in Britain prior to the COVID-19 pandemic. A non-hierarchical classification system has been developed based on two characteristics: the proportion of chain stores and the proportion of ‘essential’ stores as defined by the government during the COVID-19 lockdown periods. These two dimensions are used to establish the retail landscape before the impact of the pandemic in order to more accurately gauge pre-existing high street structures, composition and success. The chapter discusses the importance of choosing a meaningful unit for vibrancy analysis. The typology has two layers: high street level and local authority level. Since local authorities have control over their own high street intervention strategies it was important to establish how their high streets composition and performance compared both with other local authorities but also within their own boundaries. To address these aims, the chapter evaluates the results of the high street typology and provides descriptions of the resultant clusters alongside a measurement of vibrancy. The vibrancy levels have been calculated using pre-pandemic measures of vacancy and occupier change. The chapter then provides empirical evidence of the importance of selecting appropriate geographic extents based on a case study of Camden Local Authority. The significance and the limitations of the findings are discussed in relation to the level of insight this method permits to measuring the pre-pandemic landscape of high streets in Britain. Overall, this chapter argues that a straightforward and data-driven classification system can be used to pre-emptively assess the viability of high streets before the COVID-19 lockdown restrictions in a precise and transparent way.

4.1 Measures of high street performance
The economic performance of high streets is frequently measured by its vacancy rate, which is often a good indicator of any systemic problems or degradation (Wrigley and Lambiri, 2015). Patterns in vacancy can also be used to identify high streets that are becoming obsolete and comparing them at different spatial scales (Hughes and Jackson, 2015; Parker et al., 2016). Economic performance of high streets varies spatially at a local and national scale (Dolega et al., 2021). The performance of high streets depends on a number of factors including, size, composition, function and the demographic characteristics of the local population. Studies have suggested that secondary and tertiary urban centres are impacted more by economic challenges and competition from online shopping (Wrigley and Dolega, 2011; Singleton et al., 2016). In contrast, high streets that are more resilient to economic forces often have a mixed or multi-purpose composition that offers both a variety in shopping experience and acts as a centre for employment. Other characteristics associated with successful high streets include a generalised attractiveness to consumers, a variety of retail types and a mixture of leisure and key retail stores that bring in footfall (Coca-Stefaniak, 2013). Larger high streets situated in town and city centres usually consist of a higher proportion of well-known
brands, anchor stores, leisure chains and restaurant premisses. These qualities have been linked to higher footfall and consumer dwelling time, both factors with a direct link to consumer spend (Hart et al., 2014). In addition, more sizable and attractive high streets entice consumers from a wider area, whereas smaller high streets are often more likely to serve their local population (Teller and Reutterer, 2008). Another reason for the more prevalent use of city and town centre high streets is the large contribution of weekday footfall from commuters and workers. In fact, Swinney and Sivaev (2013) found a strong positive relationship between the daytime population of city centres and the proportion of retail and leisure premisses. Additional studies (Fertner et al., 2015; Roberts, 2006) have investigated the relationship between daytime population and retail performance and found links between convenience culture and multiple convenience and leisure stores located near large offices or places of employment (Wrigley and Lambiri, 2015).

Consequently, this chapter argues a more diverse classification of high streets is needed, which includes a structured analysis of the retail landscape just before the pandemic hit at both a local and national level. Several retail typologies have focused on both the supply and demand side of high street consumption such as the purpose of the trip, levels of footfall and products or services being sold. In particular, Brown (1991) devised what they term a ‘post-hierarchical’ classification that combined the form and function of retail centres. In addition, Coca-Stefaniak (2013) created a town centre classification matrix from a variety of different socio-economic indicators at varying different spatial levels. Mumford et al. (2017) trialled a classification system based on new forms of data including footfall to incorporate the dynamic elements of town centres.

Despite such attempts to break away from the convention of hierarchy, apart from Mumford et al.’s (2017) use of footfall signatures, they lack a data-driven approach. Even though Mumford et al.’s (2017) study used real world data, it lacked geographic coverage and practical applications to be of use to decision makers. Perhaps a more useful classification system would explore the diversity within town, cities and local authorities as well as measures of economic performance in order to provide novel insights to stakeholders and policy makers.
4.2 Methodology

4.2.1 Data
In this chapter a number of datasets were utilised to create a typology of high streets in Britain. The analysis uses the 3,828 high street boundaries outlined in the previous chapter (Section 3.3). The high street characteristics have been derived from data on retail occupancy, made available from the LDC. The data provides numerous attributes for each premises within a high street and was collected between 2017 and 2019, creating a clear picture of the pre-pandemic environment. The data contains detailed information about the location of the retail or service premises and the occupiers. Additional information for each premises includes the occupier’s name and a categorisation of the type of retail or service business (i.e. convenience, restaurant, supermarket) including vacant status. Further details on the variables and premises attributes within the LDC data are outlined in Section 3.2.

4.2.2 Analytical framework and approach
Within this chapter it was important to ensure the high street typology could be updated over time and represented the changing nature of high streets and their economic health. The typology was also designed to be comparable across two different spatial scales - the high street level and at the local authority level in order to identify national patterns and be actionable by local policy makers. The approach within this chapter focuses on two distinctive aspects of high street composition: proportion of chain retailers and proportion of ‘essential’ stores. Since the aim of the typology is to encapsulate pre-pandemic conditions, the composition data has been selected for Q4 2019. Firstly, the percentage of high street chains was calculated using the variable ‘MultipleName’, which indicates the name of the chain if there are multiple stores. A store was considered to be a chain if it had five or more stores in a franchise, in order to incorporate local chains. Next, to create a variable which encapsulates the proportion of ‘essential’ stores, a universal, Britain-wide definition had to be devised.

While the study includes high streets in Wales and Scotland, where lockdown restrictions differed slightly during the pandemic, the type of shops that were allowed to remain open between March 2020 and May 2021 were consistent across all three nations. The variable includes the number of stores allowed to remain open during the lockdowns. The ‘essential’ stores and services include cafés and coffee shops, as many remained open during lockdown for takeaways. Each of the store subcategories in the LDC data were manually added into a linear regression with high street-level vacancy from 2019. Each subcategory was then assessed to determine whether it added to the fit of the model and increased the R2 value. Each subcategory allowed to remain open as part of the lockdown restrictions was periodically added to the variable ‘essential stores’ then the new variable was tested in the model where pre-pandemic vacancy was the dependent variable. The final version of the variable ‘essential’ stores and services model had an R2 value of 0.62 when in a OLS regression model with 2019 vacancy (Table 10.5). The final subcategories deemed as ‘essential’ stores are displayed in full in Table 10.3 in the appendix. These
essential stores and services were then divided by the number of stores within each high street to create a percentage.

Exploratory analysis was conducted to examine the variables and the qualities of each high street. The analytical approach adopted for this chapter’s typology involved the use of a non-hierarchical clustering technique. Cluster analysis is a set of data reduction techniques designed to group similar observations in a dataset, where observations in the same group are as similar to each other as possible and observations in different groups are as different to each other as possible (Population Health Methods, 2022). A non-hierarchical method of clustering was implemented due to the non-hierarchical organisation of consumption centre networks, even at a regional level (Dolega et al., 2021). Through providing such multidimensionality, the method more accurately depicts the complex structures and functional interdependencies within and between high streets.

While there are many different clustering algorithms, this chapter has implemented the centre-based clustering algorithm of k-means. A k-means clustering algorithm is not computationally complex, making it an efficient method efficient and acceptable for clustering the large dataset used in this thesis (Gan et al., 2014). Due to this characteristic, k-means was used to explore the classification of high streets. The k-means algorithms represent each cluster by its mean with the aim of allocating each high street to the nearest cluster. While there are different distance-based measurements that can be used to calculate proximity and membership to a cluster, the most commonly selected, Euclidean distance was used. The k-means algorithm requires three user-specified parameters which are: number of clusters K, cluster initialisation and distance metric. The most important choice is of K and a number of heuristics are available for choosing K. In this chapter, the Gap Statistic Method (Tibshirani et al., 2001) and sensitivity analysis was used to select the optimum number of clusters.

The gap statistic is an approach that finds a way to standardise the comparison of log \( W_k \) with a distribution with no obvious clustering. Tibshirani et al.’s (2001) paper estimates for the optimal number of clusters \( k \) as the value where \( log W_k \) is the farthest below the reference curve. The formula for the gap statistic is as follows:

\[
\text{Gap}_n(k) = E_n^*\{log W_k\} - log W_k.
\]

The gap statistic was used as the elbow method was not conclusive, however the gap statistic was able to identify a peak in the gap at the optimum number of clusters. While the elbow method is based on an unsophisticated intra-cluster variance solution, the gap statistic formalises the approach offering an easily implemented algorithm that identifies the correct \( k \).

Due to the k-means algorithm being dependent on its initialisation and the specified parameters, it was essential to conduct sensitivity testing. The testing was comprised of
trying multiple different initial allocations assigned at random. The number of initial re-
runs for the k-means algorithm was increased to a value of 1000 iterations the
categories were then inspected for any changes in groupings and assessed against the
literature to match their qualities to secondary research of the individual high streets. K-
means clustering was predominantly selected due to its ease of implementation, efficiency and empirical success (Jain, 2010). Another additional rational for its selection
is the reliance and guidance from domain knowledge. Data representation is one of the
main factors that influences the performance of the k-means clustering algorithm. If the
representation is strong then the clusters are likely to be compact and isolated, with even
a simple algorithm such as k-means being able to identify them. While there is no
universally good representation this method carries the advantage of being guided by
subject area knowledge ensuring that the distinctions between retail types this chapter
aims to make are obtained.

One disadvantage of using k-means clustering is that it uses the mean as the measure
of centrality which can be impacted by extreme values within the data. Consequently, in
order to prepare the retail composition data an important stage involved detecting any
anomalies. Due to outliers having a significant impact on the interpretation of any results,
they were removed from the data. When identifying the outliers caution was given due to
the large sample size of data suggesting there may be many outliers. Due to the two
variables in the typology (% of ‘essential' premisses and % of chain premisses) not having
a non-linear relationship, techniques such as Mahalanobis Distance (MD) were not
suitable to detect multivariate outliers. Therefore, the two variables were assessed
individually for univariate outliers. The univariate outliers were removed using the
modified z-scores method that has been based on the median absolute deviation (MAD)
(Iglewicz and Hoaglin, 1993). More traditional criteria for identifying outliers as points are
at least three standard deviations away from the mean however, the limitation of this
approach is that this method of indication is based on the assumption that the data is
normally distributed (Leys et al., 2013). Subsequently, MAD is a method that should be
prioritised when distributions have heavier tails (Howell, 2014).

The ‘stats’ package in R has been used to define MAD as: MADn = bMi |xi − Mj (xj )|
where the Mj (xj ) is the median of the original series and Mi is the median of the deviates.
Within the equation, b is the constant linked to the assumption of normality in the data
where abnormality induced by outliers is disregarded (Rousseeuw and Croux, 1993). The
distribution of z-scores for the proportion of essential stores is displayed in Figure 4.1 and
the z-scores for the proportion of chain stores is displayed in Figure 4.2.
Figure 4.1: Distribution of z-scores for the proportion of essential stores per high street.

Figure 4.2: Distribution of z-scores for the proportion of chain stores per high street.

Figure 4.2 suggests that the data for the variable ‘% of chain stores’ is not normally distributed and is skewed to the right (skewness= 1.3) therefore, the outliers were identified by using Leys et al. (2013) definition that value > |median(x) ± 2.5MAD. Through using the definition 2.3% of the high streets identified in Section 3.3 were selected as being outliers and were removed.
The next part of this chapter compares the high street typology to a measure of vibrancy. The vibrancy measure is created using statistics for high street level vacancy and occupier change. The vibrancy data has been selected for Q1 2017- Q4 2019 to allow for a sufficient depiction of the performance of high streets in the lead up to the pandemic. Firstly, the percentage of high street vacancy was calculated using the variable ‘Subcategory’ and selecting stores that were ‘Vacant Properties’. The percentage of time each premises was vacant between Q1 2017- Q4 2019 was divided by the total number of recordings to give an overall percentage of vacancy for each high street. Next, the percentage of occupier change was calculated using the ‘Occupier ID’ variable where each occupier has a unique ID. The number of new occupiers was divided by the number of recordings to give a measure of occupier change within each high street. Since not all of the premises have been established or even existed for the whole time period between Q1 2017- Q4 2019, the total number of quarters that a premises was used for non-residential purposes was the denominator. The occupier change metric excludes cases where a premises had existed for less than two years at the end of 2019. The specific time threshold was chosen because 30% of new businesses fail in their second year and half fail in the first five years (Forbes, 2018; BLS, 2020). Therefore, a premises is likely to have recorded changes in occupiers after a two-year period, while premises under this threshold are unlikely to give an accurate depiction of overall change.

One limitation of creating a supply-side measure of vibrancy is there is an absence of a qualitative perspective, with no indication of how consumers perceive the areas in question. Therefore, the latter sections of this chapter combine both the high street typology and measure of vibrancy which start with a local focus. The case study of the London Borough of Camden has been selected for use throughout this thesis, due to unique qualitative policy insights that were able to be obtained as part of a knowledge exchange outlined in Chapter 7. Therefore, this chapter develops an in-depth depiction of the pre-pandemic landscape of Camden including comparisons between high streets, the wider regional setting including an exploration of the changing retail landscape (store openings and closures).

4.3 A typology of high street composition

The clustering within this typology consists of two geographic tiers. Firstly, the clustering was conducted at high street level and then at a local authority level. Following the use of the Elbow Method (Syakur et al., 2018) by using the ‘fviz_nbclust’ function in the ‘factoextra’ R package, multiple tests of different cluster frequencies and the evaluation of different cluster frequencies, six clusters were chosen for the high street groups. Figure 10.2 (Appendix) displays an Elbow plot depicting the optimum number of cluster at the ‘bend’ of the plot. Figure 10.3 displays plots of the typology data clustered into either 2,3,4,5,6,7 or 8 clusters. The six clusters, their averages and a description of their characteristics are presented in Table 4.1. from the number of high streets assigned to each clustered ranged from 143 to 799. The resulting clusters were analysed through examination of cluster plots, and the use of sum of squares statistics to test for cluster fit.
Finally, labels were assigned to the high street clusters using the methodology outlined by Dolega et al. (2021) based on calculating median values and index scores to account for variability between the clusters.

Table 4.1 provides descriptions of the characteristics of each cluster.

<table>
<thead>
<tr>
<th>High street cluster name</th>
<th>Cluster description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Essential (Chain and independent)</td>
<td>The cluster has 432 high streets and the highest proportion of stores that were allowed to stay open during the government enforced COVID-19 lockdown restrictions. The highest median of 63.2% of stores allowed to remain open within its high streets. The vast majority of high streets are situated in small local centres around London, Manchester and the Southeast of England.</td>
</tr>
<tr>
<td>Leisure chain</td>
<td>The cluster has 422 high streets and the second highest proportion of stores that were forced to close during the pandemic restrictions and the second highest proportion of chain stores. A median of 65.7% of shops were forced to close within its high streets and a median of 36.8% of the stores are part of a chain. The majority of the cases are town centre high streets.</td>
</tr>
<tr>
<td>Essential chain</td>
<td>The smallest cluster of 143 with the highest proportion of chain stores at a median of 52.38% and the second highest proportion of stores that were allowed to remain open during the COVID-19 pandemic restrictions at a median of 57.50%. The vast majority of these high streets are situated in small local centres situated in the Southeast of England.</td>
</tr>
<tr>
<td>Leisure independent</td>
<td>The cluster has 565 high streets with the highest proportion of stores that were forced to close during the pandemic restrictions at a median of 66.3% of stores closing. The cluster that is marginally has the second highest proportion of independent stores with a median of 88.3%. The majority of these high streets are within small local centres located in the Northwest of England.</td>
</tr>
<tr>
<td>Essential independent</td>
<td>The cluster has 757 high streets and the highest proportion of independent stores with a median of 88.4%. The cluster also has the second highest proportion of stores that were allowed to remain open during the lockdown restrictions with a median of 49.0 remaining open. The majority of these high streets are located in small centres in London, the Northwest of England and Yorkshire and the Humber.</td>
</tr>
<tr>
<td>Mixed</td>
<td>The largest cluster of 799 has no distinct composition in high street stores. Many of the high streets are situated in town and district centres in Wales, Scotland and the Midlands.</td>
</tr>
</tbody>
</table>

Table 4.1 Descriptions of the characteristics of the high street clusters.

Figure 10.4 (Appendix) displays radar plots of the attributes of each high street cluster. Figure 4.3 displays an example of the high street typology for the London borough of Camden showing the variety in composition of the stores.
The second layer of the typology aggregates the high street level clustering to local authority level. This part of the typology is important because local authorities make policies for the high street within their jurisdiction, therefore it is vital to establish the characteristics of their high streets but also the differences in their qualities compared to local governments, who may adopt different priorities and strategies to high street regeneration. A spatial join was used to identify which high streets are in each local authority. For 144 high streets there was an overlap in boundaries, therefore the high street boundaries were treated as the centroid of the boundary and allocated to the corresponding local authority. All the overlapping high streets were also manually checked for local government context. One example of Kilburn can be seen in Figure 4.4.
Figure 4. 4: Kilburn high street boundary plotted alongside the London Borough boundaries.

While both the London borough of Camden (as discussed in Chapter 7) and the London Borough of Brent have an invested interest in Kilburn, but the majority of Kilburn lies in the London Borough of Brent. In 2021, the London Borough of Camden secured £20,000 of funding from the mayors office for a regeneration project in Kilburn, however this is minimal compared to the halfway mark hit in the same year by the London Borough of Brent's 15 year regeneration project (Camden Newsroom, 2021; Brent, 2022). Therefore, due to the larger area and greater proportion of local authority funds this chapter allocates Kilburn high street in Brent, London.
The high streets within each local authority were identified. The second geographic tier of k-means clustering was then conducted. Figure 10.5 (Appendix) displays an Elbow plot depicting the optimum number of clusters for the local authorities. Figure 10.6 displays plots of the typology data clustered into either 2, 3, 4, 5 or 6 clusters which was the final selected number for K. Figure 10.7 (Appendix) displays radar plots of the attributes of each local authority cluster.

Table 4.2 outlines the characteristics of the local authority clusters and Figure 4.5 displays the local authority clusters across the whole of Britain.

<table>
<thead>
<tr>
<th>Local authority cluster name</th>
<th>Cluster description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Essential (Chain and independent)</td>
<td>The cluster has 14 local authorities and the highest proportion of stores allowed to remain open within its high streets, with a median of 53.5%. The vast majority of the local authorities are situated in London.</td>
</tr>
<tr>
<td>Leisure chain</td>
<td>The cluster has 31 local authorities and a median of 60.0% shops were forced to close within its high streets and a median of 28.5% of the stores are part of a chain. The majority of the cases are in the Southeast of England and Scotland.</td>
</tr>
<tr>
<td>Essential chain</td>
<td>The smallest cluster with 6 local authorities with a median of 46.7% of chain stores within high streets and 53.1% of its high street stores allowed to remain open. The vast majority of the local authorities are located in the East of England.</td>
</tr>
<tr>
<td>Leisure independent</td>
<td>The cluster has 41 local authorities and a median of 37.7% of its stores allowed to remain open during the pandemic and a median of 16.7% of chains. The majority of the local authorities are located in the Northwest and Southwest of England.</td>
</tr>
<tr>
<td>Essential independent</td>
<td>The cluster has 55 local authorities and a median of 47.83% of its stores allowed to remain open during the COVID-19 lockdown restrictions. The cluster also has a median of 15.8% of stores that are part of a chain. The majority of the local authorities are located in the West Midlands, the Northwest of England and London.</td>
</tr>
<tr>
<td>Mixed</td>
<td>The largest cluster has 212 local authorities and a median of 22.4% of its stores as part of a chain and 45% allowed to remain open during the various lockdowns. The majority of the local authorities have a low proportion of regional and major town centres.</td>
</tr>
</tbody>
</table>

Table 4.2: Descriptions of the characteristics of the local authority clusters.
Figure 4.5: Local authority classifications for Britain, formed using K-means clustering.
4.4 A measure of vibrancy

A measure of high street vibrancy was calculated using pre-pandemic levels of vacancy and occupier change. In order to minimise snap-shot bias, the time period of the data was selected to represent historic context. Information on occupier change and vacancy can be used to identify whether each high street is on a trajectory for growth or decline. Therefore, the measure of vibrancy is for the two years prior to the pandemic (2017-19). Two years was deemed an adequate time period to identify and account for increases or decreases on economic health in the build-up to the pandemic (Wrigley and Dolega, 2011).

Table 4.3 displays the descriptive statistics for both of the variables at high street level.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Median</th>
<th>Mean</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vacancy (%)</td>
<td>0.00</td>
<td>7.00</td>
<td>8.24</td>
<td>58.75</td>
</tr>
<tr>
<td>Occupier change (%)</td>
<td>0.00</td>
<td>2.39</td>
<td>2.67</td>
<td>15.38</td>
</tr>
</tbody>
</table>

Table 4.3: Percentage of vacancy and occupier turnover in each high street, quarter 1, 2017 to quarter 4, 2019.

Accordingly, Figures 4.6 and 4.7 display how each variable can be plotted individually at high street level using the example of the London Borough of Camden. Figure 4.6 displays the associated vacancy percentage for each high street in the London Borough of Camden from 2017-19, and Figure 4.7 presents the occupier change over the same period.
Figure 4.6: High street vacancy percentage for the high streets within the London borough of Camden, 2017-19.
Figures 4.6 and 4.7 show that there is a cluster of stable, low vacancy high streets which are all characterised by a predominance of leisure chain premises. These high streets include West Hampstead, Finchley Road, and Hampstead – notably affluent areas with a clear clustering of professional classes (Smith et al., 2020). Subsequently, the following chapter will incorporate variables which quantify income and employment to measures of high street resilience, in order to explore a possible relationship between the two concepts.

Additional patterns across Camden include the disproportionately higher rates of occupier change and higher vacancy rates within Camden Town and Kentish Town Road. Camden Town high street has a vacancy rate of 7% and an occupier change rate of 3%. Meanwhile, Kentish Town Road has a higher vacancy rate of 10% and a higher occupier change rate of 5%. In this regard, Camden Town high street appears to be gaining new occupants that curb vacancy rates in a better capacity than the new stores opening in Kentish Town Road. These findings concur with previous studies which have shown that particular areas within Camden record higher footfall during the weekends due to their touristic or recreational reputations. Such areas include Camden Town, and specifically
Inverness Street Market, Buck Street Market, and Camden Lock Market (Murico et al., 2018).

Upon closer inspection, 15% of new occupiers in 2017-19 in Kentish Town Road were restaurants, 10% were cafés & tearooms, and 5% were fashion accessory stores. In contrast, on Camden Town high street 9% of the new openings were fast food takeaways, 7% were offices, and 5% were cafés & tearooms.

4.3.1 High street level vibrancy
The next stage of this research is to take the two seemingly uncorrelated variables and use the two in conjunction with each other to determine the success and stability of high streets. Figure 4.8 explores the vibrancy of British high streets through showing the relationship between the two variables: vacancy rate in 2017-19 is displayed on the X-axis and occupier change in 2017-19 is displayed on the Y-axis. Figure 4.8 specifically shows a subset of high streets that have been selected to represent the high streets in Britain’s major town and regional centres. The subset was selected based on the Consumer Data Research Centre classification system. High streets that were classified as a ‘Major Town Centre’, or a ‘Regional Centre’ were selected. The median values for vacancy and change of the largest high streets were taken to intersect the X and Y axes. Figure 4.8 consequently divides the high streets into 4 different groups.

The first group is of high streets that are stable with high performance. These high streets had vacancy that was below the average for town and regional centres and include the central high streets in Edinburgh, Bath and the City of London. The second group also had high performance but with a higher level of instability and change. These high streets had vacancy rates below the average for town and regional centres and a higher-than-average number of new stores opening. High streets in this group include Brighton and Hove, Oxford and Cambridge. The third group contains weakly performing high streets with high vacancy and a low level of new occupiers. High streets within this category and subsequently in a state of degradation include Luton, Bolton and Wrexham (in Welsh, Wrecsam). The final group includes high streets that have a weak strategic position due to their high levels of vacancy and high number of stores opening and subsequently closing. This weak performing group contains Newport, Hull and Croydon.
Figure 4.8: High streets in Britain that are classified by the Consumer Data Research Centre as a ‘Major Town Centre’ or a ‘Regional Centre’ and their associated vacancy percentage and occupier change percentage during Q1 2017- Q4 2019. Rebased axis relative to the median value for percentage vacant and median value for percentage changed to account for the median values of the intersects and the maximum values.

Figure 4.8 can be used to demonstrate how high streets can have similar levels of success but different levels of stability. For example, the city centre high streets of Leicester and Bristol have similar levels of vacancy during 2017-19. However, Bristol had a substantially higher rate of new stores opening while the occupiers of Leicester’s high streets have predominantly remained the same. Such characteristics might suggest that Bristol’s high streets are ‘vibrant’, with vacant spaces being promptly and efficiently filled with stores that meet consumer demand. These types of high streets can have conditions where there is a constant turnover of new or pop-up businesses. There can be businesses that occupy ‘meanwhile spaces’ where short term investments or collaborative projects aim to keep up with short-lived fashionable trends.

In contrast, Leicester is efficient at preventing vacancy by retaining well established businesses that serve their local community over long periods of time. These types of high streets could be described as equally ‘vibrant’ despite their stable environment, since their longstanding occupiers provide what residents need. In this case, the occupiers themselves could have adapted to wider social forces such as providing click-and-collect services. Due to high streets often having different spectrums of occupier turnover but similar levels of success, it was important to devise a comparable measure of retail vibrancy as it can inform on the most appropriate placemaking policies. For example, high
streets focused on pop-up shops and meanwhile spaces may benefit from low business rates and financial support for start-ups.

4.3.1 Local authority level vibrancy
Looking solely at high street level vibrancy only gives a narrow perspective allowing for comparison between high streets within a local authority. Yet policy makers are also likely to compare overall characteristics with other local council jurisdictions. Therefore, this next section has aggregated the vacancy and occupier change percentages in the lead up to the pandemic to local authority level. Figure 4.9 displays the associated vacancy percentage for each local authority in Britain from 2017-19, and Figure 4.10 presents the occupier change over the same period and geographic level.
Figure 4.9: Local authority vacancy percentage for the high streets in Britain, 2017-19.
Figures 4.9 and 4.10 display some interesting patterns in the distribution of local authority level high street vibrancy characteristics across Britain. Firstly, the local authorities in Wales and the North of England had considerably higher vacancy percentages from 2017-19 than the rest of Britain, with average high street vacancy rate of 10.3-23.6%. Specifically, the local authority of Copeland in the Northwest of England had the highest average high street vacancy of 23.6%. In contrast, the local authorities in London, the Southeast and the East of England had comparatively lower vacancy rates.

In addition, Figure 4.10 displays how occupier change is unevenly distributed across Britain, with some local authorities in Scotland, Wales and the East of England having a
higher rate of new store openings. In particular, East Ayrshire in Scotland had an average high street occupier change of 9.5%. The most stable local authorities in Britain were located in the West Midlands, Northwest and East of England. The importance of using the two indicators of vibrancy in conjunction can be again illustrated at local authority level.

For example, Camden, the local authority in London can be directly compared with Ceredigion in Wales. Both local authorities had a similar level of occupier change near the British median of 2.5% with Camden having 1.9% and Ceredigion having 2.1% in pre-pandemic conditions. However, Camden had a considerably lower vacancy of 6.4% while Ceredigion had a vacancy of 10.1%. This might suggest that stores opening in Camden high streets are more likely to meet the needs of their customers, whether tourists or the local population, and remain open – thereby curbing vacancies.

It is also useful for policy makers to draw comparisons between their own local authorities and surrounding counterparts. Therefore, Figure 4.11 plots each London local authority and their associated aggregated vacancy percentage and occupier change percentage during Q1 2017- Q4 2019.

Figure 4. 11: Local authorities in London and their associated average high street vacancy percentage and occupier change percentage during Q1 2017- Q4 2019. Rebased axis relative to the median value for percentage vacant and median value for percentage changed, to account for the median values of the intersects and the maximum values.
Both Camden and Lambeth had high levels of stability during 2017-19. On one hand, Camden had a low average rate of vacancy within its high streets meaning that the stores performed successfully and remained open. In contrast, the majority of high streets in Lambeth remained in a consistent state of degeneration with persistently higher vacancy rates.

Figure 4.11 displays how the local authorities of Kensington and Chelsea, Merton, City of London and Ealing have some of the highest levels of occupier change but with accompanied low levels of vacancy. Therefore, these areas are likely to be targets of short-term and long-term investments giving a strong position in the commercial rental market.

4.3.2 Composition and vibrancy
This chapter began by developing a typology for high street composition followed by an exploration of a measurement of retail vibrancy both at high street and local authority level. This next section begins to examine the key characteristics of Britain’s high streets in terms of their composition and performance. Despite there being no consensus on the Key Performance Indicators (KPI’s) for measuring high street success, consumer and investor attractiveness alongside composition can be used as a proxy to identify their likely success and longevity. Specifically, a favourable composition relates to high streets that are most resistant to the COVID-19 lockdown restrictions. Consequently, Table 4.4 displays each of the 6 high street composition typology clusters alongside the corresponding descriptive statistics for vacancy and occupier change at high street and local authority level.
<table>
<thead>
<tr>
<th>Cluster</th>
<th>High street vacancy (%)</th>
<th>High street occupier change (%)</th>
<th>Local authority vacancy (%)</th>
<th>Local authority occupier change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Essential (Chain and independent)</td>
<td>Mean 4.70 Median 3.92 Maximum 20.62 Minimum 0.00 Standard deviation 3.89</td>
<td>Mean 2.21 Median 1.82 Maximum 10.95 Minimum 0.00 Standard deviation 2.07</td>
<td>Mean 5.90 Median 6.00 Maximum 7.79 Minimum 3.85 Standard deviation 1.37</td>
<td>Mean 2.21 Median 2.19 Maximum 3.96 Minimum 0.51 Standard deviation 0.93</td>
</tr>
<tr>
<td>Leisure chain</td>
<td>Mean 9.73 Median 8.72 Maximum 20.62 Minimum 0.00 Standard deviation 5.02</td>
<td>Mean 2.93 Median 2.91 Maximum 6.95 Minimum 0.00 Standard deviation 1.52</td>
<td>Mean 8.33 Median 7.39 Maximum 17.22 Minimum 3.75 Standard deviation 3.27</td>
<td>Mean 2.52 Median 2.38 Maximum 5.25 Minimum 0.58 Standard deviation 1.21</td>
</tr>
<tr>
<td>Essential chain</td>
<td>Mean 4.66 Median 4.60 Maximum 16.97 Minimum 0.00 Standard deviation 3.98</td>
<td>Mean 1.69 Median 1.06 Maximum 8.4 Minimum 0.00 Standard deviation 1.83</td>
<td>Mean 6.36 Median 5.86 Maximum 8.67 Minimum 4.72 Standard deviation 1.40</td>
<td>Mean 2.63 Median 2.63 Maximum 4.34 Minimum 0.67 Standard deviation 1.83</td>
</tr>
<tr>
<td>Leisure independent</td>
<td>Mean 12.00 Median 9.48 Maximum 58.75 Minimum 0.00 Standard deviation 8.70</td>
<td>Mean 3.18 Median 2.95 Maximum 12.56 Minimum 0.00 Standard deviation 2.21</td>
<td>Mean 9.96 Median 9.14 Maximum 20.25 Minimum 4.80 Standard deviation 3.88</td>
<td>Mean 3.03 Median 2.79 Maximum 6.54 Minimum 1.01 Standard deviation 1.25</td>
</tr>
<tr>
<td>Essential independent</td>
<td>Mean 8.46 Median 7.17 Maximum 40.12 Minimum 0.00 Standard deviation 6.11</td>
<td>Mean 2.69 Median 2.33 Maximum 15.38 Minimum 0.00 Standard deviation 2.17</td>
<td>Mean 8.06 Median 7.72 Maximum 18.32 Minimum 2.60 Standard deviation 2.89</td>
<td>Mean 2.68 Median 2.68 Maximum 9.49 Minimum 0.00 Standard deviation 1.28</td>
</tr>
<tr>
<td>Mixed</td>
<td>Mean 7.14 Median 6.39 Maximum 32.69 Minimum 0.00 Standard deviation 4.24</td>
<td>Mean 2.58 Median 2.34 Maximum 9.3 Minimum 0.00 Standard deviation 1.66</td>
<td>Mean 8.40 Median 7.77 Maximum 23.56 Minimum 0.34 Standard deviation 3.53</td>
<td>Mean 2.53 Median 2.48 Maximum 6.93 Minimum 0.00 Standard deviation 1.05</td>
</tr>
</tbody>
</table>

Table 4.4: Descriptive statistics for each of the high street and local authority clusters formed through k-means clustering and their corresponding vacancy and occupier change percentage, 2017-19.
The findings from Table 4.4 show that the retail composition category with the highest average vacancy in 2019 was high streets dominated by leisure independent stores (12.00%). In contrast, the high streets with the lowest average vacancy were essential chain areas (4.66%). In addition, the high streets with the greatest occupier churn were those predominantly consisting of leisure independent stores (3.18%), and the most stable high streets were essential chain areas (1.69%).

When using the performance measurements in conjunction with each other it could be suggested that essential chain high streets have lower vacancy rates because they satisfy consumer demands by catering for the rise in convenience culture (Wrigley et al., 2019). The predominance of chain stores may also mean that these high streets adapted better to the economic and political pressures of the time. Chain stores have numerous benefits including large economies of scale, enhanced purchasing power, and economies of scope which give them greater purchasing power and the ability to negotiate lower prices from suppliers. Also, smaller independent stores have limited storage room compared to large retailers with sizable warehouses, vehicles and large-scale procurement, enabling more effective procurement logistics and greater product variety (Danielis et al., 2012).

The aim of this section has been to contextualise measures of high street success in the period 2017-19. These included ‘vitality’ and ‘viability’ and particularly emphasised retail ‘vibrancy’. Consequently, this section has developed a possible measure of vibrancy though combining the performance related characteristics of vacancy rate and occupier change and a classification of composition. Previous literature has stated the importance of ‘reinventing’ within a high street regeneration framework (2017a, Parker et al.). In a high street environment, reinvention refers to a retail locations’ ability to adapt and innovate during uncertain conditions. These adaptive qualities were identified in high streets such as Bristol city centre and the City of London local authority. Specifically, using pop-up stores or store changes for reinvention can be possible even with a restricted budget. Hubbard (2017) also hailed the use of ‘pop-up’ formats to overcome challenges of filling vacant stores and bringing community-oriented configurations back to high streets.

Nevertheless, it is also important to identify well-established, stable high streets that rarely have new occupiers but which successfully provide the goods and services their customers want through longstanding businesses. Such qualities were identified in Leicester city centre high street, for example. In addition, these stable high streets might include businesses that are independently adapting to socio-cultural pressures, such as by providing catering for omni-shopping experiences (Huré et al., 2017).
4.4 Discussion and conclusions

Through development of a high street composition typology and tool for measuring vibrancy this chapter seeks to understand the high street environment and performance in the lead up to the COVID-19 pandemic. This next section will discuss the typology results. Specifically, the discussion will include reference to how the composition of high streets was changing during 2017-19, the identification of vibrant areas and considerations for local stakeholders and policy makers. The final outlook has relevance for applications including identifying high streets that are viable for commercial investment and influencing retail planning policy to help areas experiencing decline.

4.4.1 Change in retail composition

The next section of this chapter aims to develop a more detailed understanding of the individual changes in store type that make up the ‘occupier change’ variable used in Section 4.3. A more in-depth description of patterns of specific shop type openings or closures may give an indication of how a high street is changing, and of possible shifts in the supply and demand of stores in an area. As outlined in Section 4.3 individual high streets such as Kentish Town Road in Camden can have patterns of store openings such as 25% of new stores between 2017-19 being restaurants, cafes or tearooms. Figure 4.9 also suggested that at a local authority level there are some patterns in geographic distribution, highlighting that some regions with higher proportions of new stores opening. In addition, some areas such as London, the Southeast and East of England, have relatively high occupier change but low vacancy. It is therefore important to explore the type of new store types that are opening that are successfully curbing prolonged vacancy and compare them to store types that are short-lived investments. In order to further explore these regional trends, Figure 4.13 displays the breakdown of the top 5 most frequent store openings for the 11 regions in Britain.
For the ‘vibrant’ regions, the Southeast and East of England, there was a similar pattern in store openings with the top 5 most common new stores being: café and tearooms, barbers, charity shops, beauty salons and estate agents. Figure 4.12 can be used to compare the regional breakdown in store openings to the whole of Britain. In addition, Figure 4.14 displays the most frequent store closures.
The ten most frequent observed retail closures as subcategories across British high streets, 2017-19.

The most frequent store type to both open and close across British high streets during 2017-19 was cafés and tearooms. This pattern in store turnover fits in with the wider literature. Ferreira (2017) documented the rise of the British café industry, and predicted that the sector would continue to grow with about 27,000 cafés by 2020. Ferreira’s research even goes as far as describing the development of a ‘café society’ in Britain, which is reshaping consumption and production geographies. Nevertheless, the high turnover of cafés can perhaps be attributed to three main barriers to success: high business rates, high taxes, and high rents (Douglas et al., 2018).

Additional barriers can include difficulties in recruiting quality staff. Britain’s exit from the European Union (EU) had a significant impact on the availability of staff in jobs such as catering. Whilst the British public voted to leave the EU in 2016, a deal was not finalised until the start of 2020, creating long-term uncertainty over potential price rises for imports. The end of free movement between Britain and the EU also risks shortages, especially in the medium term while the labour market and industry struggle to adapt. This was predicted to be particularly difficult in industries such as leisure and hospitality that have a much higher turnover of employees and rely heavily on migrant workers, rather than workers already living in Britain (Sumption, 2022). In addition, opening a café is a high-risk business. While the barriers to entry into the café market are low, the major barriers to success are often beyond the control of owners who may lack the funds to navigate the fluctuating dynamics of the sector. Furthermore, the café industry is highly competitive with stores often clustering together, presenting further challenges for owners (Ferreira, 2017).
The increased presence of cafés from 2017 to 2019 was in conjunction with a rise in new barbers, hairdressers and beauty salons. Lee and Swann (2020) explain that the rise in these particular store types was a result of high streets adapting to rising vacancy rates by targeting the ‘experience economy’ to fill stores previously occupied by large national retailers. Similar findings were displayed by Grimsey (2018), who pointed out that traditional high street businesses such as pubs and banks have been replaced by experimental businesses such as barbers, beauty salons, and independent cafés. Figure 4.14 suggests that the LDC data presents similar findings to the wider literature, as banks were recorded as the second most frequent store closure in British high streets between 2017-19. This trend can largely be explained by the evolution of technology within the banking industry, especially the rise of digital banking and its impact on customer interaction. The large uptake of digital banking has led many banks with branches in Britain to choose to reduce their store numbers (Mbama and Ezepue, 2018). In addition, Figure 4.12 displays how the opening of new barbers is consistent across all regions in Britain, with new beauty salons opening also being a common occurrence in the East of England, the Northwest, the Southeast, the West Midlands, Scotland and Wales, during 2017-19. Despite the periodic closures of barbers, beauty salons and hairdressers during the COVID-19 lockdowns these store types have a particular competitive advantage. Barbers, hairdressers and beauty salons possess unique qualities when compared to internet services as they are conducted exclusively in person, with treatments that can benefit consumers’ confidence mental health, and relieve stress.

High street literature often blames online retail for increased vacancies and the rapid decline of brick-and-mortar stores, yet it may be more accurate to argue that online activity has changed the way consumers interact with high streets for some store categories in some locations. For example, there has been a substantial number of closures of fashion stores as seen in Figure 4.14. Yet in London, fashion shops were the third most prevalent store to open. Fashion stores can offer customer experiences such as in store cafés and beauty treatments, alongside click and collect promotions to save on delivery costs. However, as outlined by Perry et al. (2019) London is more likely to offer fashion store with an omni shopping experience. This is due to London containing lots of luxury and large chain fashion brands flagship stores. These stores include the most technologically advanced stores in Britain, merging the physical and digital world to create an experience that offers consumers the physical expression of brand’s digital capabilities.

In contrast to London, areas such as Scotland and Wales, have substantially higher rates of vacancy, with a heavier occurrence of stores such as charity shops replacing vacant stores (Figure 4.12). In Scotland in particular, the Scotland Towns Partnership (2017) believes that the charity retail sector contributed to retail vibrancy following the 2008 recession by replacing many vacant spaces. A similar pattern can actually be seen across the whole of Britain in Figure 4.13 where charity shops were the third most frequent new stores to open during 2017-19. Following the 2008 recession, there was significant economic recovery from 2013, there were limited improvements to struggling high streets
which continued to face intense competition from e-commerce (Osterley and Williams, 2019). Consequently, between 2017 to 2019, charity shops continued to play a vital role in generating footfall by filling vacant stores. This may have slightly offset the loss of other stores.

Nevertheless, Figure 4.14 also shows that charity shops were the fourth most common store type to close during 2017-19. For Scotland in particular, the Scottish government is actively addressing charity store longevity as they have also undergone a rapid increase in closures, contributing to the disproportionately high vacancy rates displayed in Figure 4.8. Therefore, the Scotland Towns Partnership (2017) is advocating for more specific tailoring of charity retail stores to suit the local demographic – for example, by creating boutique versions of retail charity stores in affluent areas. The partnership is also challenging the infrequent and geographically inconsistent granting of full business rate exemption by Scotland’s local authorities. Low business rate exemption is one possible reason for the periodic closures of charity shops. The granting of business rate relief is also inconsistent across the rest of Britain, with rate relief often being granted on an individual basis – thereby increasing shop owners’ reliance on personal contacts (Charity Retail Association, 2018). However, the likes of Bramall (2020) have argued that the recolonisation of previously vibrant high streets by stores such as charity shops, betting shops and pawnbrokers represents a shift towards the ‘wrong’ sort of retail activity.

Similar increases in the prevalence of takeaway outlets, tanning or beauty salons, and vape stores have led Townshend (2017) to describe high streets dominated by these types of stores as ‘toxic’. Reflections on what stores contribute to a ‘healthy’ high street are important are especially important given the rise in certain store categories such as fast-food takeaways in London (Figure 4.12). London was already successful as a region, filling vacant stores with new take-away food ventures putting the area in good stead for the lockdown restrictions they were able to continue throughout the pandemic. London also had a considerably larger uptake of takeaway food stores, restaurants and cafés collaborating with delivery services such as Uber Eats, Just Eat and Deliveroo to maximise sales, or by social media engagement to promote special offers. In fact, restaurant owners in London had the second largest increase in profits in Europe following cooperation with Uber Eats with an average increase in income of 69% (Ziółko, 2022). However, when a large proportion of high streets are takeaways, it contributes to a lack of healthy choice and an obesogenic environment (Caraher et al., 2014).

Figure 4.12 identifies Yorkshire and the Humber as having a particularly disproportionate level of ‘unhealthy’ new stores opening. The second most popular new store opening was fast food takeaways and the fifth most frequent was vaping and tobacconists. This trend could either suggest an increase in short-term ‘fad’ ventures, or a change to the way consumers interact with high streets. Figure 4.13 shows that while the opening of vaping and tobacconists is disproportionately high in Yorkshire and the Humber, there has been
a considerable amount of new vaping stores open within a short period of time within Britain as a whole.

The increased prevalence of new vaping stores can be attributed to the substantial rise in alternative nicotine delivery systems, including as aids to stop smoking. 2017-19 saw a large rise in the number of people using e-cigarettes and vaping products. In addition, at the time there was a regulatory environment which incentivised or discouraged the use of different nicotine products. Tattan-Birch et al., (2020) states that hundreds of vape shops were opening yearly, and notes changes in the most common places to buy vaping products. They also suggest that ex-smokers might also prefer to purchase their vapes from specialist stores rather than supermarkets or corner shops which stock cigarettes.

Therefore, policy intervention strategies should be built upon an understanding of what consumers now require from high streets – whether that is health-related, or oriented towards socialisation and experiences. However, simultaneous consideration should be given to how uneven distribution of supply and demand in the free market can lead to concentration of ‘unhealthy’ or ‘toxic’ stores in certain geographic areas.

4.3.2 Key characteristics of local authorities
Through exploration of the relationship between high street composition and vibrancy in pre-pandemic Britain, this chapter provides an important contribution to existing academic discussions. Specifically, those relating to a meaningful unit of analysis for performance indicators and the composition change of high streets. This chapter achieved such a contribution through acknowledging the role of local authorities in decision making within the high street composition typology. In particular, this chapter has provided a better understanding of the role of ‘essential’ stores in performance and the visible geographic disparities in ‘successful’ and ‘unsuccessful’ high streets and local authorities.

The analysis aimed to identify variation in vibrancy based on high street composition and the implications for local authorities. At a local council level the results of the typology identified areas with a dominant proportion of essential stores with a mixture of chain and independent owners had some of the lowest vacancy rates and consistent in their success. Local authorities with such conditions include predominantly outer London boroughs (including Harrow, Greenwich and Brent) but also Brighton and Hove and Manchester. Equally successful and arguably more ‘vibrant’ areas are those local authorities with similarly low vacancy rates but a higher proportion of new stores opening and a dominance of ‘essential’ chain stores. These local authorities including Norwich and Guildford, such areas were desirable to retail investors for investment. Nevertheless, other local authorities did not share the same level of success, in particular those with high streets predominantly made up of leisure independent stores which had both the highest levels of vacancy and instability. These areas included North East Lincolnshire, Blaenau Gwent and Inverclyde. These locations were experiencing significant decline and their ability to recover would be at a notable disadvantage due to the majority of their
stores being forced to close during the COVID-19 lockdown restrictions. Their ability to stabilise would therefore be based on a shift towards opening stores that fit in with the wider cultural shift towards convenience but also in line with the trends outlined in the previous section. These include a shift towards the opening of takeaways which were allowed to remain open during the pandemic or stores such as barbers and beauty salons that cannot be rivalled by the wholly virtual experience of online shopping.

The patterns analysed in this chapter can be used to provide insights to local authority high street regeneration teams. The changes to patterns of retail investment specifically of ‘essential’ stores can have substantial implications for the high streets within a local authority jurisdiction to remain viable. Nevertheless, as the mapping of composition and vibrancy suggests, successful areas can be situated near to local authorities that have been in a state of degradation. Addressing the issue of retail decline may therefore require direct action from local councils, especially since those areas struggling the most are more likely to be disrupted by the pandemic. Key interventions may include the potential to develop planning policy that regulates the opening of new stores that are unlikely to succeed and lead to a composition associated with low levels of vibrancy or considered to be ‘unhealthy’ (Caraher et al., 2014).

4.3.1 Key characteristics of Camden’s high streets
This chapter has made substantive methodological contributions to developing a new typology of high street composition and vibrancy that is more comprehensive to existing attempts, through accounting for the relationship between individual high streets and local authority interventions. The Britain-wide classification system is at both local authority and high street level granularity. Through inclusion of both the spatial scales within the model, it was demonstrated that vibrancy is dependent on factors associated with different spatial scales. The case study of Camden Council was selected to demonstrate how the impact of external economic and cultural forces can vary spatially depending on the local context (Hughes and Jackson, 2015). The use of the Camden Council case study builds the foundation for deeper insights into Camden’s high street performance, conducted in the latter stages of this thesis (Chapter 7).

Camden council can be characterised as being dominated by leisure chain stores and having vacancy and change rates similar to the national average. Within London, Camden is comparatively stable to other boroughs and has a relatively low vacancy rate (Figure 4.11). Nevertheless, within the borough there is a variety of different high street characteristics suggesting differing requirements in terms of intervention priorities (Figure 4.3). The classification system shows that Camden’s larger high streets are predominantly classified as ‘Leisure chain’ (such as Camden, Holborn and Fitzrovia), fitting in with the overall local authority classification. However, the majority of smaller high streets appear to have a higher proportion of ‘essential’ stores (either chain or independent), such as South End Road and Fortune Green Road. In addition, some high streets are classified as having no fixed identity because they have a mix of
leisure/essential and chain/independent stores, including Kilburn and Kentish Town Road.

In addition, through mapping the vibrancy of Camden’s high streets (Figures 4.6 and 4.7) it was determined that in line with the national trend it was identified that these smaller high streets characterised by ‘essential’ stores had lower vacancy and were more stable. However, some high streets dominated by leisure chain stores were equally as successful and portrayed similar characteristics, including West Hampstead, Finchley Road, and Hampstead. Academic studies often rank high streets based on the presence or absence of certain retail aspects, for example prioritising chain stores over independents. However, adding more socio-economic elements to indices could provide more in-depth comparisons (Hall et al. 2001; Reynolds and Schiller 1992). For instance, despite the high number of stores that were forced to close in West Hampstead, Finchley Road, and Hampstead during the lockdown restrictions, these areas are notably affluent with local residents being part of professional classes (Smith et al., 2020). Therefore, these areas are more likely to recover as it only requires shops to open again and consumers to return to the high streets for these areas to become vibrant again (Quinio, 2021).

In contrast, high streets that were struggling both in terms of performance and establishing an identity are more likely to suffer long-term challenges. Examples include Kentish Town Road and Kilburn high street that had a mixed composition, high vacancy and frequent new store openings that were restaurants, cafes and fashion accessory stores. The restaurants and café's opened in these high streets are likely to face challenges associated with Britain’s exit from the European Union (EU), low success rate and high competition. In addition, fashion accessory shops face direct competition from online retailers that can avoid high rent costs and pass on their lower overhead costs via cheaper prices to their customers. Within Kentish Town Road and Kilburn high street, pre-pandemic challenges will need to be addressed by a range of policies that will be further explored in Chapter 7.

One of Camden's biggest and most internationally known high streets, Camden Town is also characterised by leisure chain stores and high occupier change. However, the new openings were predominantly fast-food takeaways and offices. The substantial number of new offices that opened in the period is perhaps due to the work of Camden’s Business Improvement District (BID). A BID is a business-led and business funded body formed to improve a defined commercial area. A BID is formed following consultation and a ballot organised by the council where businesses vote on a BID Proposal for the area (British BIDs, 2022). BIDs are a way that local government encourages responsibility of local businesses and projects. Local authorities can also provide targeted funding or loans to BIDs to overcome limited funds.

In 2017 the BIDs in Camden devised a strategy to develop affordable co-working spaces in the hope of increasing footfall and productivity and redefining the area to regenerate
Camden’s high streets (Clifford et al., 2019). The fluctuations in office spaces in Camden over this period demonstrate how the actions of Camden’s BIDs and collaboration between local businesses who were impacted by the same policies can make a significant contribution towards change. Such decision-making processes could benefit from techniques such as the comprehensive mapping of store structure outlined in the chapter, to pre-empt how planning or COVID-19 policies might have impacted the retail landscape.

4.5 Chapter summary

This chapter has created a typology of Britain’s high streets and local authorities linking their composition to levels of vibrancy. The implications of this chapter's findings are discussed and positioned in the wider cultural and policy context. The analysis aimed to highlight the variation in occupier change, vacant, ‘essential’ and chain stores. Through using the case study of the London Borough of Camden the typology compared the areas heavily dominant leisure chain characteristics to other councils. Other local authorities with similar characteristics had comparatively higher vacancy rates than areas with more ‘essential’ stores. However, the high street level typology identified leisure areas such as Camden Town as having vibrant occupier change making it a strong location for retail investment. The ‘essential’ high streets within Camden borough located in affluent areas were comparatively more stable but equally as successful due to their low levels of vacancy.

In some local authorities and high streets there were drastically different levels of success. In some of these areas there was sustained decline in the lead up to the COVID-19 pandemic. While some high streets may have had a chance at regeneration the recovery is arguably based on existing composition. For those high streets that were already struggling and characterised by leisure stores an important question is whether the lockdown restrictions had a detrimental impact on their recovery.

The changes that are analysed in this contribution to existing predictions provide additional insights for the retail industry. The selection of locations for new retail investments can have substantial impacts on the future and success of high streets with some areas such as Guildford, Norwich, London boroughs (including Harrow, Greenwich and Brent), Brighton and Hove, and Manchester, remaining viable for investment. Such areas contain high streets that had a strong proportion of shops that were not forced to close during the lockdown and their vibrant characteristics mean they do not struggle to replace vacant stores.

In contrast, for those high streets that had been experiencing retail decline in the lead up to the pandemic direct intervention is required to prevent further degradation. Such direct intervention includes government funding and the work of BIDs exampled in Camden to change the retail landscape in order to increase footfall. As retail investments continue to prioritise the ‘café society’, health & beauty and takeaways, planning policy should be adjusted to strengthen multi-channel offerings within the visitor economy. Consequently,
gaining more in-depth insights into local policy is important to understanding national patterns in retail changes where results from intervention strategies may differ according to policy differences.
Chapter 5

The Impact of the COVID-19 Pandemic on Commuter Town High Streets

In March 2020, Corona SARS-CoV-2 (COVID-19) spread so fast that it became a global pandemic (Laato et al., 2020). Alongside claiming millions of victims in various countries around the world, the pandemic had sizeable impacts on all areas of civilisation including long term economic impacts. Various health protocols were implemented to prevent the spread of the COVID-19 pandemic and ease pressure on the health sector such as social distancing and lockdown restrictions. Such government enforced restrictions had a stark impact on human behaviour with people forced to stay at home, work from home and have considerably less contact with other people.

Consequently, working from home became established during the first lockdown which started on 23rd March 2020. During the first lockdown, the British government limited travel and all non-essential workers were told to work from home where it was possible. The prevalence of remote working was measured by Understanding Society’s (2021) ‘UK household longitudinal study’, which revealed that around half of the individuals surveyed worked from home for a period of time during the first lockdown and 36% of participants said they worked solely at home. This dramatic shift in working practices created opportunities to research how widespread remote working influenced the public’s purchasing behaviour and interactions with high streets.

Work dictates how a society is organised and influences how individuals live and find meaning. Large cities support higher employment, including of non-residents, making employment patterns within cities a major contributor to modern economic systems (Chatterjee and Crawford, 2021). Travel flows to places of work have major impacts on cities’ economic models. In addition, some specific occupation types are more concentrated within city centres, including knowledge economy jobs, whereas less specialised service jobs are more dispersed, surrounding city centres (Tochtermann and Clayton, 2011). This distribution of workers became particularly relevant during the pandemic as the change in working behaviour was not even across all occupations. For example, there was a particular divide between the information and communication sectors and less skilled service jobs in accommodation, food services and hospitality (Chung et al., 2020). In addition, individuals working in the retail or service industries largely stopped commuting to inner cities or high streets due to either being furloughed or losing their jobs (Chatterjee and Crawford, 2021).

Due to these changes, commuter towns began retaining a population of city workers whose disposable income had previously flowed out of the local area. Visits to areas surrounding workplaces and the length of time spent there was severely reduced, especially during the first lockdown when workplace presence was 70% below the January-February 2020 baseline (Google, 2020). Consequently, there were drastic
implications for retail and food stores that rely on commuter footfall. The British government’s “stay local” order issued in March 2020 advised people to stay near home and to avoid making long trips wherever possible (BBC News, 2020). The enforced rules may have resulted in the pandemic having a lasting effect on consumer behaviour, price, and preferences, possibly reshaping retail systems in the process (Cummins et al., 2020). While the lockdown restrictions penalised large retail-dense city centres which faced a drastic reduction in demand, smaller retail areas near residential neighbourhoods reaped more benefits (Panzone et al., 2021). One example of such areas that were able to harness the benefits of an increased working from home population are commuter towns. Therefore, this next chapter aims to investigate the extent to which increased remote working had an impact on commuter towns, and to measure how resilient commuter town high streets were to the impacts of COVID-19. This study area was chosen due to the possibility that the recent change in working culture may become permanent via widespread uptake of ‘hybrid’ working, in which employees continue to work from home several days a week.

The chapter investigates which commuter town high streets are most likely to be impacted by increased remote working among residents who formerly commuted to larger cities. The study will explore local populations’ economic characteristics alongside commuter towns’ retail landscapes and high street compositions, including vacancy rates and retail area classification. By including retail landscape and composition data in the study, the research aims to understand successful pre-existing structures and also areas which may be less resilient to the changes caused by COVID-19.

An in-depth understanding of the possible magnitude of change to local populations and retail structures will assist local authorities’ response to the opportunities and challenges in commuter towns in the years following the easing of lockdown restrictions. Specifically, this chapter will firstly develop a resilience index for commuter towns which encompasses an area’s wealth, vacancy, composition and consumer spending, including a magnitude of change to the working from home population. The second part of this chapter will focus on in-depth case studies selected from the resilience index to highlight areas within high streets that may need tailored intervention strategies to help them recover from the impact of lockdown restrictions.

5.1 Commuter towns and retail systems

Commuter towns are generally identified in terms of their proximity to large urban areas and low average commute distance to places of work (Powe, 2007). These towns can also have characteristics such as more affordable housing and lifestyle amenities than their nearby cities (Bird and Taylor, 2021). Commuter towns are also strongly connected to wider city regions, yet research linking the spatial configurations between commuter towns and cities is limited. The majority of spatial configuration studies focus solely on city centres (Law and Versluis, 2015). Such gaps in the academic literature could be attributed to the fact that few studies using large geographic models take an interdisciplinary approach, as well as computational limitations in models encompassing the whole of Britain.
Nevertheless, research into individual commuter towns has found that one key problem these areas face is residents’ low engagement in town activities and low contribution to the local economy (Powe, 2007). Scarce engagement in the local environment of commuter towns can decrease spending in local retail systems, which may then struggle to compete with high streets situated in larger cities. Therefore, information on commuter flow patterns is particularly useful to the retail sector.

Commuter flows are geographically unevenly distributed in Britain, with the main national commuting corridors historically being the areas around London, Birmingham, Manchester and Leeds. The commute pattern is influenced by transport infrastructure and individuals’ willingness to commute long distances for work. There has been a widening in the travel corridor towards the East and West with increased commuting activity over the South East of England (Niellsen and Hoygesen, 2008). Understanding these main corridors for commuter flows aids an assessment of whether a particular retail location is suitable for specific types of retail groups. One example is the location of coffee shops seeking to attract morning commuters and customers seeking lunch close to their offices (Lugomer and Longley, 2018). However, during the COVID-19 lockdown, these commuter flows ceased, arguably opening up the possibility for commuter towns to supply these amenities to a working population which was now staying within the area.

5.2 Commuter town resilience

With the COVID-19 pandemic came an ever-increasing use of the term ‘resilience’ within high streets literature and policy. While concern over the future of British high streets is not new (Dawson, 1988), the COVID-19 pandemic has intensified discussion of the resilience and sustainability of retail and urban areas (Sparks, 2021). The pandemic increased dependence on local shops and services, and caused a heightened focus on community and the local neighbourhood. Sparks (2021) describes a “tipping point” in which recovery from the pandemic is correlated with a desire for resilient high streets and communities. This tipping point has raised questions about what a resilient high street is, how is it achieved, and whether returning to pre-pandemic conditions is desirable if those high streets were already lacking resilience.

Commuter town high streets experienced a particularly pronounced change in activity during the pandemic, which had an enormous impact on travel and commuting patterns. As a large proportion of the population either shifted to working from home or was put onto the furlough scheme, there was a drastic decline in workplace journeys (Laverty et al., 2020). During the initial months of the first lockdown, when only key workers were supposed to be travelling to work, passenger numbers for trains fell to around 5% of the pre-pandemic rate. Following the easing of restrictions, it has become more evident that the changes to commuting patterns and travel into city centres are likely to be long-term (Vickerman, 2021). Tan and Ma (2021) found that there were multiple factors during the COVID-19 pandemic that influenced whether commuters would continue to journey into work including occupation, commuting method before the pandemic, nearest public transport station, and fear of being infected upon commute journey. In addition, there have been multiple recorded factors which contribute to commuters’ reluctance to return
back to the workplace including psychological stress and anxiety as well as a decline in physical health caused by the long-term effects of having contracted COVID-19 (Shaw et al., 2020).

Other factors that have made commuters reluctant to return to the office includes the heightened attraction to remain at home where it is argued that there are more opportunities for a ‘work-life-balance’ (Jones, 2020). This can be achieved through reducing time previously allocated to travelling/commuting to work that can now be re-allocated to focusing on mental health, family or personal interests. In fact, Robinson et al.’s (2020) study found that removal of commuting time meant that participants were more likely to report exercising in their local area. These amalgamated benefits of home working have led to the adoption of ‘hybrid working’ for many jobs where only around two days in the office is expected. Consequently, it is likely that the retention of commuter town populations during the working week at least is here to stay, making a measurement of their resilience essential.

5.3 Data and methods

This chapter is based upon central governments and local authorities’ policies towards regeneration, residential building and creative placemaking. It takes the concept of ‘resilience’ and aims to quantify its meaning and measurement, exploring vacancy, occupier turnover and retail composition for commuter towns. In the last chapter it was uncovered that some areas such as Hampstead have high average income and house prices with a stable and low vacancy high street. This next stage of analysis therefore aims to uncover the wider economic factors that may impact the resilience of a high street. Firstly, this chapter ranks resilience and development prospects of commuter towns, exploring their geographical distribution. Secondly, in order to compare the retail structures within the most and least resilient commuter town high streets, DBSCAN and hierarchical clustering with spatial constraints have been applied to identify areas within high streets which are more vibrant or experiencing decay.

The commuter towns have been selected as those surrounding the 4 major cities with the highest populations in Britain: London, Birmingham, Manchester and Leeds. The commuter towns have been selected for their applicability to the ONS’s (2017) definition of ‘major towns and cities’, which defines them as having a minimum workday or resident population of 75,000. The towns surrounding London have been selected where the commute time is less than or equal to 50 minutes (the average commute time to London was 47 minutes and the towns surrounding Birmingham, Manchester and Leeds have been selected where they are within a 20 mile radius (Moovit Insights, 2022). The commuter towns that have been selected for this study are displayed in Figures 5.1, 5.2 and 5.3. Other approaches to defining ‘commuter towns’ were considered including the ONS (2022) official census and labour market statistics. However, these statistics were both based on data from 10 years ago and only provide information on commuting patterns at a local authority level. More importantly, the research within this chapter was developed in collaboration with Retail Economics who had specific stipulations for the research project to meet the needs of their stakeholders (CDRC, 2021).
Figure 5.1: Commuter towns surrounding London, Birmingham, Manchester and Leeds with a minimum workday or resident population threshold of 75,000.
5.3.1 Identifying domains of resilience

The aim of developing a resilience index for commuter towns is to create a multi-dimensional measure which construes commuter town resilience as being made up of multiple domains. A literature review was conducted to identify factors which contribute to high street resilience of commuter towns. These factors were then grouped into four different thematic domains. Resilience is measured at commuter town level by combining the outlined domains. The four different domains within the resilience index are as follows: area wealth, vacancy, composition, and consumer spending. The indicators were selected to be the most suitable measure of each domain of resilience. For each of the domains of resilience the indicators that have been chosen are domain-specific, up-to-date, openly accessible, and can be applied consistently to all the commuter towns in the study.

Each domain includes a parsimonious selection of indicators that broadly capture the resilience for each domain, accounting for the availability of data. There are 9 indicators for resilience which are displayed in Figure 5.4.
### Domains and Indicators for the Resilience Index for Commuter Towns

<table>
<thead>
<tr>
<th>Domain</th>
<th>Indicators</th>
</tr>
</thead>
</table>
| Area Wealth     | • Income (£)  
                  • Occupation  
                  • House prices (£)  
                  • North/south of England |
| Retail Vacancy  | • High street vacancy (%)  
                  • Surrounding essential area vacancy (%) |
| Retail Composition | • High street chains (%)  
                      • High street leisure stores (%) |
| Consumer Spending | • Consumer spending (£) |

Figure 5.4: Domains and associated indicators for the resilience index for commuter towns.

**Wealth**

Wealth is one of the domains that should be allocated the highest weighting due to its indicators having a strong relationship with overcoming economic shock. Indicators such as house prices have been found to be strongly associated with consumption, offsetting other weaknesses (Miller, 2020). Variation in resilience has also been linked to income as average income within an area is considered key to coping with economic shocks; higher earners have the ability to save more, aiding an area’s economic recovery (Kativhu et al., 2018).

The occupation indicator is particularly important for the resilience index – it attempts to capture the impact of a population with higher-level managerial, professional and technical occupations who are more likely to have been working from home during the COVID-19 pandemic. In general, members of this group are more likely to be situated in high density urban fringes where infrastructure performance is higher than the national average (Singleton et al., 2016). The final component of the wealth domain is the recognition of the north/south divide in England, due to geographical regional variations in socio-economic status, employment rate, and deprivation (Möller et al., 2013).

**Vacancy**

Vacancy is weighted at an equal proportion to wealth, due to its ability to measure past retail performance. The vacancy data captures both pre-pandemic vacancy from 2019 and post-lockdown vacancy from the first two quarters of 2021. The inclusion of both these time periods will be used to predict the future ability of an area to withstand economic shock. Studies on retail resilience including Guimarães (2018) used store
vacancy rates as their main data source. Vacancy rate has also been denoted in the literature as the easiest indicator to apply to a measurement of retail resilience (Dolega and Celińska-Janowicz, 2015).

Nevertheless, as highlighted by Wrigley and Lambrini (2014), a measure of long-term vacancy is a stronger indicator than short-term rates due to the natural phenomena of yearly change. Therefore, the resilience index in this study uses a measure of vacancy which covers quarters 1-4 in 2019 and quarters 1-2 in 2021. In addition, an indicator for surrounding necessity retail area performance has been included in the domain. Vacancy rates of surrounding necessity retail areas near the main high street have been combined with high street level vacancy to create the overall domain of vacancy. The vacancy rates (quarter 1-4, 2019) of necessity dominated retail areas that are situated near town centre high streets have been included within the index for an important reason. These necessity dominated retail areas have the capacity to accommodate change for town centres and have a direct relationship to shaping the composition of nearby high streets (Findlay and Sparks, 2021). Acknowledgement of necessity area success is also an important factor to consider due to these areas being predominantly open throughout all of the COVID-19 lockdowns.

Retail composition
The composition of commuter town high streets has been included within the index due to supporting literature which indicates that store composition drives competition within an agglomeration (Reimers and Clulow, 2004). One specific indicator included in the retail composition domain is the pre-pandemic percentage of essential stores within the high street in 2019. This indicator has been included to reflect the changing landscape of high streets and consumer needs, particularly in response to the lockdown restrictions and rise in online shopping (Dolega et al., 2019).

In response to these societal changes, the indicator acknowledges the increased challenges leisure venues faced during the COVID-19 pandemic and consequently the impact on high streets which are predominantly leisure-based. Consumption facilities and consumer needs are therefore an important aspect in assessing resilience of retail systems (Barata-Salgueiro and Erkip, 2014). In addition, the proportion of retail chains within each high street has been included, to reflect the relationship between real estate investment and chain retailer tenants. The association between increased chain store presence and decreased vacancy is perhaps due to chains’ ability to obtain a strong marketing position as well as greater purchasing power and product or service turnover, enabling them to afford high rent prices (Van der Wal, 2015).

Consumer spending
The inclusion of consumer spending into the overall resilience index is an essential element for the prediction of the effects of COVID-19 on commuter town high streets. This was seen during the first lockdown (26th March-15th June 2020), when non-essential activities were banned and consumer spending was reduced, resulting in multiple large household-name stores filing for bankruptcy (Hollinger et al., 2020). The level of consumer spending is important to a high street’s resilience due to the possible
consequences of recession on spending patterns. Recessions have been found to result in decreased spending on food away from home, new cars, and durable goods, which may impact economies within main town centres (Reed and Crawford, 2014).

5.3.2 Domain score weightings

Joining each of the domains together into the overall index involves weighting each domain. Weights for the resilience index are derived from academic literature on retail resilience, alongside consideration of the robustness of each of the indicators included. The choice of weights in the index is not arbitrary and is based on a clear set of criteria supported by previous research and academic literature. The proposed weights are displayed in Table 5.1 and have been subjected to sensitivity analysis. Several weeks were allocated to secondary research of each high street via google maps, policy documents and news articles. The results from the secondary research were used to check the weightings of each domain and the final outcomes.

<table>
<thead>
<tr>
<th>Domain</th>
<th>Domain weight (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retail wealth</td>
<td>30</td>
</tr>
<tr>
<td>Retail vacancy</td>
<td>30</td>
</tr>
<tr>
<td>Retail composition</td>
<td>20</td>
</tr>
<tr>
<td>Consumer spending</td>
<td>20</td>
</tr>
</tbody>
</table>

Table 5.1 Commuter town Resilience Index domain weights.

The domains of the Index of Resilience have brought together 10 indicators of retail resilience from a wide variety of data sources. By having a variety of inputs, more reliable overall data outputs can be obtained. Therefore, for an area to be resilient overall it will be graded highly resilient in multiple domains. By using a large variety of input data sources there is less chance that a town will be identified as having low resilience due to bias in one of the included indicators. To combine all the different domains into one final index output, the domain scores have been standardised by ranking all the commuter towns. This method has the effect of pulling in the extreme values that lie at the top or bottom end of the distribution.

5.3.3 Identifying indicators of resilience

Where possible, each indicator has been created using data from the most current data set available to the research. Consequently, there is no single consistent time point for any of the indicators. In order to gain the most recent data available, different granularities of data have been used across the indicators. Trade-offs between data granularity and data time points were made where data aggregated to larger areas than Lower-Layer Super Output Areas have been used. Table 5.2 displays the index domains and the associated data sources.
<table>
<thead>
<tr>
<th>Domain</th>
<th>Indicator</th>
<th>Date</th>
<th>Granularity</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retail wealth</td>
<td>Income</td>
<td>2018</td>
<td>MSOA</td>
<td>ONS annual household income estimates for small areas.</td>
</tr>
<tr>
<td></td>
<td>Occupation</td>
<td>2020</td>
<td>LA</td>
<td>ONS labour market survey, proportion in major groups 1-3.</td>
</tr>
<tr>
<td></td>
<td>House prices</td>
<td>2020</td>
<td>LA</td>
<td>ONS, UK House Price Index.</td>
</tr>
<tr>
<td>Retail vacancy</td>
<td>Pre-pandemic high street vacancy</td>
<td>2019</td>
<td>High street</td>
<td>LDC dataset on retail type, vacancy and address data.</td>
</tr>
<tr>
<td></td>
<td>Post-restriction high street vacancy</td>
<td>2021</td>
<td>High street</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Surrounding necessity area vacancy</td>
<td>2019</td>
<td>High street</td>
<td>LDC dataset on retail type, vacancy and address data.</td>
</tr>
<tr>
<td>Retail composition</td>
<td>Proportion of high street chains</td>
<td>2019</td>
<td>High street</td>
<td>LDC dataset on retail type, vacancy and address data.</td>
</tr>
<tr>
<td></td>
<td>Proportion of high street ‘essential’</td>
<td>2019</td>
<td>High street</td>
<td>LDC dataset on retail type, vacancy and address data.</td>
</tr>
<tr>
<td></td>
<td>retail</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consumer spending</td>
<td>Consumer spending data</td>
<td>2018</td>
<td>LA; Region</td>
<td>Regional gross disposable household income; Household expenditure by countries and regions.</td>
</tr>
</tbody>
</table>

Table 5. 2 Commuter town Resilience Index domains, indicators and data source information.

**Income**
The income indicator has been taken from the ONS’s (2018) annual household income estimates for small areas. The Middle Layer Super Output Area (MSOA) has been taken and allotted to the associated high street via a spatial join.

**Occupation**
The ONS (2020) ‘Labour market survey’ has been used to derive the indicator for occupation. The data is at Local Authority level and consists of 9 groups of occupations. The final indicator is a percentage of the recorded population who are in employment groups 1-3. Groups 1-3 include: ‘Managers, directors and senior officials’, ‘professional occupations’ and ‘associate professional and technical’ occupations.

**House prices**
The median house price has been taken from the ONS’s UK House Price Index for 2019-20. The Index is at Local Authority level.

**North/South of England**
The ONS 2017 Regions Full clipped boundaries in England have been joined with the commuter town high street boundaries to determine a north or south categorisation. The result indicator associated those commuter towns closest to London as ‘South’ and the towns closest to Manchester, Leeds and Birmingham as ‘North’.
**High street vacancy**
The two indicators for high street vacancy were developed by joining the LDC’s dataset, retail type, vacancy and address data with the commuter town high street boundaries. The first indicator determines pre-pandemic vacancy as the proportion of stores vacant from Quarter 1 2019 to Quarter 4 2019 as a percentage of the total number of stores. The second indicator determines post-lockdown vacancy as the proportion of stores vacant from Quarter 1 2021 to Quarter 2 2021 as a percentage of the total number of stores.

**Surrounding necessity area vacancy**
The indicator for surrounding necessity area vacancy was developed by selecting those high streets from the 2019 typology developed in the previous chapter as ‘necessity chain’, ‘necessity independent’ or ‘necessity mixed occupants’. The selected retail areas lie within a buffer of 10 miles from the centre of the associated high street boundary centroid. A distance of 10 miles was selected based on the literature which implies that this buffer size accounts for both adequate distance to incorporate competition between retail areas and also the distance consumers are willing to travel to a shopping destination (Mark and James 1996; Lee and Pace, 2005). The overall indicator determines the proportion of stores vacant from Quarter 1 2019 to Quarter 4 2019 as a percentage of the total number of stores.

**Proportion of high street chains**
The percentage of high street chains was calculated using the LDC’s dataset, retail type, vacancy and address data. A store was considered as a chain if it had 5 or more stores in a franchise, in order to incorporate local chains.

**Proportion of high street essential stores**
The percentage of high street essential stores was calculated using the LDC’s dataset, retail type, vacancy and address data. The British government’s COVID-19 lockdown restrictions were used to determine whether a store was classified as ‘essential’.

**High street consumer spending**
The proportion of high street consumer spending per household has been calculated by combining two data sets: the ONS’s 2018 ‘Regional gross disposable household income’, and the ONS’s 2018 ‘Household expenditure by countries and regions’. Firstly, the household expenditure data per household per week was taken to calculate high street household expenditure data per household, which included the following categories: clothing and footwear, household goods and services, health, recreation and culture, restaurants and hotels, personal care, and postal services. Secondly, the local authority gross disposable income per person per year was taken and aggregated up to household level using the regional average household figure. Next, the local authority gross domestic household income (GDHI) per week was combined with the regional average GDHI per week to calculate a local authority weighting. Finally, the weighting was used to calculate a figure for consumer spending per week per household on the high street.
5.3.4 Indicator weightings
For each of the domains of resilience, a single measure or ranking has been developed. When developing the overall index, the scores from each domain have been made comparable by weighting the domains so as to not distort each sector, which individually have different distributions. Therefore, all the domain scores have been standardised so that they are measured on the same metric.

In the majority of the domains, the indicators have been ranked and transformed by applying a Rankit rank-based normalisation in order to merge the rank-based indicators. The indicators within the consumer spending and composition domains were given equal weighting. For the retail vacancy domain, pre-pandemic high street vacancy was given a 40% weighting, post-restriction high street vacancy was also given a weighting of 40%, and surrounding necessity area vacancy was given a 20% weighting. The weightings were based on the literature and were used to reflect this study’s focus on high street performance while also accounting for the increased orientation of local necessity consumption practices as a result of COVID-19 lockdown restrictions.

For the wealth domain, factor analysis has been used to combine the multiple indicators into a new overall score representing the subsequent latent variable. The new single score is grounded in the underlying inter-correlations between the indicators. The process of creating the weight domain from its indicators firstly involves converting the indicators to standard normal distribution. Secondly, weights were derived from the standardised scores in Maximum Likelihood factor analysis. Finally, the indicators were combined using their allotted weight. Once the various indicators of each domain were combined, exponential transformation was applied to the domain scores, which aimed to avoid the cancellation effect. Exponential transformation also has the impact of biasing the lower rank values.

5.4 Commuter towns analysis
In order for the indicators and domains to be included in the commuter town resilience index, a number of underlying assumptions must be made. Firstly, the items that have been selected for the index have face validity, thus they have some indication of resilience. Secondly, the items are unidimensional, meaning that each element only represents one aspect of resilience. Thirdly, the items have been selected to fit the specific resilience of commuter towns by including a balanced set of items which touch upon a wide range of resilience aspects. Finally, the items have been checked for the amount of variance each item provides to ensure they are useful assets to the index.

5.4.1 Examining empirical relationships
The empirical relationships among the items in the index were examined. If two factors were empirically related to each other, it could be suggested that they both reflect the same concept and can therefore both be included in the index. To determine if the variables were empirically related, correlation coefficients and crosstabulations were
used. The correlation coefficients for each of the indicators included within the index have been displayed in Table 5.3.

<table>
<thead>
<tr>
<th>High street essentials %</th>
<th>Proportion of individuals who work from home</th>
<th>High street chain %</th>
<th>House prices</th>
<th>Income</th>
<th>North/South divide</th>
<th>Pre-pandemic necessity vacancy %</th>
<th>High street consumer spend</th>
<th>Pre-pandemic High street vacancy</th>
<th>Post-restriction High street vacancy</th>
</tr>
</thead>
<tbody>
<tr>
<td>High street essentials %</td>
<td>-0.21</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion of individuals who work from home</td>
<td>-0.34*</td>
<td>0.36*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High street chain %</td>
<td>-0.01</td>
<td>0.65**</td>
<td>0.33</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>House prices</td>
<td>-0.21</td>
<td>0.61**</td>
<td>0.46**</td>
<td>0.86**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>North/South divide</td>
<td>0.13</td>
<td>0.31</td>
<td>0.32</td>
<td>0.68**</td>
<td>0.62**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pre-pandemic necessity vacancy %</td>
<td>-0.07</td>
<td>0.07</td>
<td>0.05*</td>
<td>0.03</td>
<td>0.01</td>
<td>-0.41*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High street consumer spend</td>
<td>-0.11</td>
<td>0.22</td>
<td>-0.12</td>
<td>0.48**</td>
<td>0.44</td>
<td>0.51**</td>
<td>-0.29</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pre-pandemic High street vacancy</td>
<td>-0.20</td>
<td>-0.37*</td>
<td>-0.23</td>
<td>-0.48**</td>
<td>-0.42*</td>
<td>-0.38*</td>
<td>-0.10</td>
<td>-0.17</td>
<td></td>
</tr>
<tr>
<td>Post-restriction High street vacancy</td>
<td>-0.33</td>
<td>-0.33</td>
<td>0.10</td>
<td>-0.36*</td>
<td>-0.21</td>
<td>-0.21</td>
<td>-0.05</td>
<td>-0.17</td>
<td>0.81**</td>
</tr>
</tbody>
</table>

Note.  **P < 0.01; *P < 0.05
Table 5.3: Correlation co-efficients between each of the indicators in the commuter town Resilience Index.

5.4.2 Resilience Index rankings
In order to create the commuter town resilience index, a method for creation of multi-dimensional indices was devised through adaption of the Ministry of Housing, Communities and Local Government’s (2019) ‘English Indices of Deprivation’ and the Consumer Data Research Centre’s (2019) index of ‘Access to Health Assets and Hazards’. Therefore, the data sources for each commuter town were individually ranked and re-ordered. Next, the data was transformed using the Rankit rank-based normalisation to enable the merging of the rank-based indicators. In the case of the wealth
domain, factor analysis was used to determine the weights of the indicators. For the retail composition domain, the essential store proportion and chain proportion were given the same weighting, as both had moderate correlation with multiple indicators in different domains. Within the vacancy domain, high street pre-pandemic vacancy and post-restriction vacancy were both given a weighting of 0.4 and necessity area vacancy within 10 miles of the central town high street were given a weighting of 0.2, due to the central focus of this chapter on town centre high streets. Exponential transformation was applied to the resultant domain scores in order to mitigate the cancellation effect. The exponentially transformed domain ranks were then combined with the selected weightings, based upon the literature and sensitivity analysis. The final ranking and domain rankings are displayed in Table 5.4.
<table>
<thead>
<tr>
<th>Resilience rank</th>
<th>Town</th>
<th>Wealth</th>
<th>Consumer spending</th>
<th>Low vacancy</th>
<th>Retail composition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>St Albans</td>
<td>1</td>
<td>6</td>
<td>5</td>
<td>12</td>
</tr>
<tr>
<td>2</td>
<td>Chelmsford</td>
<td>7</td>
<td>20</td>
<td>1</td>
<td>15</td>
</tr>
<tr>
<td>3</td>
<td>Guildford</td>
<td>2</td>
<td>3</td>
<td>15</td>
<td>21</td>
</tr>
<tr>
<td>4</td>
<td>Watford</td>
<td>6</td>
<td>18</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>Basildon</td>
<td>9</td>
<td>14</td>
<td>2</td>
<td>12</td>
</tr>
<tr>
<td>6</td>
<td>Woking</td>
<td>3</td>
<td>13</td>
<td>21</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>Maidstone</td>
<td>11</td>
<td>2</td>
<td>6</td>
<td>29</td>
</tr>
<tr>
<td>8</td>
<td>Hemel Hempstead</td>
<td>5</td>
<td>29</td>
<td>8</td>
<td>3</td>
</tr>
<tr>
<td>9</td>
<td>Solihull</td>
<td>10</td>
<td>25</td>
<td>3</td>
<td>8</td>
</tr>
<tr>
<td>10</td>
<td>Luton</td>
<td>21</td>
<td>1</td>
<td>11</td>
<td>18</td>
</tr>
<tr>
<td>11</td>
<td>Crawley</td>
<td>13</td>
<td>12</td>
<td>13</td>
<td>3</td>
</tr>
<tr>
<td>12</td>
<td>High Wycombe</td>
<td>4</td>
<td>5</td>
<td>26</td>
<td>21</td>
</tr>
<tr>
<td>13</td>
<td>Salford</td>
<td>26</td>
<td>26</td>
<td>17</td>
<td>1</td>
</tr>
<tr>
<td>14</td>
<td>Chatham</td>
<td>19</td>
<td>4</td>
<td>9</td>
<td>15</td>
</tr>
<tr>
<td>15</td>
<td>Reading</td>
<td>8</td>
<td>8</td>
<td>22</td>
<td>10</td>
</tr>
<tr>
<td>16</td>
<td>Slough</td>
<td>12</td>
<td>11</td>
<td>16</td>
<td>7</td>
</tr>
<tr>
<td>17</td>
<td>Bedford</td>
<td>16</td>
<td>16</td>
<td>7</td>
<td>18</td>
</tr>
<tr>
<td>18</td>
<td>Harrogate</td>
<td>17</td>
<td>7</td>
<td>10</td>
<td>31</td>
</tr>
<tr>
<td>19</td>
<td>Peterborough</td>
<td>22</td>
<td>19</td>
<td>12</td>
<td>6</td>
</tr>
<tr>
<td>20</td>
<td>Milton Keynes</td>
<td>14</td>
<td>17</td>
<td>19</td>
<td>15</td>
</tr>
<tr>
<td>21</td>
<td>Stevenage</td>
<td>15</td>
<td>27</td>
<td>20</td>
<td>9</td>
</tr>
<tr>
<td>22</td>
<td>Harlow</td>
<td>18</td>
<td>10</td>
<td>23</td>
<td>21</td>
</tr>
<tr>
<td>23</td>
<td>Bury</td>
<td>24</td>
<td>30</td>
<td>14</td>
<td>18</td>
</tr>
<tr>
<td>24</td>
<td>Stockport</td>
<td>20</td>
<td>9</td>
<td>32</td>
<td>28</td>
</tr>
<tr>
<td>25</td>
<td>Dudley</td>
<td>25</td>
<td>23</td>
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<td>Halifax</td>
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<td>Rochdale</td>
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<tr>
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<td>26</td>
</tr>
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<td>Wolverhampton</td>
<td>28</td>
<td>31</td>
<td>30</td>
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</tbody>
</table>

Table 5. 4: Commuter town Resilience Index final ranking and individual domain ranking.
5.5 Commuter town case studies

Following on from the development of the commuter town resilience index, the second part of this chapter is dedicated to exploring the retail composition and performance of four different commuter town case studies. Firstly, the retail area boundaries surrounding the case study high streets have been defined and classified. Secondly, the vacancy of the surrounding retail areas has been explored. Finally, areas of stores with similar performance characteristics within each high street have been identified.

The four case studies have been selected based on their ranking within the resilience index. St Albans has been selected for being the most resilient commuter town and Wolverhampton has been selected for being the least resilient. The town centre high street in St Albans has been classified as predominantly consisting of leisure chain stores. Wolverhampton town centre high street is also classified as being dominated by leisure chain stores. Consequently, the additional case studies of Guildford and Rochdale have been selected. Guildford is the third most resilient commuter town and is dominated by leisure chain stores. While four of the top five most resilient commuter towns are in the east of England, Guildford is in the southeast of England, therefore it is important to explore differences in regional policy contexts and intervention strategies. In contrast, Rochdale is the third least resilient commuter town and has mixed occupants. Therefore, an important part of this chapter is to compare how high streets with different retail composition and high street identity can drastically differ in performance and resilience.

5.5.1 High street classification and performance

The high street classification developed within the previous few chapters has been used to define the commuter town high streets’ boundaries and composition. The high street typology has been based on England’s retail lockdown restrictions in order to determine which areas were able to predominantly remain open throughout the majority. It also considers the proportion of stores owned by independent retailers. The resultant six high street categories across Britain are as follows: Essential independent, Essential chain, Essential mixed occupiers, Leisure independent, Leisure chain, and Mixed stores mixed occupants. Figure 5.5 displays the four case studies of Guildford, St Albans, Wolverhampton and Rochdale’s town centre high streets and surrounding high streets.
The classification system displayed is a useful tool to map changes in retail performance and composition following the COVID-19 restrictions. For example, despite the main town centre high streets in St Albans and Guildford predominantly consisting of leisure chain stores which would have been forced to close during the lockdowns, the smaller high streets which surround them and are still within the town centres are mostly clusters of essential stores. In contrast, the least resilient high street of Wolverhampton is surrounded by high streets with no clear identity due to its mix of store and occupier types.
Rochdale’s main town centre high street has similar traits. Figure 5.6 displays the commuter town high streets associated vacancy rates in post-restriction conditions and Figure 5.7 shows the occupier change in pre-pandemic conditions to show which high streets were already changing before restrictions were implemented. The figures include break margins in the legend from data of all British high streets to maintain comparability.
Figure 5.6: High street vacancy percentage in quarter 1 and 2 of 2021 for Guildford (top left), St Albans (top right), Rochdale (bottom left) and Wolverhampton’s central town high street (bottom right) and surrounding high streets.
Figure 5.7: High street occupier change in quarter 1 2017 to quarter 4 of 2019 for St Albans (top left), Guildford (top right), Rochdale (bottom left) and Wolverhampton’s central town high street (bottom right) and surrounding high streets.

The high street classifications, vacancy and occupier change percentages show some interesting findings regarding vibrancy across the commuter town centres. Firstly, while the main town centre high street in St Albans was ranked as the most resilient with a post-restriction vacancy of 13.9%, there is a nearby essential mixed occupier high street area along Victoria Street that had even lower post-restriction vacancy. The nearby leisure independent high street along London Road has similarly low rates of post-restriction vacancy to the town centre high street at 11.6%.
The figures also show that Guildford has three essential chain high streets relatively near the main town centre, all classified as essential with mixed occupiers. All three essential high streets have lower post-restriction vacancy compared to the town centre high street made up of predominantly leisure stores. However, they are perhaps not in direct competition due to offering different store types. In particular, one of the essential chain store areas is Slyfield Industrial Estate, which includes multiple builders merchants and shops marketed towards traders.

In comparison, Rochdale has two smaller high street areas surrounding the central town high street which are categorised as essential independent. One interesting area is the retail cluster on Yorkshire Street, which is an independent essential store dominated area with comparatively lower vacancy rates and higher stability compared to the nearby central high street. The area has stores which are orientated towards ethnic minorities and include international money transfer stores, Asian-style fashion stores, continental food stores, Asian confectionaries and takeaways. The relatively low vacancy rates may suggest that the Yorkshire Street area is more successful at catering to the needs of the local population through the geographical grouping of specific stores and services used by a particular demographic.

The least resilient commuter town, Wolverhampton, has rates of vacancy and occupier change for both its main town centre high street and also the mixed occupant and essential dominated highstreets which surround it. The combination of high rates of occupier churn and high vacancy suggest that the predominantly leisure chain stores are not meeting the needs of the local population.

Nevertheless, there are two more successful high streets further away from the town centre located along Cannock Road which consist of a cluster of essential chain stores and essential independent stores. These two high streets are arguably well situated on a main road towards the M54 and M6 with ample parking outside the shops. The array of chain stores includes supermarkets, convenience stores, fast-food outlets and a pharmacy. The area dominated by essential independent stores is predominantly made up of independent takeaway stores. Both high streets have low post-restriction vacancy and high stability suggesting that stores within these locations were able to both stay open during lockdown restrictions and survive the economic and social impacts of the pandemic.

5.5.2 Store performance within high streets
The aim of this next section is to compare the retail structures within the case study high streets and identify specific clusters of stores which face degeneration and could benefit from tailored intervention strategies. In order to identify, both successful areas within high streets and areas of high vacancy, additional cluster analysis has been conducted. In order to capture both the pre-pandemic, lockdown, and post-restriction performance of stores within commuter town high streets, the two key performance indicators used within this research – vacancy and occupier change – were used. In this section the metrics were calculated from Q1 2017 to Q2 2021 to capture an understanding of the areas over
the last five years, and also throughout economic and cultural shock caused by the pandemic. Firstly, a vacancy rate has been calculated by taking the sum of all the premises that were listed as vacant in quarterly recordings from Q1 2017- Q2 2021 and dividing them by the sum of all the quarterly recordings in the same time period. Secondly, a percentage of change has been calculated by taking all the unique instances of a premises changing hands from one occupier in a quarter to a different one in the consecutive quarter and dividing it by the total number of quarterly categories. The vacancy and change calculations have been conducted at store level.

To be able to explore the variation of characteristics within the high street boundaries, a combination of hierarchical clustering with spatial constraints and modified DBSCAN clustering has been applied. New polygons have been made which outline areas of stores with similar rates of vacancy and occupier change within a close geographical proximity. Firstly, a ward clustering method is applied using the ClustGeo package which allows for the implementation of a ward-like hierarchical clustering algorithm with soft contiguity constraints (Chavent et al., 2018). There are many methods which have been proposed in the literature to cluster a set of n objects into k clusters by either finding a suitable partition based on dissimilarity-based homogeneity criterion or by fitting mixture models with a multivariate distribution function. Yet, within this chapter the imposition of constraints on a set of allowable solutions is required. Therefore, a hierarchical clustering and not partitioning method is used including spatial constraints.

The benefits of this method for this section is that exclusion of strict contiguity means that locations of stores with similar characteristics will not be placed in different clusters if they are spatially apart. The method also does not require weights to be given to the geographical dissimilarities, which raises the problem of defining the weight. Therefore, the ClustGeo algorithm allows for the vacancy rates and occupier turnover of each premises to be clustered based on an associated dissimilarity matrix, and a second matrix can be calculated defining the distance between the premises. Through using the ClustGeo approach the geographical information can be taken into account, refining the vacancy and turnover clustering without disrupting it.

The algorithm is implemented to create a matrix giving the dissimilarities between the vacancy rate and occupier change percentages for all the premises in a given area. A second matrix also gives information regarding how geographically close each of the premises are. A mixing parameter – alpha – is then selected to set the importance of the geographical constraint in the clustering process. The end result is the categorisation of premises into clusters where the stores have similar vacancy and change percentages taking into account geographical constraints.

Each of the high street clusters were then subsequently analysed using a modified DBSCAN clustering method (Pavlis et al., 2018). A DBSCAN method was implemented to identify smaller retail centres by adjusting a radius perimeter and setting a minimum number of points for the new clusters. The rationale behind selecting smaller areas of high streets with similar characteristics is to attempt to reveal possible areas of decay following core store closures or areas with a high turnover of occupiers yet low vacancy
rates. The modified DBSCAN clustering method has been chosen to identify smaller retail agglomerations from the larger sections of the high street as defined by the hierarchical clustering method, due to its ability to represent retail areas relative to formal definitions; its rapid speed in creating cluster solutions; and its ability to calibrate optimised input parameter values.

Through applying Pavlis et al's (2018) modified DBSCAN clustering method, smaller clusters were derived from within the specific distance of 150m. These new clusters with only \( \geq 15 \) location points were included. The restraints have been chosen to fit the Ordnance Survey's and ONS's definition of a high street; namely, “a cluster of 15 or more retail addresses within 150 metres, linked to roads” (ONS, 2019: 3). The resulting polygons have been transformed into H3 format, which is Uber’s (2018) Hexagonal Hierarchical Spatial Index. The system takes data points and buckets them into hexagons, which allows for easy approximations of radiuses.

5.5.3 Clustering with spatial constraints
In order to explore the variation in occupier change and vacancy within high street areas the four commuter town case studies of St Albans (most resilient), Guildford (second most resilient), Rochdale (third least resilient) and Wolverhampton (least resilient). While Wolverhampton and St Albans are at the opposite ends of the spectrum in terms of post-restriction vacancy, with St Albans having considerably lower vacancy (13.9\%) than Wolverhampton (24.13\%), they both have relatively high occupier change (Table 5.5).
<table>
<thead>
<tr>
<th>Town</th>
<th>High street</th>
<th>Post-restriction vacancy (%)</th>
<th>Pre-pandemic occupier change (%)</th>
</tr>
</thead>
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<tr>
<td>Wolverhampton</td>
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<td>4.79</td>
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<tr>
<td></td>
<td>Chapel Ash</td>
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<td></td>
<td>Bargate Drive</td>
<td>5.00</td>
<td>8.82</td>
</tr>
<tr>
<td></td>
<td>Dudley Road</td>
<td>16.00</td>
<td>2.88</td>
</tr>
<tr>
<td></td>
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<td>5.00</td>
<td>8.82</td>
</tr>
<tr>
<td></td>
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<td>10.00</td>
<td>0.00</td>
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<td></td>
<td>Oldham Road</td>
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<td>0.00</td>
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</tr>
<tr>
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</tr>
<tr>
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<td>Westfield Road</td>
<td>3.33</td>
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<td>London Road</td>
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<td>4.67</td>
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<td>St Albans</td>
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<td>Britain</td>
<td>All British high streets</td>
<td>13.34</td>
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</tr>
</tbody>
</table>

Table 5. 5: Percentage of pre-pandemic occupier change (quarter 1 to quarter 4, 2017-19) and post-restriction vacancy (quarter 1 to quarter 2, 2021) for the high streets in Wolverhampton, Rochdale, Guildford and St Albans.

The method for conducting hierarchical clustering with spatial constraints outlined in Chavent et al.’s (2017) work has been applied to all four case study high streets. The method considers two dissimilarity matrices. Firstly, D0 is the Euclidean distance matrix between the n retail store locations performed with the variable, occupier change and vacancy. Secondly, D1 is the dissimilarity matrix used to account for the geographical proximity between the n retail store locations. Each commuter town case study has its own data consisting of 4 objects: an occupier change data frame, vacancy rate, a data
frame of geographical distances, and a SpatialPointsDataFrame. D0 is equal to the change and vacancy distances and D1 is equal to the geographic distances between the municipalities. In order to select a suitable number of K clusters, a Ward dendrogram for each case study high street was created using D0 only. The dendrogram for each high street displayed a tree-like plot outlining each hierarchical step in the model allowing for different clustering solutions to be visually explored. All the samples favoured a two-cluster solution which reflects high and low vacancy and change groups, with the next split being further down on both graphs.

The four high street samples showed different results regarding the next best split. St Albans, Guildford and Wolverhampton high streets can be interpreted as indicating the existence of four distinct clusters, while Rochdale high street showed five clusters. The St Albans, Guildford and Wolverhampton data was partitioned into four clusters and the Rochdale data was split into five clusters. In order to gain more geographically compact clusters, the matrix D1 of geographical distances was introduced. The introduction of a geographical constraint required a mixing parameter to be obtained to improve the geographical cohesion of the clusters, without jeopardising the cohesion between the vacancy and change percentages of the premises. Geographically more compact clusters were obtained through introducing the matrix of geographical distances. A \( \alpha \) value between 0 and 1 is then selected which sets the importance of the geographical distances and the distances between the vacancy and change values in the clustering process. When \( \alpha = 0 \) the geographical dissimilarities are not taken into account. When \( \alpha = 1 \) the distance between the change and vacancy percentages for the premises are not taken into account.

An \( \alpha \) value which provides a compromise between the loss of vacancy and change homogeneity and a gain of geographic cohesion was selected for each case study. An alpha value of 0.6 was chosen for Guildford, 0.5 for Wolverhampton, and 0.7 for both Rochdale and St Albans. New modified partitions were then obtained with \( \alpha \) values using the ‘hclustgeo’ function in the ClustGeo package to gain geographic cohesion.

In order to group together areas of the high street that need targeted intervention, polygons have been created which cluster together shops with similar characteristics in terms of vacancy and change rate. Smaller clusters have been obtained by individually analysing the hierarchical clusters via Pavlis et al.’s (2018) modified DBSCAN clustering method for retail centres. Smaller clusters were derived from within the specific distance of 150m. These new clusters were then grouped with clusters with only \( \geq 15 \) location points being included. While the minimum number of neighbours within a cluster is usually considered 10 as a formal definition for retail centres in the United Kingdom, 15 was chosen in line with the Office for National Statistics’ (2019) definition of a high street.

The DBSCAN method means that each subgraph is used to select clusters with a point density close to an overall study area. In order to display the retail clusters with similar vacancy and occupier change rates, the polygons have been created using H3 format, which is Uber’s (2016) Hexagonal Hierarchical Spatial Index. The system takes data points and buckets them into hexagons, which allows for easy approximations of
radiiuses. Resolution 11 was selected resulting in each cell having an average hexagon edge length of 25m. Agglomerations with 1 H3 cell were kept as these retail islands still contain 15 or more retail units within their associated cluster.

Figure 5.8 displays polygons for areas within St Albans, Guildford, Rochdale and Wolverhampton town centre high streets which have similar qualities and the aggregate values have then been displayed for vacancy. Figure 5.9 displays the percentage of stores occupier change within each of the new clusters.
Figure 5.8: Average vacancy for the clustered retail areas within Guildford (top left), St Albans (top right), Rochdale (bottom left) and Wolverhampton’s central town high street (bottom right) during Q1 2017–Q2 2021 based on their attributes and proximity.
The new retail areas in both cities have been allocated an individual ID number. As can be seen in Figures 5.7 and 5.8, while St Albans and Guildford have clusters of very low vacancy (between 4.7% and 6.7%), even the more successful clusters in Wolverhampton and Rochdale still have vacancy rates between 14.2% and 18.1%. In addition, the clusters in both Wolverhampton and Rochdale generally have a higher turnover of new occupier but in almost all instances are accompanied by a low success rate, displayed through high vacancy. When inspecting the individual retail areas some stand out for having particular qualities.
Firstly, St Albans – the most resilient commuter town – has store clusters which generally have low vacancy and stable conditions. Nonetheless, one area which experienced some new store opening was the intersection between London Road and High Street. Some interesting store changes include the opening of a home extension store and the replacement of a betting shop with a home tiles store, both during the summer following the easing of the lockdown restrictions. Such changes in store type may reflect the cultural shift to focusing disposable income on home improvements, especially due to the increase in working from home that saw residents travel less frequently to London. Such small-scale granular findings within this section also reflect the wider trend in re-mortgaging to fund home improvements since the pandemic hit (BuyAssociation, 2021). This perhaps further widens the gap between resilient and non-resilient commuter town high streets as house prices will disproportionately rise in those areas which are heavily populated by residents in higher paid white-collar jobs who can work from home.

The second example of a resilient commuter town high street is Guildford. Figures 5.7 and 5.8 show the majority of Guildford high street as having low levels of vacancy and to be relatively stable. One area of interest includes the part of the high street which intersects with North Street. There are disproportionately high levels of vacancy – a trend which has persisted throughout 2017-2021. The area has seen some consumer-based cultural changes with closures of music stores, the main post office, and a large bank. While these closures are perhaps in line with wider consumer spending trends (in particular the increase in online shopping), leaving large or corner premises vacant can lead to decay in wider areas of the high street.

In comparison the west of North Street is the location for the Friary shopping centre. The Friary prides itself on having a strong asset management strategy which enables it to continue to attract leading global brands (Edwards, 2016). The high street data reflects this, showing the area around the Friary centre to have low vacancy but relatively high occupier turnover. Therefore, it could be suggested that the strategic selection of stores and global brands such as Zara, Urban Outfitters and the Kokoro sushi chain creates stability for the area while collectively drawing people to it. The Guildford borough council’s 2020 North Street Regeneration plan included proposals to extend the Friary centre’s successes to North Street. While a pop-up village in the area saw very little success, it could be suggested that the North Street area should not try to directly compete with or replicate what the Friary centre is already successful at (SurreyLive, 2018). Nevertheless, the North Street area may benefit from more stable longstanding necessity-based stores which would fit in with the council’s plans to deliver affordable housing within the town centre (Guildford Borough, 2021).

In comparison, also displayed in Figures 5.7 and 5.8 is Rochdale’s high street, which ranked as third-last in the commuter town resilience index and was characterised as being predominantly a mix of occupiers and store types. The majority of the clusters within the high street have high levels of vacancy and occupier turnover. In particular, Drake Street can be seen to have high levels of vacancy with fairly high levels of occupier change. The area may need particular attention when it comes to an intervention strategy as its consistently low performance can been seen to have been exacerbated by the 2008
recession. Consequently, the area is likely to be hit in a similar way by the economic strain caused by the pandemic.

Drake Street is peppered with unaesthetic boarded-up buildings, in contrast to the way that vacant stores in Guildford’s Friary centre contain vibrantly coloured window stickers and displays. The street is also full of closed-down and boarded-up pubs and bars, whilst many open stores look equally dilapidated, with tired or temporary shop fronts. Such reasons may have prompted Rochdale council’s regeneration programme, which includes the Drake Street area and focuses on revamping shopfronts to highlight their heritage (Northwest Place, 2018). However, such efforts and expenditure may make little impact to the area unless stability-promoting store types and a more characterful composition are introduced. The more successful high street along Yorkshire Street, located off the town centre high street, offers an example of this, with its high prevalence of communal necessities and unified personality. The Yorkshire Street area caters to the needs of an ethnically diverse local population, yet Drake Street does not appear to have a clear target market or unified brand image.

Another area of interest in Rochdale’s high street is Hunters Lane and the stores on the small roads off Yorkshire Street. The stores in this area also have a high vacancy and occupier turnover rate. Long-term vacancies include a large bed and breakfast and a building society, alongside a string of failed takeaways and cafes. The only stores which have seemed to thrive in these side streets are those which Townshend (2017) would consider to be ‘unhealthy’, such as a tattoo parlours, tanning studios, and lingerie stores. The apparent success of these stores is perhaps because consumers are going to these side streets for specific purchases. One way to increase the success of the area could be to have a route set out with signage to facilities such as a car park or providing people with a reason to walk through the area. Additional footfall could be created through occupancy of the vacant large and historic-looking bed and breakfast with a necessity store such as a chain supermarket. The area already has a Farmfoods and M&S Food but could benefit from a mid-range supermarket with room for parking.

Finally, within Wolverhampton – the least resilient commuter town high street – most of the clusters have high vacancy rates but some areas have higher change than others. One section of the high street which has experienced significant decay is Victoria Street, especially where it intersects with Salop Street. The area has both high vacancy and high occupier change. Such characteristics saw Wolverhampton council receive £15.7m from the Government’s Future High Street Fund (City of Wolverhampton Council, 2022). The main development plan includes the creation of a boxpark on Bell Street to provide food, beverages and live entertainment. In addition, unused buildings in Cleaveland Parade are going to be demolished to make way for a new car park to accommodate the boxpark visitors.

However, a pop-up style area with high occupier churn and with a leisure/entertainment focus is perhaps not the most efficient way of regenerating Wolverhampton’s town centre high street. The high street is lacking in vibrant areas with low vacancy, high occupier change, and stores which cater for local cultural needs – conditions which are arguably
required to maintain a successful boxpark, such as the one in Shoreditch which helps local black and minority ethnic businesses to gain visibility (Hackney Gazette, 2022). Acknowledgement of the essential stores that the local community needs is particularly important since Homes England has been supporting Wolverhampton city council in its levelling up plans to attract new residents to the centre by creating a more diverse mix of housing. Plans might therefore focus on creating stable clusters of essential stores within the city centre. This would help ensure sustainable conditions and help overcome difficulties in achieving new residential value, which have already prevented some new developments.

Within the main central high street in Wolverhampton there are some clusters which present such stable qualities and include essential services. Despite the struggling conditions for businesses within Wolverhampton high street, there is one area which appears to have remained relatively stable between 2017 and 2021 and maintained low vacancy rates. The area surrounding Queen Square mainly consists of banks which have been there for several years, alongside bars, pubs and cafes. The historic buildings combined with the outside seating provisions around the fountain areas have been complemented by the ‘Lighting up the City’ project; a light curtain has been built in Exchange Street, and new lights installed in the Queen Square fountain and steps (Black Country LEP, 2018). The project aimed to draw attention to some of the architecturally interesting features and buildings in the city centre with the intention of gaining economic benefits from increased footfall.

However, despite the area’s apparent stability it could potentially be threatened by the wider cultural trend of bank closures due to the rise of online banking. If they become vacant, the large historic buildings could lead to a decrease in footfall to the area and make the decay hard to reverse – especially since regeneration strategies funded by the Future High Street Fund are targeted at the other side of the city centre and focus on new structures and buildings.

5.5 Chapter summary

This research has created a resilience index for commuter towns surrounding London, Manchester, Birmingham and Leeds. The index included a measure of those individuals in the population likely to be able to work from home throughout the COVID-19 lockdowns and therefore no longer commuting into the four major cities. Case studies of commuter towns with varying levels of resilience have been used to display how town centre high street success can vary compared to surrounding smaller high streets, as well as between different commuter towns. Smaller scale store analysis was then conducted using hierarchical cluster analysis and DBSCAN. These methods were able to identify parts of the high street which have either deteriorated or were experiencing high levels of change as they developed into up-and-coming areas.

The commuter town index revealed a north/south divide in England, where commuter towns in the south were generally more resilient due to lower vacancy rates, greater wealth resulting in higher consumer spending, and more investment reflected in higher proportions of chain stores. Furthermore, analysis of vacancy rates of individual smaller
high streets surrounding the commuter town centre high streets revealed that surrounding retail areas may have significantly different characteristics and success rates compared to the central high street. An understanding of the success of surrounding smaller high streets may aid analysis of the central high street and possible intervention strategies. Moreover, this research also displayed how commuter towns’ central high streets could be further isolated into smaller areas with different qualities and ranks of performance. To achieve substantial outcomes from limited intervention funds for regeneration strategies, it is important to fully understand and identify high street areas that have experienced degradation. Pinpointing the start of area decay, such as the closure of a long-residing large or corner store, may inform decision-making for the area’s future. Previously successful parts of the high street that have degraded due to specific store closures may need new, stable attractions or services in the area in the form of necessities or a cultural activity, in order to encourage people to return to the area.

Cluster analysis also enabled the identification of high street areas with low vacancy rates and high occupier turnover, suggesting these sections are possibly desirable for short-term business ventures, which are often trend-related. Intervention strategies for these areas should therefore continue to promote investment in new occupiers and in-fashion experiences by improving the external appearance of vacant premises and strategically prioritising businesses which fit the brand of the area. High street literature often blames online retail for increased vacancies and the rapid decline of brick-and-mortar stores, yet it may be more accurate to argue that online activity has changed the way consumers interact with high streets. Coupled with the financial and lifestyle implications of the COVID-19 lockdowns it is apparent that regeneration strategies should be built upon an understanding of what consumers now want, need, or desire from high streets – whether that is necessity-driven, health-related, or oriented towards socialisation and experiences. This chapter has also acknowledged how commuter towns’ local councils are hoping to build more affordable residential properties within high streets. Increasing the population living within high streets perhaps intensifies the need for tailored intervention strategies to ensure that high street environments suit those who live locally.

The pandemic has changed economic behaviour and working patterns with a particular impact on commuter towns. Distance has become less of a barrier to working and as a result for some residents some workers spending could be redirected away from office areas and redirected to their local high streets, creating less of a barrier to local shopping. As a result, the rise in working from home could benefit more geographically remote commuter towns, especially in less well-performing areas. Boroughs such as Camden within inner London have experienced a reduction in commuters which led to a heightened focus on ensuring their high streets supported their local residents during the lockdowns.

Commuter towns surrounding London have experienced greater wealth retention, with higher disposable income leading to increased spending on local high streets that could further exacerbate the north/south divide. Such trends have led the UK Government to take action to ensure that levelling up is not solely directed from London, where the high street environment, job opportunities, and local community needs are very different to
many areas outside the capital. In fact, the Department for Levelling up, Housing and Communities is being moved to the commuter town of Wolverhampton to create local jobs and bring decision making closer to the communities that are most in need of regeneration funding.

The applications of this chapter are multiple and multi-dimensional. Less resilient commuter towns might try to lure in remote workers with higher disposable incomes, who may be attracted by lower property prices. The continued future success of these areas may be dependent on decision making aimed at understanding the composition and stability of high streets – in particular, the provision of necessities that reflect the area-specific population.
Chapter 6

Measuring High Street Resilience

The previous chapter introduced the concept of resilience and some of the possible factors influencing the ability of high streets to withstand economic and social shock, including retail composition, wealth, vacancy and consumer spending. Nevertheless, the analysis was confined to a specific type of high street (those located within commuter towns) and the influence of a rise in ‘working from home’. Consequently, this next chapter aims to develop a Britain-wide measurement tool for evaluating the impact of the government enforced lockdown restrictions as a result of the COVID-19 pandemic.

In this chapter, retail resilience will be viewed as the ability of high streets to respond to the economic and cultural challenges posed by the pandemic (Holling, 1973; Hollnagel et al., 2006). Previous literature includes various models for measuring resilience, yet each high street and its governing authority will have specific criteria to capture what is meant by associated terms such as sustainability and regeneration. That said, a national measure of resilience is a useful tool for planning since it enables a baseline for comparison between areas that can be used to benchmark successes and failures. It can also reveal the differences in high streets’ ability to withstand external shocks, which are often driven by the geographical contexts in which they are operating, a factor that can be overlooked in policy strategies (Whitworth, 2021).

The need for a national high street resilience measure has been catalysed by the impacts of the UK Government’s restrictions enacted in response to the COVID-19 pandemic. On 24th March 2020 Britain went into the first COVID-19 lockdown, closing premises deemed ‘non-essential’ such as pubs, restaurants, gyms and other social venues. These were not fully free from restrictions to business practice until 12th April 2021 in England and Wales, when non-essential retail could reopen and 20th April 2021 in Scotland, when cafes, pubs and restaurants could reopen. The various lockdown restrictions across the three nations particularly impacted the leisure industry and also exacerbated high street competition with e-commerce as more people turned to delivery services. Meanwhile, stores offering ‘essential’ goods or services were allowed to remain open. Essential retailers included food shops, supermarkets, hardware stores, off-licences, petrol stations, vehicle repair services, banks, medical services, pet shops, launderettes, and funeral directors. In addition, pubs, bars and restaurants were allowed to remain open to offer takeaway food and drink in sealed containers (BBC, 2021). The COVID-19 lockdown restrictions also mandated ‘working from home’ unless workers met strict exemption criteria. Consequently, some smaller towns and residential areas retained a population of commuters whose disposable income had previously led to predominant capital flows outside of local high streets, creating further geographic divides in high street success (Crols and Malleson, 2018).

Measuring the impact of the government enforced restrictions using the concept of resilience can help to explain why a post-pandemic high street might ‘bounce-back’ (recovery results in the return to an area’s previous state) or ‘bounce-forward’ (in a post-
shock environment, the area has various trajectories for recovery) (Grinberger and Felsenstein, 2014).

In response to the socio-economic shock caused by the pandemic, some high streets might adapt through building upon technical, environmental and economic capabilities to keep in line with wider changes and trends within the urban landscape (Couclelis, 2020). In this regard the COVID-19 lockdowns have arguably acted as a testing ground for the building of adaptive capacity. High street capacities consist of numerous characteristics including: the range and interdependencies of existing businesses, high street attractiveness, strength of local planning policies and the socio-demographic characteristics of the local population (Ntounis et al., 2021; Singleton et al., 2016).

Throughout the post-pandemic recovery period of high streets, they will need to develop what Khalili et al. (2015) considers as the four aspects of resilience: economic, temporal, social and environmental, which are all strongly linked to the structure of high streets. Literature including Florida et al. (2021) has gone as far to say that the impact of the pandemic may lead high streets to lose their commercial role but rather become amenity centres and places to window shop to advertise buying online. In addition, a decline in the demand for working spaces and offices within high streets may decrease commercial rent prices and lead to an increase in residential properties. These types of changes depend on factors such as financial markets and political regimes. Therefore, following the re-opening of nonessential retail in Britain including hospitality, commercial and recreational businesses, a vital research area is an assessment of the level of exposure of individual high streets are to the impact of the pandemic and how vulnerable British high streets still are.

This next chapter aims to explore the levels of vulnerability on British high streets based on both their pre-existing success or weakness and the likelihood of the premises within their high streets to become vacant. The LDC dataset on retail type, location and address which spans across the whole of Britain has been used to create a measure of resilience. In order to fully assess the impact of lockdowns on British high streets, this research explores whether the COVID-19 pandemic compounded pre-existing inequalities for some areas while creating opportunity for others. In order to achieve this, the series of heuristics that have been developed to measure high street resilience include vacancy rates, occupier change and proportion of ‘essential’ stores. Secondly, the impact of specific stores that were allowed to remain open in Britain during the restrictions and their impact on high street performance will be analysed. Finally, the chapter uncovers those high streets in Britain that were more adaptable to change during the COVID-19 pandemic. The results from this chapter aim to highlight the differences between pre-pandemic high street success and the proportion of ‘essential’ stores and their role in determining resilience. The findings will also indicate geographic patterns and considerations that can contribute to the prioritisation of funds and policies targeted at specific areas to enhance resilience.
6.1 The British Retail System

High streets have traditionally been a structural subsection of town or city centres in Britain, acting as focal points for work, leisure, shopping and housing (Philips et al., 2021). Previous studies (Stocchi et al., 2016) have suggested that what consumers desire from British high streets is a holistic experience offering a mix of products, stores, and social experiences. Consumers also see value in high streets that can create novel and exciting experiences, alongside functional features such as efficient transportation systems and parking. More specifically, Theodoris et al. (2017) found that high streets and town centres can have a vast array of desired functions for the local population including a supply of “wellbeing” related facilities, free activities for children, and attractions for younger people. Different types of retail centres have been found to react differently to changing consumer behaviours, therefore classification systems that draw distinctions between different types of centres are important (Singleton et al., 2016).

In the British context, the work of Reynolds and Schiller (1992) illustrates that at the start of the 1990s retail hierarchies could be entirely built upon town centres. Their research proposed a five-tier system comprising 370 minor ‘district centres’ and six ‘provincial cities’ determined by the number of retailers in each location. More than two decades later, Dolega et al.’s (2016) retail hierarchy was derived using a composite index based on centre size, a diversity index, proportion of leisure and anchor stores, and vacancy rates. However, Jones and Livingstone’s (2018) study criticised the more complex index for not considering the long-term changes to the variety and roles of shopping centres, as it is predominantly focused on town centres. A similar challenge faces this piece of research due to its emphasis on high streets.

Other hierarchies that are based on town centres as opposed to high streets include Mumford et al.’s (2021) classification of retail centres based on footfall signatures and volumes as a measure of attractiveness. However, footfall signatures do not necessarily directly reflect success, acting as more of an indicative measure with research often relying on qualitative data from local stakeholders to validate models (Crols and Malleson, 2019). Dolega et al. (2021) have also utilised new forms of data to classify shopping and consumption spaces across Britain. The study develops a dynamic taxonomy in the form of a two-tier classification with 5 distinct clusters and 15 additional nested sub-clusters. While the study determines key characteristics relating to each retail area such as vacancy rate, type of retail and diversity, the typology is not directly related to the COVID-19 restrictions. Consequently, a retail hierarchy recognising the specific stores allowed to remain open between the time span of retail and leisure restrictions - March 2020 to May 2021 - is needed in order to capture the structural changes caused by the COVID-19 pandemic.

6.2 High Street Resilience

Within the wider literature and government policy reports (Wriley and Lambiri, 2014; GOV.UK, 2021) and consequently within this chapter the terms ‘high streets’ and ‘town centres’ are used in conjunction with each other. The rationale behind the merged or interchanging definition is because while some ‘secondary centres’ are not locally
considered as main town centre high streets, they can often be more robust to economic crisis and change (Findlay and Sparks, 2012). Consequently, a town centre or high street’s resilience can be defined as the ability of the area to return to pre-shock conditions or to adapt into a new environment brought about by wider social and economic change (Fernandes and Chamusca, 2014; Hudson, 2010). The 2008 recession exposed the socio and spatial inequalities across Britain and led certain high streets to have sharper rises in store vacancy, leaving policy makers to rethink visions for regeneration (Dolega and Celińska-Janowicz, 2015). Therefore, high street research aiming to encapsulate a wider understanding of resilience should include the area’s ability to sustain long-term development and adapt to its local population’s needs.

Studies specifically measuring the resilience of retail to lockdown restrictions include Appel and Hardaker’s (2021) qualitative analysis of the experiences of retailers in Germany through in-depth interviews. The study separates retailers’ resilience strategies into two categories – those who intend to return to their former stage of success utilising their pre-pandemic methods, and those who view the pandemic as an opportunity for fundamental change, such as pursuing an online approach in search of sustainable growth. The findings suggest that retail resilience research should consider two different aspects of resilience – firstly, the rate at which a high street can return to its original performance, and secondly, the ability of a high street to transform and adapt in line with wider social and cultural changes (Fernandes and Chamusca, 2014; Hudson, 2010). Dolega and Celińska-Janowicz (2015) have described a town centre’s period of relative stability as when there is low retail churn, high capacity and slow responsiveness to change. In contrast, ‘adaptive resilience’ is the state of continual adaption and redesign in pursuit of a core goal (Robinson, 2010). Consequently, local councils’ understanding of retail resilience is important; while there are many resilience models, each high street will have specific goals relating to the spectrum of self-preservation and redesign.

In the context of the COVID-19 pandemic and the restrictions that resulted from it, it is important to select appropriate performance measures that can distinguish the differing levels of resilience exhibited by individual high streets. The first crucial factor linked to high street success and resilience is the dominant store category. For example, Powe (2006) found that rural high streets with high individuality, cultural activities and eateries such as Hexham, Alnwick and Morpeth in Northumberland were found to attract a high volume of urban visitors. In addition, Dolega and Lord (2020) have found that retail composition is shaped through the growth of different retail types occurring at different rates, with different areas plateauing and expanding simultaneously in the same high street.

Generally, across most high streets there has been a reorientation towards leisure and convenience services driving positive growth in both sectors (Coca-Stefaniak, 2013). Consequently, Pinkerton et al.’s (1995) work on residents’ consumption behaviour within their local community could be applied to the present rise in convenience shopping. Pinkerton et al. (1995:1) suggest that consumers’ socio-economic status, personal location and community satisfaction influences whether an individual shops locally (‘inshopping’). In contrast the range of goods and services available dictates whether an
individual travels to shop (‘outshopping’). Consequently, a precise assessment of resilience could be made through building an understanding of the specific high street stores, including essential and convenience stores, that are available to the local population. By understanding existing retail structures and users, high street re-imagination strategies can be tailored to satisfy existing consumers or attract new ones (de Noronha et al., 2017).

The second important component of high street resilience is the vacancy rates of high streets before the COVID-19 pandemic. Prior to the pandemic, high streets had already been facing numerous problems, including loss of attractiveness to investors (Jones, 2010). Grenadier’s (1995) work on real estate cycles can be applied to explain the reluctance of landlords to fill vacant spaces in downward markets, as seen during the 2008 recession. This is because it is a more cost-effective option for landlords to retain the current environment of vacancy. The cost of vacancy is enough to offset the possible benefits of filling a vacant space. Therefore, if high streets were already struggling with high vacancy rates, the economic shock caused by the pandemic may have exacerbated their inability to fill vacant premises. For example, following the 2008 recession, vacancy rates rose substantially, further intensified by multiple large national retailers falling into insolvency (Jones, 2010). The Local Data Company (LDC, 2009) reported that during the year after the recession hit, 10.8 per cent of high streets across the UK consisted of empty floor space. Nevertheless, LDC also reported that some towns displayed double the national average, revealing clear disparities in the impacts of the downturn.

Therefore, it is important to investigate high streets’ vacancy rates before the pandemic and the degree to which they rose or fell following the easing of restrictions on non-essential retail in May 2021. The last recession resulted in clothing, footwear and personal goods stores being hardest hit, while food and household stores had the lowest levels of closures (Thomas and Shah, 2009). Post-lockdown conditions may result in rises in vacancy due to similar patterns of store closures, especially since clothing and leisure facilities were among those forced to close.

One final indicator for high street resilience is occupier turnover. Such a measure is critical to understanding an area’s pace of change, controlling for other aspects including assets or unavoidable losses. A measure of occupier change should be used in conjunction with vacancy rates to measure and rank the speed at which retail locations change the business that occupies their premises. An exploration of high street resilience should be able to incorporate the probability of a shop thriving in an area and the consequential evaluation of consumer needs.

6.3 COVID-19 Lockdown Impacts

British high streets were already facing a multitude of different challenges resulting in low numbers of visitors prior to the COVID-19 pandemic. The arrival of the pandemic then added a number of additional reasons for consumers to be deterred from high streets including risk of transmission and various restrictions. The timeline number of restrictions
is multiple and complex to follow. Therefore, details outlining the restrictions and events relating directly to retail or high street experience have been outlined in Table 6.1.

<table>
<thead>
<tr>
<th>Date</th>
<th>Key event</th>
</tr>
</thead>
<tbody>
<tr>
<td>16/03/2020</td>
<td>Social distancing, working from home and cease of non-essential travel encouraged. People encouraged to avoid leisure premises such as pubs, clubs and theatres.</td>
</tr>
<tr>
<td>20/03/2020</td>
<td>Shops selling non-essential items forced to close.</td>
</tr>
<tr>
<td>24/03/2020</td>
<td>Lockdown put in place.</td>
</tr>
<tr>
<td>15/06/2020</td>
<td>Non-essential shops allowed to re-open in England with social distancing measures.</td>
</tr>
<tr>
<td>29/06/2020</td>
<td>In Scotland, high street shops and retail allowed to re-open.</td>
</tr>
<tr>
<td>04/07/2020</td>
<td>Pubs, cafes, bars and self-care businesses allowed to re-open in England.</td>
</tr>
<tr>
<td>13/07/2020</td>
<td>Hairdressers, outdoor areas of pubs and restaurants, outdoor cinema, most indoor visitor attractions and places of worship allowed to re-open in Wales.</td>
</tr>
<tr>
<td>15/07/2020</td>
<td>In Scotland, hairdressers, pubs, restaurants, visitor attractions, cinemas and places of worship allowed to re-open.</td>
</tr>
<tr>
<td>27/07/2020</td>
<td>‘Close contact’ services such as beauty salons, indoor cinemas and museums allowed to re-open in Wales.</td>
</tr>
<tr>
<td>03/08/2020</td>
<td>Eat Out to Help Out scheme, offering a 50% discount on meals up to £10 per person in the UK. Pubs and restaurants, bowling alleys and bingo halls allowed to open indoors in Wales.</td>
</tr>
<tr>
<td>14/08/2020</td>
<td>Indoor theatres, bowling alleys and soft play allowed to re-open in England.</td>
</tr>
<tr>
<td>22/09/2020</td>
<td>Across the UK hospitality businesses forced to close at 10pm and only able to provide table service.</td>
</tr>
<tr>
<td>23/09/2020</td>
<td>Scotland enforces a national 10pm curfew for pubs, bars and restaurants.</td>
</tr>
<tr>
<td>19/10/2020</td>
<td>Wales has a ‘circuit break’ lockdown until the 9th November.</td>
</tr>
<tr>
<td>05/11/2020</td>
<td>Local lockdowns put in place. Shops selling non-essential items forced to close.</td>
</tr>
<tr>
<td>02/12/2020</td>
<td>Lockdown ends with England having a three-tier system of restrictions.</td>
</tr>
<tr>
<td>04/12/2020</td>
<td>In Wales pubs, bars, restaurants and cafes forced to close at 6pm and not allowed to serve alcohol.</td>
</tr>
<tr>
<td>24/12/2020</td>
<td>In Wales all non-essential retail, close contact services and leisure and fitness centres forced to close.</td>
</tr>
<tr>
<td>25/12/2020</td>
<td>In Wales all hospitality services forced to close</td>
</tr>
<tr>
<td>05/01/2020</td>
<td>Scotland goes into lockdown.</td>
</tr>
<tr>
<td>06/01/2021</td>
<td>Lockdown put in place. Shops selling non-essential items forced to close.</td>
</tr>
<tr>
<td>22/03/2021</td>
<td>In Wales, restrictions on the sale of non-essential items listed for those shops already open.</td>
</tr>
<tr>
<td>05/04/2021</td>
<td>In Scotland, hairdressers, garden centres, car showrooms and homeware stores and non-essential click and collect services allowed to re-open.</td>
</tr>
<tr>
<td>12/04/2021</td>
<td>Non-essential retail, hairdressers, public buildings (eg. Libraries and museums) allowed to re-open. Outdoor venues including pubs also allowed to re-open in England. In Wales, non-essential retail allowed to reopen.</td>
</tr>
<tr>
<td>15/04/2021</td>
<td>In Wales, hairdressers and barbers allowed to re-open.</td>
</tr>
<tr>
<td>26/04/2021</td>
<td>In Scotland, hospitality venues including cafes, pubs and restaurants allowed to re-open.</td>
</tr>
<tr>
<td>17/05/2021</td>
<td>Indoor venues allowed to re-open including pubs, restaurants and cinemas with ‘Rule of six’ or two households allowed for indoor gatherings in England and Wales.</td>
</tr>
</tbody>
</table>
From this table, the two major events that occurred relating to retail were perhaps the enforcement of the Britain-wide lockdown on the 23rd March 2020 and then the re-opening of non-essential retail hospitality in May 2021 with the total removal of all restrictions impacting high streets being lifted in July and August 2021.

During the periods of time which consisted of continual shifts between being in lockdown and somewhat normal functioning, the implications for trade within high streets became apparent (Enoch et al., 2021). In 2020 economic indicators suggested that Britain had entered a recession with stark implications for high street businesses. However, the impact on businesses was not uniform with some types actually benefiting from the crisis. Stephenson (2020) found that varying retail performance indicated that high streets that are predominantly retail focused were impacted to differential degrees. The reasons behind differing high street resilience include their e-presence or e-resilience (Jones and Livingstone; Singleton et al., 2016) and their retail offering and service provision (Dolega et al., 2019). Other factors contributing to resilience to the lockdowns could include pre-pandemic vacancy. A similar case study of the impacts of economic shock were explored in Tselios’s (2018) study on the implications of the 2008 recession on high streets. The study found that for those high streets with lower vacancy rates before the recession, they were less negatively affected. Nevertheless, these effects were also found to be influenced by the size and location of the high street. Despite this evidence, Enoch et al. (2021) has stated that the ways in which high street activity relates to their vulnerability against economic shock remains under researched alongside high streets capacity and trajectory to recover.

The first lockdown that was enforced by the UK government on the 23rd March 2020 aimed to reduce the spread of the COVID-19 virus, yet it produced a unique opportunity to investigate the factors influencing high street resilience. To date there is arguably limited research that measures high street research. The majority of existing measures of high street resilience predominantly rely on vacancy rates that are typically difficult to determine at a high street level across the whole of Britain. Nevertheless, this research’s access to the nationwide dataset on store location provided by the LDC enables a fuller indication of business resilience. The high spatial granularity of the data alongside frequent updates allows for in-depth analysis to inform decision making and reactive interventions. Another additional under researched area of resilience analysis is a comprehensive investigation of short-term recovery from economic shock and the relationship to adaptive resilience and ability to develop new trajectories to achieve growth (Dolega and Celińska-Janowicz; 2015). Such an understanding of short-term
resilience and recovery can inform future strategies and contextual understanding of the resulting stages of reorganisation within high streets.

6.4 COVID-19 Policy Impacts

Even before the COVID-19 lockdown restrictions triggered the local purchasing of essential items, smaller formats of grocery and convenience stores had been growing at a more rapid rate than large out-of-town supermarkets (Nielsen, 2015). Consequently, in 2016 IGD estimated that convenience stores accounted for 20.9% of food sales in the UK and predicted an 11.7% increase by 2021 (Wood, 2017). Furthermore, Dolega and Lord’s (2020) research also pointed to a rise in convenience culture and suggested that some retail areas that are in decline stabilise through a change in their wider retail environment that emphasises convenience stores, charity shops or discount stores.

In light of the COVID-19 lockdown restrictions leisure destinations in dynamic central settings suffered the largest reductions in activity, while retail centres which catered for the local population’s needs had a faster recovery in activity (Trasberg et al., 2021). Batty et al.’s (2021) analysis of Google Mobility Reports for London boroughs revealed that local grocery shopping declined the least out of all activity types during the lockdown to no less than 50% of normal activity. The analysis notably uncovers trends within the City of London, which experienced a pronounced drop to about 90% below normal activity before only returning to no more than 50% of the baseline, between 10th February 2020 up until the time of data collection on 18th October 2020.

Modified mobility patterns due to the lockdown restrictions have resulted in some areas recovering at faster rates than others. Quinio’s (2021) preliminary study found that Britain’s largest cities were the slowest to recover after the lockdowns. However, whilst Quinio suggests that large cities such as London, Manchester and Birmingham, or cities with many food and drink amenities, only require a return in footfall to recover, it may be undesirable for some smaller towns to return to their pre-pandemic state if they struggled with high vacancy and high occupier turnover.

While Quinio’s (2021) study utilises activity levels as a measure of resilience; there may be room to expand the analysis into a more concrete reflection of high street success. Other early studies into the impact of the pandemic, such as Gathergood et al.’s (2020) paper on the lockdown’s impact on consumer behaviour, begin to uncover the uneven regional nature of retail recovery. The strongest recovery has been in online spending in outer London as working from home practices have been seen to displace the location of spending. The study draws distinctions between online and offline spending during the second half of 2020. However, there is scope to explore whether there is a relationship between the retail composition of high streets and their associated resilience under lockdown.

This research aims to acknowledge and integrate current policy, which has adapted and responded to the changes created by the pandemic. One particular government response introduced in August 2020 to target the hospitality sector, which was particularly hard-hit by lockdown restrictions, was the Eat Out to Help Out scheme (GOV.UK, 2020). Via
government subsidies, this enabled participating businesses in Britain to offer a 50% discount from Monday to Wednesday with up to £10 off per person for food or non-alcoholic drinks consumed at the venue. González-Pampillón et al.’s (2021) study on the impact of the Eat Out to Help out scheme found that there was higher footfall associated with recreational activities on the days when the discount was available. However, the scheme was not a resounding success in terms of high street regeneration, with the study finding that on the whole it did not persuade people to use high streets for other purposes or to continue eating out once the subsidy had come to an end.

During the pandemic, city planning orientated around convenience also gained more traction. The “15-Minute City” originally proposed by Carlos Moreno in 2016 has increased in popularity due to its emphasis on proximity-centric planning, whereby neighbourhoods are planned to provide residents with basic essential services within a 15-minute walk or bicycle ride. The original concept has been reimagined and adapted to promote sustainability and resilience, and to emphasise identity in the post-pandemic era of town centres (Moreno et al., 2021). In particular, the authors argue that proximity-based planning may be more beneficial than aspects of the Smart Cities concept, which can arguably strengthen underlying social inequalities (Allam and Dhunny, 2019). Examples of local high street action adopted in response to the pandemic include the Mayor of London’s ‘High streets for all challenge’ that funded 35 projects, aiming to address local challenges and promote strategies to re-imagine high streets across London (Mayor of London, 2021). The Greater London Authority’s mission acknowledges that the pandemic-related challenges faced by high streets are uneven across the London boroughs. Such initiatives may therefore benefit from a quantitative measure of resilience which can be used to prioritise funding for individual high streets within boroughs that have been particularly impacted by the pandemic.

6.5 Data and Methods

For this chapter, the same primary dataset used throughout this thesis has been used. Consequently, the data used for this chapter is the LDC dataset on retail type, address and vacancy and comprises of the location, occupier status (including if vacant) and retail category (e.g. pub, clothing store, restaurant) for 500,000 premises in Britain. Why this dataset is vital to the analysis conducted within this chapter is because it provides the exact location and subcategories of premises across the whole of Britain. Therefore, premises can not only be identified as being part of a high street or not, but it also enables an evaluation of the premises business function. This allows for the identification of stores that were allowed to remain open during periods of lockdown covered in this chapter. The end date for the dataset is 28th June 2021, during this time across all three British nations, the majority of businesses were allowed to re-open, never to have restrictions imposed on them again. However, there is the exception of nightclubs that were allowed to re-open on the 19th July 2021 in England, the 7th August 2021 in Wales and 9th August 2021 in Scotland. The last nation to completely remove restrictions that could impact the way consumers interact with high streets was Scotland where legal requirements for physical distancing and limits on social gatherings were not removed until 9th August 2021 (see Table 6.1).
In addition, in-line with the previous chapters within this thesis, alongside the store location data, the Consumer Data Research Centre's (CDRC) retail centre boundaries and classification system has been used to define the geographic extent of each of the high streets. The CDRC retail boundaries were developed using open-source geo-coded retail unit location and land use data. The retail data was then aggregated to Uber’s (2018) Hexagonal Hierarchical Spatial Index (H3), which offers nested hexagon geometries at a range of granularities. The CDRC’s resulting hierarchical classification system is based on retail count, density and ranking within the respective local area to identify the prominence of each retail centre, aiming to capture variation between regional centres, market towns, small local centres, shopping centres, and retail outlets. This research selected the CDRC boundaries classified as either a district centre, small local centre, local centre, major town centre, regional centre, market town, town centre. The different categories have been included in order to encapsulate both ‘town centres’ and ‘secondary level’ high streets and local town centres within conurbations, local parades and neighbourhood centres. Other retail structures such as out of town retail parks are excluded (Wrigley and Lambiri, 2014:5). This is particularly important since secondary level high streets and local town centres are often under-reported and can be more resilient to economic shock (Findlay and Sparks, 2012). The LDC retail location dataset was then joined with the selected CDRC retail boundaries. Only the boundaries that included 15 or more retail location points were used within the analysis, a threshold in line with the Office for National Statistics (ONS) and Ordnance Survey (OS) joint definition of a ‘high-street’ (Ordnance Survey, 2019). The full description of how the high street boundaries were developed are in section 3.3.

This chapter builds upon the resilience variable and resilience analysis used in the previous chapter to extend the research to all the high streets in Britain with a central focus on measuring the impact of the government enforced lockdown restrictions. The LDC store location data within each high street boundary was used to create 4 new variables, summarised in Table 6.2: Occupier Change 2019, Vacancy 2019, Vacancy 2021 and Proportion of Essential Stores/ Services 2019.

<table>
<thead>
<tr>
<th>Variable label</th>
<th>Attribute</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vacancy (2019)</td>
<td>6-month average for January - June 2019 for number of vacant properties/ total stores within a high street.</td>
</tr>
<tr>
<td>Vacancy (2021)</td>
<td>Number of vacant properties/ total stores within high street for June 2021.</td>
</tr>
<tr>
<td>Occupier change (2019)</td>
<td>Number of new stores opened between January-June 2019/ total number of stores within a high street.</td>
</tr>
<tr>
<td>Essential Retail/ Services (2019)</td>
<td>6-month average for January- June 2019 for number of stores allowed to remain open during lockdown restrictions/ total number of stores within a high street.</td>
</tr>
</tbody>
</table>

Table 6.3: Variable descriptions and attributes.

Firstly, in order to acknowledge what Dolega and Celińska-Janowicz (2015) suggest as adaptive resilience, this chapter includes a measure of pre-pandemic occupier change. This is due to resilient high streets often having the ability to develop new paths of growth
including expanding its composition diversity or adapting to changing consumer trends. Consequently, to secure a robust basis for encapsulating the pre-pandemic occupier change, the first six months of 2019 have been selected as the baseline time period, due to January-June being the period in which most new businesses open for the first time (Aldermore, 2017). For January-June 2019 the number of new shops that opened was divided by the number of stores within the high street, to gain a measure of the percentage of premises which had new occupiers.

The second measure aimed to encapsulate pre-pandemic high street performance. Therefore, for the same period, the number of shops that were vacant at the end of each month were divided by the number of stores within each high street, to gain a measure of the proportion of stores which were vacant. A six-month average for the vacancy of each high street was then calculated for January-June 2019. While vacancy is used as a measure of success or high street performance within this chapter it openly acknowledges the limitations of such use. While the LDC’s high granularity does give Britain wide coverage of vacant premises, allowing for a calculation of vacancy at high street level there are some conceptual issues with using their data as a measure of success or resilience. Firstly, vacancy rates often are more likely to indicate the viability of a business based on rental charges, the aesthetics, functionality and location of a premises as appose to an accurate depiction of the vitality of the business itself (Findlay and Sparks, 2010). Secondly, the LDC data that is collected by researchers surveying the status of premises is not recorded at consistent intervals across the whole of Britain. Therefore, there was a risk that the pre-pandemic vacancy rates calculated within this chapter would be what Enoch et al. (2021:1094) denotes as ‘generic percentages’ missing out important temporal granularity that is essential for high street management decision making and dynamic placemaking strategies. Therefore, to overcome this limitation, the pre-pandemic vacancy rate has been calculated in the same time period as occupier change enabling a 6-month average, to minimise discrepancies in the frequency of LDC premise surveys. Thirdly, to measure post-lockdown vacancy, the number of vacant stores at the end of June 2021 was divided by the number of stores within each high street. Due to inconsistent data collection during the lockdown and temporary closures of stores, June 2021 was used to calculate the post-lockdown measurement of vacancy. In this case, minimising the error caused by the disruptions in recordings during the lockdown periods was deemed more important than creating an average vacancy rate for the first 6-months of 2021. In addition, by the end of June 2021 all retail premises which had temporarily closed due to the lockdown restrictions would have re-opened by 17th May 2021.

While the data includes high streets in Wales and Scotland, where lockdown restrictions differed slightly during the pandemic (see Table 2.1), the general distinctions between shops that were allowed to remain open between March 2020 and May 2021 and those deemed as ‘non-essential’ and forced to close were relatively consistent. With this in mind the final attribute was calculated as the 6-month average (January-June 2019) of the number of stores allowed to remain open during the various retail specific lockdown restrictions occurring between March 2020 and May 2021. The essential store categorisation are the same as those described in Chapter 3, where more detail is provided on the variable.
Assessing the impact of retail lockdown restrictions between March 2020 and May 2021 in Britain presents numerous empirical challenges, given that a number of factors may explain vacancy rates before the pandemic and additionally changes to vacancy following the lockdowns. Therefore, this research utilises the 4 high street characteristic variables to investigate the relationship between pre-pandemic vacancy, occupier change and ‘essential’ store and services proportion on post-restriction vacancy through using two ordinary least squares (OLS) regression models. The first model tests the hypothesis that pre-pandemic levels of occupier change, vacancy and essential retail proportions are associated with vacancy levels following the easing of lockdown restrictions. Consequently, the second model tests the hypothesis that pre-pandemic vacancy moderates the association between proportion of essential retail stores and services with post-restriction vacancy.

Central to this study is the idea that we should account for the geographical distribution of performance-related characteristics. Literature relating to retail distribution and hierarchy has been drawn upon to select appropriate methods for the creation of a high street hierarchy. The majority of retail distribution models combine 20th Century land use theories with central place theory or growth pole theory (Forbes, 1972; Parr, 2017). Such broad and early analyses are conditional on simple datasets and consist of small snapshots in time, making it difficult to monitor the changing nature of the retail areas. Consequently, the final outcome of this research is the formation of a high street typology, using the LDC’s wide coverage and granular data and created using hierarchal clustering with spatial constraints. The ClustGeo package has been used for the implementation of a ward-like hierarchical clustering algorithm with soft contiguity constraints (Chavent et al., 2018). The package aims to increase spatial contiguity without deteriorating the quality of the homogeneity of the socio-economic variables included in the calculation. The ward-like hierarchical clustering approach has been selected to ensure that store locations with similar characteristics will not be placed into different clusters if they are spatially distant. The geographic constraint is an important part of this chapters measure of resilience as it enables the incorporation of factors such as high streets benefitting from strong regional supply chains (Wrigley et al., 2015). Additionally, the method avoids the issue of having to define weights for geographical dissimilarities. An overview of the whole methodological process for the this chapter is presented in Figure 6.1.
Methodological Process

- Select CDRC boundaries that are district centres, small local centres, local centres, major town centres, regional centres, market towns or town centres.
- The selected boundaries are used as high streets in Britain.
- LDC retail location data spatially joined with the high street boundaries.
- High streets selected with 15 or more stores within them.
- First model tests the hypothesis that Vacancy (2021) is related to Vacancy (2019), Occupier Change (2019) and Essential Stores or Services (2019).
- Ward-like hierarchical clustering algorithm with contiguity constraints creates clusters and final ranking of resilience.

Figure 6.1: Overview of methodology.

6.5 Results

The granularity of the LDC data enables a straightforward distinction between stores forced to close and those essential stores allowed to remain open during lockdown. Descriptive statistics for all the variables can be found in Table 6.3. The overall vacancy rate for all high streets in 2019 was 9.0%, rising to 12.0% in 2021. The mean occupier change was 0.68% and the average essential retail proportion for British high streets was 43.61%.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Average</th>
<th>Median</th>
<th>Standard Deviation</th>
<th>Maximum</th>
<th>Minimum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vacancy (2019)</td>
<td>9.00</td>
<td>8.27</td>
<td>4.75</td>
<td>30.23</td>
<td>0.81</td>
</tr>
<tr>
<td>Vacancy (2021)</td>
<td>11.95</td>
<td>10.62</td>
<td>5.82</td>
<td>34.20</td>
<td>1.55</td>
</tr>
<tr>
<td>Occupier change (2019)</td>
<td>0.68</td>
<td>0.34</td>
<td>0.86</td>
<td>5.36</td>
<td>0.00</td>
</tr>
<tr>
<td>Essential Retail/Services (2019)</td>
<td>43.61</td>
<td>44.10</td>
<td>9.26</td>
<td>72.17</td>
<td>17.86</td>
</tr>
</tbody>
</table>

Table 6.4: Descriptive statistics for the dependent and predictor variables.
The Pearson’s correlation coefficients between the dependent variable, vacancy (2021) and the predictor variables of vacancy (2019), occupier change (2019) and essential retail and service proportion (2019) have been calculated and presented in Table 6.4. Vacancy in 2019 and percentage of essential stores and services within a high street were found to be significantly correlated to vacancy in 2021. The correlation coefficient between vacancy 2019 and vacancy 2021 is positive. In contrast, the correlation coefficient between essential retail and services % in 2019 and vacancy 2021 is negative. Meanwhile, occupier change, 2019 was found to be positively correlated with vacancy in 2019. Variance inflation factor (VIF) was used to test for multicollinearity, due to one of the correlation coefficients being as high as 0.8 (Menard, 2002).

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Vacancy (2019)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vacancy (2021)</td>
<td>0.79**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Occupier change (2019)</td>
<td>0.06</td>
<td>0.13**</td>
<td></td>
</tr>
<tr>
<td>Essential Retail/ Services (2019)</td>
<td>-0.56**</td>
<td>-0.40**</td>
<td>-0.08</td>
</tr>
</tbody>
</table>

Note: *Sig. <0.05 **Sig. <0.01 (two-tailed)

Table 6.5: Pearson’s correlation coefficients between the dependent and predictor variables.

OLS regression has been conducted to investigate the influence of the 3 independent variables on vacancy in 2021. The results of estimating the stepwise OLS regression models are reported in Table 6.5. Model 1 shows the results for the direct effects of Vacancy %, Essential Retail/ Service % and Occupier Change % in 2019 on Vacancy 2021. It indicates a clear relationship between the predictor variables and the high street vacancy levels following the lockdown restrictions, despite other additional exogenous variables being excluded (e.g. local lockdown restrictions and local authority interventions). From Model 1 it can be observed that Vacancy 2019 has a strong significant effect on Vacancy in 2021 (b=0.84, p=<0.001. Additionally, % of essential stores and services in 2019 was found to have a moderate negative effect on Vacancy in 2021 (b=-0.18, p=<2e-16), holding constant all other independent variables. Occupier change % was also found to have a moderate negative effect on vacancy 2021 b=-0.39, p=0.023). For the independent variables in model 1, the highest VIF value of 1.21 was well below the cut-off measure of 10, suggesting that multicollinearity was not having a biasing effect on the OLS estimations (Menard, 2002).

Model 2 shows the results for the interaction effect between Vacancy and Essential Retail/ Service % in 2019. It can be observed that Vacancy 2019 retains its significant effect on Vacancy in 2021. In addition, the model shows that the interaction term is negatively and significantly associated with Vacancy 2021, therefore the strength of the association between Vacancy 2019 and Vacancy 2021 is weaker in high streets that had a higher proportion of stores that were allowed to remain open during the retail related lockdown restrictions.
### Table 6.6: British high street level vacancy for 2021. Estimation method: Robust OLS.

The second stage of this research was to create a geographical typology of high street resilience using all the indicators of resilience explored so far in this chapter. The variables used within the hierarchical clustering with spatial constraints are Occupier Change (2019), Essential Retail/Service % (2019) and Vacancy (2019). A typology has been devised based on pre-pandemic high street characteristics in order to evaluate which geographical areas of specific attributes had the lowest rise in vacancy. The method for conducting hierarchical clustering with spatial constraints outlined in Chavent et al.’s (2017) considers two dissimilarity matrices. Firstly, D0 is the Euclidean distance matrix between the n high streets determined by the variables, occupier turnover vacancy, and essential retail and services %. Secondly, D1 is the dissimilarity matrix used to account for the straight-line Euclidean distances between the n high street centroid locations. D0 is equal to the occupier turnover and vacancy and essential retail and services distances and D1 is equal to the geographic distances between the municipalities. In order to select a suitable number of K clusters, a dendrogram for the high streets was created using D0 only. The dendrogram captures each hierarchical step in the model, allowing for different clustering solutions to be visually explored. Based on Kirk’s (2021) interpretation guidance the dendrogram favoured a four-cluster solution.

The introduction of a geographical constraint (D1) required a mixing parameter to set the importance of the constraint in the clustering process and improve the geographical cohesion of the four clusters, without jeopardising the cohesion between the vacancy, occupier change and essential retail and service percentages of the high streets. The geographic constraint is an important part of the resilience measurement, since it can be a proxy for factors such as ‘linked shopping behaviour’, which is influenced by the proximity of high streets to larger retail centres (Wrigley et al., 2015). Additionally, research has found that while the resilience of individual retailers can be inadequate in responding to external shock, retailers even with an indirect association with the wider town centre or regional centre can benefit from what the network has to offer such as

<table>
<thead>
<tr>
<th>Predictor variables</th>
<th>Model 1: Direct effects</th>
<th></th>
<th>Model 2: Interaction effect</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>p-value</td>
<td>VIF</td>
<td>Estimate</td>
</tr>
<tr>
<td>Intercept</td>
<td>12.5288</td>
<td>&lt;2.2e-16</td>
<td></td>
<td>7.26***</td>
</tr>
<tr>
<td>Vacancy (2019)</td>
<td>0.84***</td>
<td>&lt;2.2e-16</td>
<td>1.21</td>
<td>1.46***</td>
</tr>
<tr>
<td>Essential Retail/Services (2019)</td>
<td>-0.18***</td>
<td>&lt;2.2e-16</td>
<td>1.19</td>
<td>-0.049</td>
</tr>
<tr>
<td>Occupier change (2019)</td>
<td>-0.39*</td>
<td>0.023</td>
<td>1.02</td>
<td>-0.30</td>
</tr>
<tr>
<td>Vacancy (2019) X Essential Retail/Services (2019)</td>
<td>-0.016***</td>
<td>5.47e-06</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R2</td>
<td>0.701</td>
<td></td>
<td></td>
<td>0.7136</td>
</tr>
<tr>
<td>Adjusted R2</td>
<td>0.6991</td>
<td></td>
<td></td>
<td>0.7112</td>
</tr>
<tr>
<td>p-value</td>
<td>&lt;2.2e-16</td>
<td></td>
<td></td>
<td>&lt;2.2e-16</td>
</tr>
</tbody>
</table>

*Note: *Sig. <0.05 **Sig. <0.01 (two-tailed)
shared knowledge and partnerships (Edström, 2018). An \( \alpha \) value of between 0 and 1 could be used to set the relative importance of the geographical constraints against the resilience variables whereby \( \alpha = 0 \) meant no geographical constraints whilst \( \alpha = 1 \) excluded the resilience variables. The separate calculations for the performance indicator homogeneity and for the geographic cohesion of the partitions obtained a range of values between 0 and 1 for the four high street clusters. The values were plotted and used to choose an \( \alpha \) value that provides a compromise between the loss of performance indicator homogeneity and a gain of geographic cohesion. A value must be chosen that does not lose too much performance indicator value homogeneity but also increases geographic homogeneity. The value of \( \alpha = 0.4 \) was chosen on this basis, resulting in a loss of homogeneity between the resilience indicator values of 22% but an increase of geographical homogeneity of 37%. New partitions were then obtained with \( \alpha = 0.4 \) using the ‘hclustgeo’ function in the Clustgeo package to gain geographic cohesion.

Table 6.6 records the descriptive statistics for each hierarchical cluster formed with spatial constraints, alongside the geographic regions within Britain that the high streets are situated.
Table 6.7 displays the 4 different clusters ranked in order of their average rise in high street vacancy following the easing of retail specific lockdown restrictions and their associated qualities to create a typology of resilience.
<table>
<thead>
<tr>
<th>Resilience (Highest to lowest)</th>
<th>Location</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average stability with low pre-pandemic vacancy, high essential retail and services %</td>
<td>London, Southeast, East of England, Wales</td>
<td>- Average number of new stores opening pre-pandemic.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Low vacancy pre-pandemic.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Many convenience or essential retail stores and services, pre-pandemic.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Lowest increase in vacancy following easing of retail lockdown restrictions.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Moderate vacancy pre-pandemic.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Moderate number of convenience or essential retail stores and services, pre-pandemic.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Average increase in vacancy following easing of retail lockdown restrictions.</td>
</tr>
<tr>
<td>Unstable with high pre-pandemic vacancy, low essential retail and services %</td>
<td>Scotland, Northwest, Northeast, East Midlands, Yorkshire and the Humber, West Midlands</td>
<td>- Many new stores opening pre-pandemic.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- High vacancy pre-pandemic.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Low proportion of convenience or essential retail stores and services, pre-pandemic.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Moderate increase in vacancy following easing of retail lockdown restrictions.</td>
</tr>
<tr>
<td>Unstable with average pre-pandemic vacancy, lowest essential retail and services %</td>
<td>London, Southwest, Southeast, East of England, Wales</td>
<td>- Many new stores opening pre-pandemic.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Average vacancy pre-pandemic.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Lowest proportion convenience or essential retail stores and services, pre-pandemic.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Highest increase in vacancy following easing of retail lockdown restrictions.</td>
</tr>
</tbody>
</table>

Table 6.8: British high street resilience qualities. Estimation method: Hierarchical clustering with spatial constraints.

Figure 6.2 displays the 4 different clusters visually as the centroid of each high street boundary with their associated cluster and resilience qualities.

Figure 6.2: High streets in Britain, as the centroid of the Consumer Data Research Centre’s retail boundaries (classified by hierarchical cluster with spatial constraints)

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The findings from the hierarchical clustering with spatial constraints show that the most resilient high streets to the impact of the retail specific lockdown restrictions were those with average occupier change averaging at 0.69% and the lowest average vacancy of 7.21% in the first 6 months of 2019, before the pandemic hit. The high streets predominantly situated in London, and the East of England, with the additions of Southern Cross, Brighton and Splott, Cardiff, also have the highest proportion of essential retail stores or services at an average of 56.63% of stores allowed to remain open during the retail specific lockdown restrictions. As a result, the most resilient cluster had an average rise in high street vacancy of 0.89%. In contrast, the least resilient cluster of high streets had an average increase in vacancy of 5.13% and are situated within the regions of the Southwest, Southeast, London, East of England and Wales. The cluster of high streets with the lowest resilience, also had an unstable retail environment with the proportion of occupier change in January-June of 2019 to be 0.81%. Interestingly, the cluster of high streets had an average vacancy percentage for the first 6 months of 2019 at 9.89%. However, the cluster did have the lowest proportions of essential stores or services which were allowed to remain open at 31.17%.
Figure 6.3 displays a hexagonal heatmap of the 2d bin counts for each individual classified hierarchical cluster with spatial constraints for vacancy before the COVID-19 pandemic and after all lockdown restrictions to retail were lifted. Figure 6.4 shows a scatterplot for the relationship between the proportion of essential stores and services allowed to remain open during the COVID-19 retail specific lockdown restrictions and vacancy % following the easing of those restrictions. The scatterplot displays the relationship per hierarchical cluster and outlines some specific high streets.
Some interesting case studies have been highlighted on Figure 6.4, including Northolt Road in Harrow, London, with the highest proportion of essential stores at 72%. The high street consists of what could be deemed as ‘traditional’ necessities such as banks, pharmacies, grocers and supermarkets alongside other categories that were allowed to remain open during lockdowns such as takeaways. This mixture and composition of stores proved successful in maintaining low vacancy rates as the high street recovered from the various lockdowns. In contrast, Swansea high street was situated within the category with the lowest levels of resilience due to its unstable conditions, high pre-pandemic vacancy and high proportion of stores which were forced to close during the lockdowns. These findings perhaps equate to the policy outcomes outlined within the Levelling Up the United Kingdom (2021) white paper. The UK government has suggested growth investment deals for Swansea Bay including City and Growth Deals, the Community Renewal Fund and Strength in Places Fund. Swansea’s high street is a prime example of how the COVID-19 pandemic has accentuated some pre-existing underlying trends. The area has arguably been hit harder than the rest of Britain due to a higher proportion of workers unable to work from home, particularly in the aerospace and automotive industry. In addition, there is also a history of government failure to support the industries in the area (such as steel and infrastructure), including the cancelling of the Swansea Bay Lagoon project in 2017 has held back to regions success (Sykes and Nurse, 2020). In addition, while new stores are opening within the city centre high street, they are accompanied by high vacancy rates suggesting the occupiers are unsuccessful in maintaining viability. This may be due to the area not shifting and evolving with the rise in ‘convenience culture’ and reduction in brick-and-mortar stores within successful high streets. Rodrigues et al. (2021) concurs these findings suggesting that while many cities
increase in complexity, Swansea is an area that has become less complex and has taken a step back in the last 40 years as it continues to specialise in the same activities it did in 1981 while other parts of Britain have shifted and adapted with wider economic and social trends.

6.6 Discussion

The analyses presented in this chapter have given an insight into the resilience of British high streets in response to the economic and social shock caused by the COVID-19 pandemic. The first stages of analysis found that high streets with higher proportions of stores deemed by the government as essential before the lockdown restrictions in 2019, had lower rates of vacancy following the lifting of the restrictions. Additionally, high streets that had high proportions of essential services and low vacancy before the pandemic, had resulting lower rates of vacancy in 2021, following the end of retail specific lockdown restrictions. Therefore, when the pandemic hit, pre-existing successful high streets with higher levels of essential stores and services were allowed to keep a higher proportion of their stores open during the lockdown, making them more resilient.

For those high streets with high vacancy before the pandemic, Grenadier’s (1995) work on real estate cycles can be applied to explain the reluctance of landlords to fill vacant spaces in downward markets, as seen during the 2008 recession. This is because it is a more cost-effective option for landlords to retain the current environment of vacancy is enough to offset the possible benefits of filling a vacant space. The COVID-19 pandemic has arguably exacerbated the market persistence of this type of vacancy pertaining behaviour. The pandemic has contributed to the persistence of prolonged cycles in the retail real estate market due to demand uncertainty, adjustment costs, and lags in construction.

The second part of this chapter’s research developed a typology of high street resilience based on the indicators of vacancy, essential stores or services proportion, occupier change and geographical proximity. It revealed that some high streets located in London, the Southeast, the East of England and Cardiff with average occupier change, low pre-pandemic vacancy and high essential stores or services and convenience proportion to have had the lowest rise in vacancy following the lockdown restrictions. This group of high streets included Northolt Road in Harrow, London, with the highest proportion of essential stores at 72%, and Wanstead High Street, London, which had the lowest vacancy rate following the lockdown restrictions at 2%.

The second most resilient category of high streets had pre-pandemic conditions including very low occupier churn, moderate vacancy, and an ample level of stores allowed to remain open during the lockdown restrictions. Within this category is Stockport Road in Manchester, which only had a 2% rise in vacancy after the COVID-19 restrictions due to approximately half of the stores on the high street being allowed to remain open. These high streets managed to retain their prior success through having pre-exiting stores that sufficiently met the local consumers’ needs and were mostly able to remain open for business during March 2020 to May 2021.
In contrast, high streets in London, the Southwest, Southeast, East of England and Wales with characteristics before the pandemic including: the opening of many new stores, average level of vacancy and an extremely low proportion of stores that were allowed to remain open during the lockdown restrictions were found to have the highest average rise in vacancy.

Within the least resilient cluster of high streets is Swansea which had a rise of 9.3% in vacancy and the City of London with a 9.7% rise. Specifically, the disproportionate rise in vacancy for the City of London could arguably lie in the reduced commuter population to the area caused by the lockdown restrictions. As discussed in the previous chapter, some commuter towns retained a large proportion of their population during the lockdown period with increased working from home leading to localised spending. While some commuter towns and their high streets such as in St Albans and Guildford have arguably benefitted from the pandemic, the destinations for their workers have struggled. These non-resilient high streets also had an above average proportion of new stores opening. However, these new stores were perhaps not in line with the wider cultural changes to consumer behaviour (Coca-Stefaniak, 2013; Dolega and Lord’s, 2020) – specifically, the persistent growth in convenience culture, a trend arguably exacerbated through the lockdown orders to shop locally. The instability of these high streets should be of particular importance to policy makers.

The overall findings from the resilience classification could be interpreted as quantifying Appel and Hardaker’s (2021) in-depth interviews that categorised retailers by their strategies to either return to their prior success or to attain sustainable growth by making fundamental change to adapt to fit in with the relentless encroach of the online realm into our lives. Our study found that those high streets close to the average number of store openings to be more resilient to the impact of the COVID-19 pandemic and restrictions. Such high streets also exhibited low vacancy rates to suggest that the new stores that were opening fitted in with wider societal and cultural trends making them more resilient to the economic and restrictive implications of the pandemic. One such example is Trafalgar Road in Greenwich, London, which saw multiple new stores occupy previously vacant locations, including cafés and bakeries with outside seating. The same type of high streets also had the highest proportions of essential stores and services before the pandemic. Therefore, it could be suggested that the new stores opening on these resilient high streets were either in line with the rise in convenience culture or were able to adapt to provide ‘pandemic-friendly’ options such as takeaway service or outdoor seating. The lack of restrictions on these new businesses and an additional rise in demand for their products following panic buying and consumption displacement, arguably gave these new stores a greater chance of survival (Hall et al., 2020). While this study has focused on distinctions between high streets based on the number of stores allowed to remain open during the lockdowns, there is the possibility that the regression model omitted essential explanatory variables leading to errors. Such potential explanatory factors include the impact of the 3 and subsequently 4 Tier system in England between 14th October 2020 and 6th January 2020 where local restrictions were enforced. Unevenly distributed restrictions across English authorities may have led to disproportionate economic impact.
across high streets. Other influential factors might include high street businesses response to Government support including business rates relief, the lease forfeiture moratorium and the furlough scheme.

6.6.1 London borough of Camden high street examples

Within chapter 4, the success of the high streets within the London borough of Camden were evaluated in the context of ‘vibrancy’. Therefore, this next section will briefly compare some examples of high streets within Camden in terms of their pre-lockdown and post-lockdown success using the concepts of vibrancy and resilience. Prior to the pandemic, West Hampstead and Finchley Road high streets were characterised by their stability, presence of leisure chain premises and low vacancy. When measuring their resilience, both high streets fit into the second most resilience category ‘Stable with moderate pre-pandemic vacancy and essential retail and services %’ with an average rise in vacancy of 2%. Both high streets had a reasonable number of stores that were able to remain open during the lockdown period with Finchley Road having 41% and West Hampstead having 50%. Nevertheless, as defined by the k-means clustering composition typology in chapter 4, the majority of the stores forced to temporarily close would have been leisure chain stores. Although, academic studies (Hall et al. 2001; Reynolds and Schiller 1992) have ranked high streets as more successful based on prioritising chain stores over independents, due to a lack of chain stores often indicating poor business conditions and a low population which are undesirable conditions for chain businesses to invest in. Consequently, this raises an important point on the distinction between vibrancy and resilience. As while Finchley Road and West Hampstead can be classified as resilient, their large dominance of national chains can cause the inevitable displacement of smaller independent stores with homogenisation of local places leading to a reduced diversity in what high streets offer (Duignan, 2018). These threats to the urban landscape are of particular problem in communities made up of vibrant projects and where small businesses play an essential role in the areas economic and social vibrancy, identity and market competition (Everett, 2016).

Prior to the pandemic Camden Town high street had disproportionately higher rates of occupier change and higher vacancy rates. Consequently, Camden Town fell into the least resilient category characterised by being ‘Unstable with average pre-pandemic vacancy, lowest essential retail and services %”. Before the pandemic, Camden town was characterised as a vibrant place that had the capacity to have a high turnover in occupiers while maintaining relatively low vacancy rates. However, due to Camden Town’s high street having a low proportion of shops allowed to remain open during lockdown periods (only 33%) the high street and the businesses within it were arguably at risk. Nevertheless, as outlined in chapter 4, Camden Town predominantly relies on its tourist industry. As Quinio (2021) has suggested resilience is subject to relative recovery with some areas relying on specific populations of consumers to return. Therefore, Camden Town high street will require the return of tourists for the area to become vibrant once again which is likely, since the pandemic has done little to alter the rich history and culture of the area.
6.7 Chapter Summary

Through reporting geographical disparities in high street resilience, this chapter has aimed to inform discussion related to policy tools for town centre recovery and revitalisation following the lockdowns. Large, up-to-date granular data sets such as that of the Local Data Company provides the possibility for local authorities to understand their high streets’ composition and resilience qualities. In particular, geographically targeted policies can be tailored to promoting adaptive resilience in vibrant areas or stability in those areas which have unstable occupier conditions.

More specifically, this chapter found that high streets with a higher proportion of essential stores before the lockdown restrictions, had lower rates of vacancy following the lifting of the restrictions. Additionally, high streets that had high proportions of essential stores and low vacancy before the pandemic, had resulting lower rates of vacancy in 2021. Therefore, when the pandemic hit, high streets with higher levels of essential stores pre-pandemic were allowed to keep a higher proportion of their stores open during the lockdown, making them more resilient. The COVID-19 induced closures were in sectors that were already in a state of decline, while essential retail and café culture were ascendant components of high street culture. From this perspective, the COVID-19 restrictions accelerated a secular trend but did not itself cause it.

The second part of this chapter developed a typology of high street resilience utilising hierarchical clustering with spatial constraints with the indicators vacancy, essential stores, occupier change and geographical proximity. It revealed that some high streets in London, the South East, the East of England and Cardiff with average occupier change, low pre-pandemic vacancy and high essential stores to have had the lowest rise in vacancy. This group of high streets included Northolt Road in Harrow, London, with the highest proportion of essential stores at 72%, and Wanstead high street, London, which had the lowest vacancy rate following the lockdown restrictions at 2%. Through reporting geographical disparities in high street resilience, this paper has aimed to inform discussion related to policy tools for town centre recovery following the lockdowns. Large, up-to-date granular data sets such as that of LDC provides the possibility for local authorities to understand their high streets’ composition and resilience qualities. In particular, geographically targeted policies can be tailored to for adaptively resilient areas or those that could benefit from stable occupier conditions. Nevertheless, the caveats of these findings include the possible crucial role of rent renegotiation and landlord attitudes alongside the decline in profitability of retail property investment in the lead up to the pandemic.

While this chapter has developed a comprehensive and Britain-wide measurement of the resilience of high streets and the impact of the government enforced lockdown restrictions, a limitation of this chapter’s research approach must be acknowledged. Firstly, this chapter has provided a demand side model that does not accommodate supply side considerations such as rent, holidays/renegotiations. Secondly, identifying biased coefficients and error terms related to omitted variables cannot be achieved through use of this paper’s existing methods. Within this chapter there is the possibility that the regression model omitted essential explanatory variables leading to errors. Such
potential explanatory factors include the impact of the 3 and subsequently 4 Tier system in England between 14th October 2020 and 6th January 2020 where local restrictions were enforced. Further releases in the LDC data in 2022 might provide additional insights to this impact. In addition, all the variables selected within the regression model were grounded in pre-existing literature and the findings were in line with previous studies on retail resilience based on spending data and qualitative research.
Chapter 7

Data Analytics for High Street Policy

One of the roles of local authorities across Britain is to support the vitality and viability of the high streets located within their boundaries. While high streets play a critical role in supporting the health and wellbeing of local communities, they have been subject to an array of challenges, trends and changing consumer habits which have been exacerbated by the COVID-19 pandemic. In addition, local authorities face complexities including conflicts with national planning policies, which can constrain their efforts to plan and adapt effectively to economic and cultural shock (Clarke et al., 1997). The collection of high street related data, academic research and media attention has yet to make a large impact in resolving these complexities and constraints (Parker et al., 2016).

To overcome some of these challenges, academic collaboration can help inform local authorities of research techniques and data validity in a high street context. Previous successful high street collaborations between academics and practitioners include the High Street UK 2020 project, which took a participatory approach to research (Ntounis and Parker, 2017). Such approaches can create opportunities for a mutually beneficial exchange of knowledge between academics and government authorities (Phillips et al., 2013).

The knowledge exchange this chapter presents is a collaboration between UCL and the London Borough of Camden during 2021-22. Camden Council commenced the Camden Future High Streets (2021:4) programme to support their “high streets through the pandemic and into a robust recovery and re-imagined future”. The programme identified three main challenge areas: vacancy, the night-time economy, and digital high streets. Data quality is a theme that underpins all three of the challenges Camden set out. Local policies aimed at developing resilience need to be informed by datasets that are able to capture the many factors that determine the success or decline of a high street. Factors relating to high street resilience include measures of the perceived attractiveness of locations, awareness of national planning and local policies, the socio-demographic and cultural characteristics of high street catchment areas, and the changing picture of store composition (Singleton et al., 2016). Camden Council required a better understanding of the data available to it and how that data might be used to inform its work on high street regeneration. Therefore, UCL worked collaboratively with Camden on the specific issue of data to help improve their data-driven policy making for high streets.

This chapter aims to demonstrate the benefits of coproducing knowledge between academia and public sector institutions during a pivotal time in which high streets are struggling with the ongoing impact of the COVID-19 pandemic. In particular, this chapter offers an insight into the availability and reliability of data to Camden Council with the aim of demonstrating the power of new forms of data and what they can offer when informing Camden’s Future High Streets programme. Specific attention has been given to the ways in which pre-existing data can be used to show changes over time and distinguish...
between high streets in order to inform priority-based local policy decisions. The research has been well informed by regular meetings with various Camden Council teams and provides a firm basis for further work in this area, as set out in the discussion and research prospects of this thesis. The role of this thesis in the knowledge exchange collaboration included providing the data driven insights that were used by Camden Council to inform their high street regeneration project.

The knowledge exchange is presented as follows: firstly, an exploration of the concept, engaged scholarship followed by an explanation of the aims and objectives of UCL’s collaboration with Camden council. Next, a description of the methods used, including a comprehensive audit of available data, sensitivity analysis and a description of the high street boundaries used. The following section contains an exploration of data sets from the following sources: the Food Hygiene Rating Scheme, OpenStreetMap, Tables and Chairs Permits, the London Borough of Camden Retail Survey and an online property portal. The chapter concludes with a discussion of the successful outcomes of the collaborative project including the adoption of UCL’s recommendations.

7.1 Engaged Scholarship and High Streets

Within academia, and particularly the discipline of business studies, addressing the theory-practice gap and attempting to align research with current societal issues is a common theme (Phillips et al., 2013). As a result, there has been an increased desire to use research styles that harmonise theory and practice to work towards research outcomes which can accomplish societal advancements while upholding academic research quality standards (King and Learmonth, 2015; Cuthill, 2010). One way to achieve a more cohesive understanding of practice in research is through adopting Engaged Scholarship, a participatory style used to understand a problem within its context and the stakeholders impacted by the particular social issue (Van de Ven, 2007). Through adopting an engaged scholarship approach this chapter aims to develop high street models of resilience that “better fit the problems they intended to solve” (Van de Ven, 2007:8). The engaged scholarship method seeks relevant theorisation and explanation in the high street context through an immersive and collaborative process with Camden Council, as opposed to seeking generalisability (Wells, 2016).

Across various academic disciplines including geography, retailing, and planning, engaged scholarship focused on high street vitality and development can often be categorised into three types of engagement: business engagement, multiple stakeholder engagement, and community engagement (Coca-Stefaniak et al., 2005; Omholt, 2013; Woolrych and Sixsmith, 2013). Moreover, Geddes (2006) suggests that engagement with established town partnerships including local government can develop inclusive and efficient pluralist local governance by identifying local area and community needs and providing solutions that can meet those needs. In that sense, engaged scholarship has the potential to integrate into already well-established forms of local governance and town planning and further strengthen stakeholder participation in the regeneration of high streets, creating opportunities for symbiotic knowledge production for all parties involved (Peel, 2003).
Engaged scholarship is particularly useful in town partnership projects where there are competing interests at play, as it can create an environment where all stakeholder values are appreciated (Albrechts, 2015). Research frameworks that involve stakeholder compromise can lead to knowledge which is more insightful and grounded in context for both academic research and local planning partnerships (Arkestein and Volker, 2013). One example of the application of engaged scholarship to high street research is the High Street UK 2020 project (Ntounis and Parker, 2017). The project used Van de Ven’s (2007) diamond model of engaged scholarship to gauge the outcomes of the collaboration. The model consists of four different parts: problem formulation, theory building, research design, and problem-solving. The model used in the High Street UK 2020 project expanded on Van de Ven’s (2007) model to include numerous case studies and stakeholders in the knowledge exchange loop. Outcomes of the project included conducting a Delphi model (Paliwoda, 1983) to identify the top 25 priorities for high street recovery, identifying a framework for high street recovery and identifying practitioner implications such as decision-makers needing to develop their management and decision-making skills.

Nevertheless, the High Street UK 2020 project does leave room to expand and develop the application of engaged scholarship in high street development partnerships. Firstly, the High Street UK 2020 project included the ten British retail centres of Alsager, Altrincham, Ballymena, Barnsley, Bristol (Church Road, St George), Congleton, Holmfirth, Market Rasen, Morley, and Wrexham. The geographically dispersed selection of towns raises questions of whether differences in location and performance qualities led to totally localised development of knowledge, something that is often central to engaged scholarship approaches.

Secondly, the High Street 2020 project began in 2014 and its findings were first published in 2017, therefore the knowledge formation was before the impact of the COVID-19 pandemic. In addition, when the High Street 2020 project research was being conducted, it was during a time when local policy agendas were primarily focused on high street vitality whereas the pandemic has prompted a shift toward the centralisation of high street resilience.

The previous chapter showed how the COVID-19 lockdown restrictions disproportionally impacted some high streets and exacerbated the struggles with pre-existing high vacancy rates. Therefore, it is important explore whether partnerships have changed or updated their strategies to adapt to the impact of the pandemic.

Thirdly, the basis of an engaged scholarship approach is the notion of knowledge creation. Therefore, a partnership which extends beyond the creation of a framework and develops active solutions could be more beneficial in helping partnerships to meet their goals.
7.2 London Borough of Camden Knowledge Exchange

7.2.1 Future High Streets Camden

The London Borough of Camden ‘Future High Streets Camden’ initiative was created to respond to changing consumer habits, which had been accelerated by the pandemic. It takes a form of ‘adaptive resilience’ approach similar to that described by Dolega and Celińska-Janowicz (2015), in which it is acknowledged that Camden’s high streets would have to change and reinvent themselves while still maintaining their role as a centre point for communities.

At the start of the project the council clearly expressed its interest in supporting local high streets to become creative hubs, centres of employment, innovation and areas which are sustainable and accessible to all. At the time of the project, the trends on Camden’s high streets that were highlighted were numerous and broad. They included higher business rates and rent prices, and an increase in vacant units that was exacerbated by the pandemic. The council also suggested that their high streets did not reflect wider community needs and demands, stating that the shops within their high streets are often predominantly restricted to retail, food and drink, and that their opening hours do not reflect the needs of the diverse community.

To help shape the vision and objectives of the ‘Future High Streets Camden’ project, the council launched a consultation in July 2020 in which the opinions of businesses and residents were collated. The ideas and feedback from 320 contributors were then combined with discussions with other stakeholders. The feedback from the Camden communities suggested four main improvements that needed to made: reduction of vacant properties, urban greening, a sense of community, and better public spaces.

Camden then laid out its overall ‘vision’ of ensuring that future high streets are “safe, family-friendly, environmentally responsible, diverse, accessible and vibrant places to shop, work, socialise, share knowledge and skills, network, learn, make, live and play”. An overview of Camden council’s objectives for high streets can be seen in Figure 7.14.
To supplement the prospectus, the council launched a ‘Camden Future High Streets Action Group’ with the aim of supporting stores after the lockdown restrictions, participating in the Greater London Authorities (GLA’s) High Streets Challenge Fund, and continuing to trial new projects. The action group was invited to offer solutions to three challenges: firstly, the development of a diverse cultural evening and night-time economy; secondly, the utilisation of vacant units; and thirdly, the development of digital high streets. In order to tackle the challenges, Camden council proposed a 4-part framework depicted in Figure 7.2.
Each of the framework elements were placed on a timeline between June and August 2021, followed by the plenary testing and evaluating new schemes.

7.2.2 Aims and objectives
The purpose of this chapter is to explore and expand upon part of the results from a knowledge exchange project conducted between UCL and Camden Council. In May 2021 Camden Council set up a High Streets Action Group which brought together a collective of experts and stakeholders. The stakeholders included the Greater London Authority (GLA), BIDs, data providers, and charities, alongside a UCL team consisting of myself, Professor James Cheshire (Director of the Social Data Institute) and Dr Michael Reynier (Principal Partnerships Manager) and Hamish Gibbs (Research Assistant, Consumer Data Research Centre).

The first session involved collaboration through an online platform where experts noted their expertise and what they could contribute to the partnership. Camden Council had three challenge areas: digital high streets, vacant units, and the night-time economy. Each of the experts were allocated a challenge and separate brainstorming sessions were set for each. Within these meetings practitioners were able to voice their views, concerns and insights into how best to improve the health of Camden’s high streets.

From continued attendance in the workshops, it became apparent that the role of data – including a better understanding of what data sources are available and how these could be used to inform their work – was an underlying theme across all three areas. Camden Council expressed the benefits of a co-created piece of work which explored and audited the available data relating to the local high streets. Figure 10.8 (see Appendices) shows the letter of support from the London Borough of Camden for a collaborative project between UCL and Camden’s Future High Streets programme. Table 7.1 outlines the aims and objectives of the collaborative project.
Aims

To provide Camden Council with detailed insights about the range and appropriateness of available data to support its Future High Streets Programme.

To build a network between the council, its stakeholders and UCL Geography/Consumer Data Research Centre to offer a platform for further data sharing, co-production of research and broader impact.

To lay the foundations for a more ambitious scheme of work tackling the impacts of COVID-19 on London’s high streets.

Objectives

Author a report that outlines the available data – and its resulting insights – for establishing changes to Camden’s high streets both at the Borough level and at the high-street level for a couple of exemplars.

Work closely with Camden Council’s planners and analysts to determine key gaps in knowledge to be addressed by the report and establish knowledge exchange practices between them and UCL.

Plan a more ambitious follow-up project that seeks to provide more detailed analysis for the policy interventions determined by the Camden Future High Streets Task Force.

<table>
<thead>
<tr>
<th>Table 7. 1: Table of the proposed aims and objectives of the knowledge exchange between Camden Council and UCL.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Aims</strong></td>
</tr>
<tr>
<td>To provide Camden Council with detailed insights about the range and appropriateness of available data to support its Future High Streets Programme.</td>
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</tr>
<tr>
<td>To lay the foundations for a more ambitious scheme of work tackling the impacts of COVID-19 on London’s high streets.</td>
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The main proposed outcome of the knowledge exchange was a ‘Data for Future High Streets’ report which details the range of datasets available to Camden for its high street work. It included several recommendations for best practice and use of such data, and offers a series of exemplar high streets that show how the data can be used and mapped for informing policy interventions in these areas. The report emanates from studying Camden’s data landscape and whether it can be used to reveal trends about the impact of the pandemic at a borough and high street level.

The broad perspectives outlined in the report capture the demand and supply sides of high streets. The demand side encapsulates the population that uses the high street (examples include measures informed by mobile phone data and TfL data), and the supply side encompasses the offer and characteristics of the high streets themselves (examples include vacancy rates and composition). At the borough level many of the datasets offer important context, however, they do not offer sufficient granularity to provide meaningful insights for the specific challenges facing an individual high street. The case study examples therefore explore this issue further and seek to augment the broader data with Camden Council’s contacts and knowledge of the high streets.

Throughout the partnership I was able to gain insight into government organisation pipelines, which helped to enrich and contextualise the high street analysis within this thesis. I was able to gain unique insights from Camden Council in terms of the data they have including special licences, its integrity, and their current data capabilities. Through regular dialogue and meetings I was also able to learn what questions they wished to address using the data including their post-pandemic priorities.

During the ‘problem formulation’ stage (Van de Ven, 2007) it became apparent that a knowledge gap between the academic research contributing to this thesis and the local authority knowledge existed – in particular the study of intervention strategies for struggling high streets and how these high streets were selected. Pre-pandemic vibrancy was explored for the high streets within Camden in chapter 4. Their characteristics would suggest that high streets such as Camden Town, which had relatively high pre-pandemic vacancy and occupier churn, would be an area of interest, especially given the high...
proportion of leisure stores which were forced to close during the lockdowns. In addition, Chapter 6 measured the impact of the pandemic and the associated restrictions on Britain’s high streets and found that Camden Town’s vacancy rate rose from 10.9% to 15.9% between 2019 and 2021. Other areas of interest include Kilburn, where the vacancy rate rose from 12.1% to 17.4%, and the central Bloomsbury and Holborn area, which saw a rise from 10.0% to 15.9%. Central areas such as these were presumed to be the target of intervention strategies especially given the shift to working from home outlined in Chapter 5. Even with commuters returning to work, the popularisation of a hybrid approach to working just some days a week in the office may continue to impact businesses and high streets which relied upon commuter footfall.

Nevertheless, Camden Council wanted the Data for Future High Streets report to focus on the case studies of Kilburn High Road, Tottenham Court Road, and Kentish Town Road. These areas were suggested due to the Camden Planning Guidance (2021) listing them as areas of interest for intervention. Tottenham Court Road has also been identified as an Opportunity Area in the London Plan (2021) and fits within the London Plan West End Special Retail Policy Area, which is aimed at supporting retail and leisure provision of national, city-wide and local importance. In contrast, Kilburn High Road and Kentish Town Road are more oriented towards performing a functional role to meet the needs of their local residents. Another reason for the selection of Kilburn as a case study may be due to the area securing £20,000 in funding from the Mayor of London in August 2021 to bring vacant buildings into use, protect cultural spaces, and support employment on the high street.

The local community organisation Life in Kilburn and Transport for London (TfL) put forward a combined project to bring together bids from community groups and landowners to help develop a comprehensive strategy for Kilburn High Road. The GLA received other funding proposals from Fitzrovia, Kentish Town and Camden Town. However, in December 2021 the high streets project in Kilburn managed to secure a further £155,000 of funding from the Mayor of London. In addition, another engagement that Camden Council has is the Kentish Town Healthy Streets Project, which aims to gather views on the area’s transport, air quality, and public spaces. The project utilised a platform called ‘Commonplace’ that aims to connect local councils to their communities. The service specifically provides an interactive map where people can add comments to geographic locations where they think improvements are needed such as improvements to pedestrian crossings. Therefore, it appeared that case studies were selected based on funding that had already been allocated to an area or in locations where projects were already under way, rather than using a data-driven approach to select high streets which were most impacted by the pandemic.

Nevertheless, the collaboration still offered the possibility of producing research outcomes that can make more substantial advancements to theory and practice than the traditional approaches used within the previous chapters (Van de Ven, 2007).
7.3 Method

It was necessary to conduct an in-depth search and review of data related to the high streets in Camden. Table 10.4 (see Appendices) outlines the extensive search of data where all of the datasets have been spatially referenced and cover a range of geographic scales, sources and availability. The data is broken down into six categories: high street boundaries, mobility, economic, retail, social & demographic, and sustainability. The variety of different data sources aims to encapsulate the retail and service structures within Camden’s high streets; the characteristics of consumers who use them; and how they are changing or adapting in response to economic shocks – especially the COVID-19 pandemic.

This survey of available data sources demonstrates the wide range of both public and private organisations collecting relevant data. Public sources include in-house data collected by Camden as well as the GLA, and Central Government. Private data sources include estate agents, restaurant booking services, and online application providers. Such organisations typically only collect data that is relevant to their business or operations, so by combining disparate data sources we can gain a more comprehensive understanding of the evolving status of high streets.

While there is a diversity of available data sources, each source has limitations that can create challenges when extracting insights about individual high streets. For example, most open-source datasets are low granularity, for example at local authority level or Middle Super Output Layer (MSOA; each with average population of 8,698 in Camden as recorded in the 2011 census), creating difficulty in allocating larger geographical boundaries to individual high streets. One example of this is the Office for National Statistics’ Income Estimates for Small Areas in England and Wales (2018), which cannot be used to make any assumptions about the distribution of income within MSOAs because the data is an estimate-based ranking across all MSOAs. However, more granular frequently updated data, for instance from the CACI data on equivalised pay checks, is costly. Further examples and more detailed information on the datasets were included in the Data for Future High Streets report which can be seen in Figure 10.9 in the appendix.

Throughout the knowledge exchange process Camden Council shared a multitude of new data sources, including granular postcode-level income data purchased from CACI. For some of the datasets such as the CACI income data, Camden Council have conducted in-depth analysis and published the findings in their business bulletin. Yet, some of their readily available datasets had seemingly not been explored in relation to informing high street policy. Therefore, this chapter will focus on the analysis and validation of four of the datasets covered in the Future High Streets report. These datasets have been selected due to being open source and therefore readily available to the council.

The analysis within this chapter will take these 4 datasets and cross-validate them with the commercially available LDC data used throughout this thesis in an attempt to evaluate the data sources used by Camden Council to inform policy on the resilience of its high streets and resultant intervention strategies. The four open data sources include two
measures of high street vacancy, one from the Camden Retail Survey and one from an online property portal. The other two data sources include an indication of high street competition from the Food Hygiene Ratings Scheme (FHRS) and an indicator of resilience and adaptability from a dataset of “Tables and Chairs Permits”.

7.3.1 High Street Boundaries
While working on the high street specific research during the knowledge exchange a compromise had to be made on the definition of high street extents. Camden Council had predefined boundaries which were part of the Local Plan’s “Centres Boundaries”, which have been developed by the Strategic Planning and Implementation Team. As Figure 7.1 shows the boundaries cover the town centres of Hampstead, West Hampstead, Kilburn High Road, Finchley Road/Swiss Cottage, Kentish Town Road, and Camden Town. In addition, there are boundaries for “Central London Frontages”, which are major shopping areas within Central London. Frontages located within Camden are: Tottenham Court Road/ Charing Cross Road, Holborn, and King’s Cross/Euston Road. In addition to the policy-led boundaries high street boundaries developed in Chapter 3 can also be used (derived from LDC store location data and CDRC (2021) retail centre boundaries). In Figure 7.3 these are compared to the high street boundaries used by the London Borough of Camden.
Figure 7.3: London Borough of Camden Council’s Local Plan’s “Centres Boundaries” and “Central London Frontages” alongside high street boundaries derived from the Consumer Data Research Centres (2021) retail boundaries and LDC (2021) retail location data.

The figure raises some interesting differences between the two delineations. Firstly, in the case of the Finchley Road boundaries, the one used by Camden Council merges with Swiss Cottage, suggesting that local planning policies encompass both areas, while the CDRC derived boundaries treat the two areas as having two separate high streets. In the majority of cases the CDRC boundaries have covered the retail areas outlined by the Camden Council boundaries and often extend further to include parts of high streets. However, there are cases where there are small or stand-alone boundaries in the Camden Council dataset. From further inspection, these building boundaries can be seen to be community assets such as community centres and medical centres. This examples the difference between the CDRC boundaries, which are based off geocoded retail-specific locations and land use, and the boundaries used by the local authority, which must encompass services required by Camden’s local communities.

One important issue which arises from the use of Camden’s boundaries is the precise nature of the building outlines for high streets classified as Central London Frontages. These boundaries are confined to the area of the frontage of ground floor uses in the data.
supplied. Therefore, such boundaries do not provide a sufficient buffer when joined with other data sources to conduct valid analysis. As part of the Data for Future High Streets report, UCL manually estimated a new boundary for Tottenham Court Road which is one of the examples from the three locations of Kilburn High Road, Kentish Town Road, and Tottenham Court Road. The comparison between the Primary Frontages boundaries and the boundary developed within the Data for Future High Streets report are displayed in Figure 7.4.

![Figure 7.4: Geographical boundary used for Tottenham Court Road. A comparison of Primary Frontage boundaries for Tottenham Court Road and an inclusive high street boundary defined for the purposes of the Data for Future High Streets Report.](image)
7.4 Retail Data

When exploring the retail landscape, it is important to factor in individual premises type as well as wider clusters of goods or service since they can exhibit different behaviours across and within high streets. The next section focuses on the use of open-source data including the Food Hygiene Ratings Scheme (FHRS), the Camden Retail Survey, and “Table and Chairs Permit” data.

7.4.1 Foods Standards Agency

In order to gain an understanding of the changing composition of high streets, the Food Standards Agency (FSA) Food Hygiene Ratings Scheme (FHRS) can be used to provide a valuable insight into the locations of new businesses. FHRS are given to places where food is supplied, sold or consumed, such as restaurants, pubs and cafes, takeaways, food vans and stalls, canteens, hotels, supermarkets and other food shops, schools, hospitals, and care homes. Businesses that pose a higher risk are inspected more often than businesses that pose a lower risk; for example a small retailer selling a range of refrigerated pre-packaged items will warrant fewer visits than a restaurant cooking fresh food. The time between inspections varies from six months for the highest risk businesses to two years for lower risk businesses. For some very low risk businesses, the interval between inspections can be longer than two years, however there may be some exceptions to this. Businesses must register at least 28 days before opening. After assessment businesses are provided with a hygiene rating within 14 days of the visit.

The time periods are important as they dictate how up to date the FHR dataset is in the context of monitoring changes to food outlets.

The FSA data used within this chapter is a combination of two sources. Firstly, the historic records were available through the CDRC where the data is held on behalf of local authorities participating in the National Food Hygiene Rating Scheme (FHRS) in England, Northern Ireland and Wales, or the Food Hygiene Information Scheme (FHIS) in Scotland. The second source of data was the most up to date weekly release from Camden Council of the 29th November 2021, where the data contained the most up to date rating from the 23rd November 2021. In order to combine and clean the two sources of FSA data, a series of steps were taken. These have been summarised in Figure 7.

During the data cleaning process, a number of issues arose. The CDRC’s historic FHRS data is in the format of 11 zip folders with each variable in a separate zip folder. The zip files can be joined via a ‘BusinessID’. Within the CDRC historic data the ‘la_id_business_id’ can be linked to what Camden Local authority terms ‘Local.Authority.Business.ID’ and ‘Local.Authority.Code’ combined in one string. The first issue to arise was that when linking the files together, the result is a ‘date created’ and ‘date updated’ for each zip file. It is consequently uncertain why in many cases there are different dates for different variables for one business. Secondly, when looking at the location file by itself, some BusinessIDs are duplicates (for example businessID 38 has 28 location rows). There are often different ‘date created’ and ‘date updated’ variables for the different coordinates. There are also discrepancies with the recordings of the locations (such as businessID 138, where there are 3 location rows – the location changes to ‘0’
then back to its original recording). Similarly, in some cases it was observed that some premises disappear from the data for periods of time then re-appear again, yet the premises has not actually shut. Table 7.2 outlines some examples where there is evidence of missing location data but an inability to match ID’s with duplicated business names.

<table>
<thead>
<tr>
<th>Business Name</th>
<th>Rating Date</th>
<th>Address Line</th>
<th>Coordinates</th>
<th>FHRS ID</th>
<th>LA Business ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walkmisu</td>
<td>30/09/2020</td>
<td>Russell Square</td>
<td>51.523053, 0.126506</td>
<td>1278153</td>
<td>198725</td>
</tr>
<tr>
<td>Walkmisu</td>
<td></td>
<td></td>
<td></td>
<td>1398304</td>
<td>199989</td>
</tr>
<tr>
<td>Curry Zone</td>
<td>12/11/2019</td>
<td>28 Leather Lane</td>
<td>51.520447, 0.109737</td>
<td>424952</td>
<td>41635</td>
</tr>
<tr>
<td>Curry Zone</td>
<td>22/07/2019</td>
<td></td>
<td></td>
<td>1181588</td>
<td>197175</td>
</tr>
<tr>
<td>Hola Guacamole</td>
<td>10/06/2019</td>
<td>Unit M 191, Hawley Wharf</td>
<td></td>
<td>1420402</td>
<td>196983</td>
</tr>
<tr>
<td>Hola Guacamole</td>
<td></td>
<td></td>
<td></td>
<td>1152054</td>
<td>200409</td>
</tr>
</tbody>
</table>

Table 7.2. Inconsistencies and missing data in the FHRS in reference to location and ID’s.

Another recording issue when the data had been joined was the duplicates that were created due to the way the business type is named. For example, a children’s centre which was ‘created’ in 2021 as a ‘restaurant/cafe/canteen’ that was first recorded in 2012, then called a ‘hospital/childcare/caring premises’ in 2020. The final major discrepancy is in how certain businesses such as the “Salt Yard” has 3 different BusinessID’s and local authority numbers, yet one set of coordinates. When this business is matched with the most up-to-date Camden Council release of the data, only one of the local authority numbers matches.

Some of the causes for these errors are due to the way that Local Authorities report their FHRS data. Firstly, if a premises is closed for refurbishment, it gets removed from the supply, then re-added when it re-opens – possibly due to reinspection. This also happens if a premises is taken over. In these two instances, when the case is a new legal entity, it will be classed as a change of ownership and in some situations is allocated a new ID. Secondly, Local Authorities report the FHRS data weekly to food.gov.uk therefore the date this data is supplied is the date the data was sent over. Consequently, due to the data being presented as a weekly snapshot of the food premises register, the FHRS historical data available through the CDRC is not the full history. Thirdly, when gauging an indication of when a premises opened, for the data accessed through the CDRC there is a time series of inspections associated with a singular premises. Therefore, the earliest date is a relatively substantial indication of the time period in which a business opened, although the FHRS data was not published prior to 2012.

The historical data providers derived the ‘date of opening’ variable from the date a premises was first seen as being reported by a local authority. While there is often a delay in this time period, there is no more efficient method of deriving an opening date. Therefore, a more accurate interpretation of the ‘date of opening’ variable might be ‘date first reported’. Finally, there was a delay in inspections caused by the COVID-19
pandemic and several premises have been given virtual inspections, which caused a jump in the number of cases reported.

In an effort to overcome the discrepancies in FHRS data, the series of data cleaning steps have been summarised in Figure 7.5.

![Diagram of data cleaning steps](image)

Figure 7.5: Overview of the methodology used to clean Food Hygiene Rating Scheme (FHRS) Ratings data.

More specifically, to minimise errors in the data and maintain consistency across time, the most up-to-date business categories were chosen when there was a discrepancy in how the same business was classified. In addition, for the data that had a Local Authority ID of 506, equating to the London Borough of Camden, the data was manually checked. The majority of the manual changes were made to the business names, which enabled matching their recordings over time. There were some discrepancies in the spelling of some businesses such as “Guanabana Caf” for one inspection recording and “Guanabana Café” the next. In some instances, a business would be recorded as its limited company name making it hard to match over time even using a partial string match. Through the knowledge exchange, Camden Council explained how the data is recorded using the information a business reports on the FHRS form, which causes the discrepancies.
The cleaned data can then be spatially joined with the high street boundaries provided by Camden Council. Figure 7.6 displays the three highest frequency categories for four Camden high street boundaries: Restaurant/Canteen, Retailers-Other (Retailers that are not a supermarket or hypermarket), and Takeaway/Sandwich shops.

The FHRS data can therefore be used to compare overall trends of the most frequently opened types of food premises over the past five years, but cannot specify if the data purely shows openings or if an existing business has decided to begin offering food. While Tottenham Court Road had a continued increase in restaurants, cafes and canteens even after the pandemic hit, there ceased to be any recorded new retailers serving food in 2021. Kentish Town Road can be seen to have had a substantial rise in the proportion of newly opened shops being takeaway/sandwich shops, with Kilburn High Road also experiencing an increase in the proportion of takeaways. These trends fit within the wider increase in demand for takeaways in London, where restaurants have sold an extra 900,000 meals a week since the pandemic began through apps such as Deliveroo and Uber Eats (Magnet, 2022).
Next, the data has been used to draw comparisons between the FHRS recordings before (2018-2019) and during (2020-2021) the COVID-19 pandemic. The different business type descriptions and locations for the selected case studies have been displayed in Figure 7.7.
Figure 7.7: The locations of newly opened businesses. A comparison of the opening locations of new food businesses in 2018-19 (left) and 2020-21 (right). Business opening information collected from Food Hygiene Ratings data.
Mapping the FHRS data reveals some interesting clusters. For example, in Figure 7.5 a group of new takeaway stores can be seen to have opened around Kentish Town Station. It is important to consider the potential shift in composition of Camden’s high streets in response to changing consumer trends, especially in relation to the rise in restaurant and takeaway demand. Consequently, an advantage of the FHRS data is that it can be used to capture the increase in ‘dark kitchens’ or ‘ghost kitchens’, which generally comprise multiple outlets in the same premises with a takeaway only option. One example is a Burger King that opened on Regis Road (Kentish Town) in May 2021 that is takeaway only. With large chain takeaway stores trialling the use of dark kitchens that are away from the high streets and without ‘eat-in’ dining in order to exploit cheaper rents, there could be resultant changes to the structures and appeal of high streets, especially for the night-time economy.

7.4.2 Food Hygiene Rating, OpenStreetMap and Local Data Company data
The presentation of the FHRS data represents a descriptive picture of the data relating to high street composition that is available to Camden Council. Further analysis is required to determine the reliability of the data. One previous study by Kirkman et al. (2021) used a field audit for a sample of LSOAs to determine the FHRS data validity against the field data. The study found the FHRS data to have high validity in the North of England and suggested it might be a valuable resource for research, yet the paper focuses on the data’s use for public health interventions, rather than high street composition and occupier change.

Another project which has aimed to validate the FHRS data is the ‘Food Hygiene open data OpenStreetMap tool’ (2022) which has been developed by an OpenStreetMap (OSM) user. The tool matches FHRS data to OSM data where matching objects are considered to have the same postcodes when the FHRS postcode matches either the OSM object’s ‘addr:postcode’ or its ‘not:addr:postcode’. The data matching tool has found that for the FHRS establishments in Camden, 366 businesses matched (same postcodes), while 2,983 did not match with the OSM data, resulting in just 11% matching with the same postcodes. This rate is considerably lower than other London boroughs, such as Richmond-Upon-Thames with 83% of data matching. However, OSM as a source of store data does carry some limitations, the main one being that the data is obtained from a variety of sources and therefore the accuracy of one location does not provide an indication of the accuracy of other locations. There is also a lack of information regarding how the OpenStreetMap data has been captured, alongside incomplete recordings of features including buildings. Consequently, this next section will utilise a blend of OSM data of store locations and commercially sensitive store location data from the LDC to validate the FHRS data.

The FHRS data has 5,053 recordings between 05-12-2012 to 23-11-2021 within the London Borough of Camden boundary, with 3,316 unique addresses. The LDC data has 8,600 recordings from 01-01-1999 to 23-06-2021 with 5,821 unique addresses. The OSM data has been taken from a historical achieve snapshot downloaded in December 2020 to capture a period of time situated during the COVID-19 pandemic which has 3,291 recordings with 3,288 unique coordinates. To make the data easier to compare, all the
LDC shops which had been closed before 2012 have been deleted. Since the “Food Hygiene Open Data OpenStreetMap tool” (2022) had already matched the FHRS data with the OSM data at a Camden borough level, the LDC data was used to see if more FHRS addresses could be matched to the LDC data. The FHRS and LDC data were linked via their business name and address location, resulting in 1,024 matches. Consequently, only 20% of the FHRS data recordings were matched to the LDC recordings.

To explore possible reasons for the low match rate the linked data has been inspected further. Firstly, of the 4,869 locations in Camden which could not be matched in the LDC data, the categories and subcategories of the occupiers have been displayed in Table 7.3.

<table>
<thead>
<tr>
<th>Category</th>
<th>Unmatched Addresses (%)</th>
<th>Subcategory</th>
<th>Unmatched Addresses (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shops and amenities</td>
<td>23.9</td>
<td>Offices</td>
<td>9.7</td>
</tr>
<tr>
<td>Nonretail</td>
<td>19.8</td>
<td>Vacant properties</td>
<td>9.4</td>
</tr>
<tr>
<td>Health and beauty</td>
<td>15.5</td>
<td>Café and tearoom</td>
<td>3.0</td>
</tr>
<tr>
<td>Food and drink</td>
<td>12.9</td>
<td>Estate agents</td>
<td>2.9</td>
</tr>
<tr>
<td>Home and garden</td>
<td>8.2</td>
<td>Hairdressers</td>
<td>2.5</td>
</tr>
<tr>
<td>Restaurants</td>
<td>6.1</td>
<td>Convenience stores</td>
<td>2.3</td>
</tr>
<tr>
<td>Clothes and fashion</td>
<td>5.1</td>
<td>Jewellers</td>
<td>2.2</td>
</tr>
<tr>
<td>Pubs, bars and clubs</td>
<td>2.9</td>
<td>Public houses and inns</td>
<td>2.1</td>
</tr>
<tr>
<td>Hotels</td>
<td>2.1</td>
<td>Fashion shops</td>
<td>2.0</td>
</tr>
<tr>
<td>Taxi and transport</td>
<td>2.1</td>
<td>Dry cleaners</td>
<td>1.8</td>
</tr>
<tr>
<td>Events</td>
<td>1.4</td>
<td>Barbers</td>
<td>1.7</td>
</tr>
</tbody>
</table>

Table 7.3: LDC occupier recordings that did not match with FHRS data 2012-2021 presented as their category and subcategory classification.

Table 7.3 displays high numbers of occupiers in categories which would receive a food hygiene rating and so should therefore be present in the FHRS data, including the 12.9% of food and drink occupiers, 6.1% of restaurants and 2.9% of pubs, bars and clubs. This would suggest that there might be a high proportion of error in the data linkage process. For the small sample of stores in Camden which could be joined, the dates of the two data sources were compared. 89% of the dates recording the presence of an occupier were earlier in the LDC data than in the FHRS data. This was to be expected given the
delay between registering a new business and receiving a Food Hygiene Rating and the more frequent field research conducted by the LDC. When taking the earliest recordings from the last few years between 2017 and 2021 (to minimise error caused by historic recording issues), the LDC data recorded the shops an average of 641 days earlier (min=1 day, max=2,736 days).

In addition to the address information, both datasets have longitude and latitude coordinates. Some of the FHRS points were vastly outside of the London Borough of Camden area but the ones linked to the LDC data did all lie within the boundary. For example, Figure 7.8 displays the FHRS recorded coordinates that are within the London Borough of Camden’s boundaries but also those within surrounding boroughs.

For example, 4 businesses have their address as the ‘Brunswick Centre’ recorded on various dates between 2017-2019, which is actually in Bloomsbury, Camden but their coordinates have been recorded as being situated in the London Borough of Barnet.

Therefore, the Great Circle Distances were calculated between the two sets of coordinates for each matching occupier recording, a method that accounts for the curvature
of the earth. As a result, the average discrepancy in the location recordings between the FHRS and LDC data is 36 metres (min=0 metres, max=1,434.45 metres).

To further investigate the possible sources of recording discrepancies, the Tottenham Court boundary has been selected alongside the points that lie within it for the FHRS, LDC, and OSM data. The first error that was spotted was that the FHRS data had multiple recordings of the same business in the same location, with different variations in the spelling of the business name, thus the earliest recording was selected. Within the Tottenham Court Road boundary, the FHRS data had 265 recordings, the LDC 472 recordings and the OSM data with 227 recordings. The R package ‘fuzzyjoin’ was used to identify similar business names and addresses across datasets. Firstly, the addresses between the FHRS and LDC data were matched using the ‘stringdist_join’ function with a maximum distance threshold of 1 to identify locations on the same street or subtle spelling errors. Next the business/occupier names were matched with a threshold of 6, leaving 122 matches. These matches were then manually checked and 37 errors were found. The result was 32% of the FHRS data matching the LDC data within Tottenham Court Road. 389 business names and addresses were left unmatched, the Categories of these data points have been presented in Table 7.4.

<table>
<thead>
<tr>
<th>Category</th>
<th>Unmatched Addresses (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shops and amenities</td>
<td>26.1</td>
</tr>
<tr>
<td>Nonretail</td>
<td>22.9</td>
</tr>
<tr>
<td>Food and drink</td>
<td>17.5</td>
</tr>
<tr>
<td>Health and beauty</td>
<td>9.8</td>
</tr>
<tr>
<td>Home and garden</td>
<td>9.8</td>
</tr>
<tr>
<td>Restaurants</td>
<td>7.2</td>
</tr>
<tr>
<td>Clothes and fashion</td>
<td>2.3</td>
</tr>
<tr>
<td>Pubs, bars and clubs</td>
<td>1.8</td>
</tr>
<tr>
<td>Hotels</td>
<td>1.5</td>
</tr>
<tr>
<td>Events</td>
<td>1.3</td>
</tr>
</tbody>
</table>

Table 7.4: LDC occupier recordings that did not match with FHRS data 2012-2021 within Tottenham Court Road’s boundary presented as their category classifications.

17.5% of the unmatched data fits into the ‘Food and Drink’ category, suggesting these occupiers should have a hygiene rating. The 68 cases were reinspected with a maximum distance constraint in the ‘stringdist_join’ package of 1 for addresses and an unlimited distance for business names. An extra 7 recordings were matched taking the total up to 92, and 35% of the FHRS data matched to the LDC data. Next, the OSM data was compared to the FHRS data with the same constraints, however the OSM data only had coordinates. Therefore, the locations were matched based on the coordinates being
within 150m of each other, in line with the OS (2019) definition of a high street. 20% of the FHRS data recordings matched with the OSM data within Tottenham Court Road, representing 53 shops. The OSM categories are very infrequent, since there is no standardised input format for users to add information. The majority of recordings consist only of the name of the data point and the coordinates rather having the full picture of its ‘Amenity’, ‘Building’ and ‘Shop’ Category.

Table 7.5 shows a snippet from the matched data within Tottenham Court Road across all three data sources, matching their names and addresses where available.

<table>
<thead>
<tr>
<th>FHRS Name</th>
<th>FHRS Address</th>
<th>LDC Name</th>
<th>LDC Address</th>
<th>OSM Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>THE COLLEGE ARMS</td>
<td>18 STORE STREET</td>
<td>COLLEGE ARMS</td>
<td>18 STORE STREET</td>
<td>THE COLLEGE ARMS</td>
</tr>
<tr>
<td>CRAZY BEAR</td>
<td>26-28 WHITFIELD STREET</td>
<td>CRAZY BEAR</td>
<td>26-28 WHITFIELD STREET</td>
<td>BEAR FITZROVIA</td>
</tr>
<tr>
<td>BROSKI LOUNGE</td>
<td>112 WHITFIELD STREET</td>
<td>BROSKI</td>
<td>112 WHITFIELD STREET</td>
<td>-</td>
</tr>
<tr>
<td>JINJA @ MY HOTEL BLOOMSBURY</td>
<td>11-13 BAYLEY STREET</td>
<td>MY HOTEL BLOOMSBURY</td>
<td>11 BAYLEY STREET</td>
<td>-</td>
</tr>
<tr>
<td>ARBINA RESTAURANT</td>
<td>110 WHITFIELD STREET</td>
<td>ARBINA</td>
<td>110 WHITFIELD STREET</td>
<td>ARBINA</td>
</tr>
<tr>
<td>WEST ELM # 7006</td>
<td>209-210 TOTTENHAM COURT ROAD</td>
<td>WEST ELM</td>
<td>209 TOTTENHAM COURT ROAD</td>
<td>WEST ELM</td>
</tr>
<tr>
<td>GAIL’s BAKERY &amp; KITCHEN</td>
<td>11-13 BAYLEY STREET</td>
<td>GAIL’S</td>
<td>11 A BAYLEY STREET</td>
<td>GAIL’S</td>
</tr>
</tbody>
</table>

Table 7.5: LDC occupier recordings matched with FHRS data and OSM data 2012-2021 within Tottenham Court Road’s boundary presented as their business name and address.

The table shows some of the discrepancies in the recordings of names and addresses between the three data sources. Despite the spelling errors in the recordings of the FHRS data, Table 7.5 demonstrates some of the benefits of allocating more time to verifying the data being inputted. For example, the Gail’s bakery on Bayley Street was originally located in 11A with another café (‘Central Working’) next door in number 1; the LDC data recorded this in 2012 and opened a new occupier recording for Gail’s in number 13 in 2014. However, the FHRS data was able to pick up the merging of the properties sooner in 2013, recording the new address change as one whole business (‘11-13 Bayley Street’). The FHRS might therefore have applications such as studying which businesses within high streets are successful enough to expand and take over neighbouring premises.
Figure 7.9: OSM store locations selling food data (2020) within the London borough of Camden.
Figures 7.9 and 7.10 display the individual store locations for premises selling food in 2020 from the two data sources, OSM and FHRS. When comparing the two data sources over the same time period, the FHRS data has greater coverage even despite the often-erroneous recordings. There are benefits of using OpenStreetMap to derive the composition of high streets, including the fact it is “flexible and can be quickly updated in the event that a new business opens” (Penn State, 2022). Yet, unlike other government sources, the FHRS data is not fixed to be updated in fixed cycles but rather the law for food business operators to register new food business establishments at least 28 days before food operations commence creates a benefit of continuous and relatively up to date data collection throughout the year.
7.4.2 Camden Retail Survey

One detailed dataset on the composition of Camden’s high streets is the Camden Retail Frontage Survey, which while not a survey of all shopping frontages, does cover the Local Development Framework Town Centres, Neighbourhood Centres, Central London Frontages and some frontages in the Central London Local Areas. The latest available Retail Frontage Survey is from 2019, with the next due in Summer 2022. Through the knowledge exchange it was learned that the survey is conducted by one surveyor employed on a short-term contract. This perhaps accounts for the inconsistencies in recordings of the data and business categories. The data contains variables relating to the business including a ‘use class’, description, and name. Nevertheless, 19% of the recordings within the survey have either a blank business name “NO NAME” or a recorded name of ‘0’, despite often having a business type description.

The Retail Frontage Survey arguably produces an accurate snapshot of one point in time in the Camden retail landscape, given that the results were collected with consistency by one researcher with local knowledge of the area. Therefore, the recordings from the 2019 Retail Frontage Survey have been compared with the more frequently updated LDC data. Again, Tottenham Court Road and its associated boundary has been used as reference. The 2019 Retail Frontage Survey has 286 recordings within the Tottenham Court Road boundary, once the recordings with no shop name have been deleted. When excluding the vacancies there were 278 recordings. Due to the lack of full addresses within the retail survey data and possible inaccuracies in the recording of coordinates, the vacant recordings between the LDC and Retail Frontage Survey data were unable to be joined. However, the other 278 recordings were joined to the LDC data via the ‘stringdist_join’ function with a threshold of 6 and then cross referenced with the variable ‘PD name 1’ that contains the street name. 169 recordings from the Retail Frontage Survey were matched with the LDC data resulting in 61% being matched. This match rate is considerably higher than the proportion of FHRS recordings that could be matched with the LDC data, possibly suggesting the retail survey has fewer spelling errors or inaccuracies in business name recordings.

Aside from identifying the vacant premises and occupiers of Camden’s high streets, the Retail Frontage Survey data also has community-focused applications. One technique that can be used to identify the current strengths of an area is Community Asset Mapping (Beaulieu, 2002). The technique highlights existing resources within a community, covering all types of populations including those who face economic hardship and poverty. High streets have pre-existing assets such as libraries, community spaces, businesses and parks, as well as the individuals associated with the area with their skills and capabilities (Preston City Council, 2019). An accurate depiction of ongoing resilience should therefore take into account the community capacity of high streets. In order to gain an understanding of the pre-existing community assets and locations for potential expansion, Camden’s Retail Survey from 2019 has been used. Table 7.6 displays how the high street locations have been selected and categorised into 3 different types of community assets: Medical, Education, and Community Outreach.
<table>
<thead>
<tr>
<th>Medical</th>
<th>Education</th>
<th>Community Outreach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clinic</td>
<td>School</td>
<td>Charity</td>
</tr>
<tr>
<td>Dental clinic/practice/surgery</td>
<td>College</td>
<td>Community centre</td>
</tr>
<tr>
<td>Health centre/ health monitoring services</td>
<td>University</td>
<td>Community service</td>
</tr>
<tr>
<td>Hospital</td>
<td>Academy</td>
<td>Day centre</td>
</tr>
<tr>
<td>Medical centre/practice</td>
<td>Language classes/school/learning centre</td>
<td>Day centre- Homeless</td>
</tr>
<tr>
<td>NHS care centre/surgery</td>
<td>Learning centre</td>
<td>Homeless and violence victims support</td>
</tr>
<tr>
<td>Optician/Optometrist</td>
<td>Library</td>
<td>Housing cooperative</td>
</tr>
<tr>
<td>Osteopath/Osteopathy</td>
<td>Training centre</td>
<td>Jobcentre</td>
</tr>
<tr>
<td>Pharmacy</td>
<td>Tuition</td>
<td>Nursery</td>
</tr>
<tr>
<td>Physiotherapy</td>
<td></td>
<td>Place of Worship</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Public Hall (Camden Council)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Social Club</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Youth centre</td>
</tr>
</tbody>
</table>

Table 7.6: Categorisation of community assets from the Camden Retail Survey, 2019.

Figure 7.11 displays the community assets along Tottenham Court Road, Kilburn High Road and Kentish Town Road high streets, alongside vacant premises in 2019 as outlined in the Camden Retail Survey.
Figure 7.11: The location of community assets in Tottenham Court Road (top left), Kentish Town (top right) and Kilburn High Road (bottom left). The location of the community assets in the high streets as recorded in the 2019 Camden Retail Survey.

These asset maps can help to provide information on resources that already exist in local high streets and identify how they could be further utilised – for example, by demonstrating the potential to expand community outreach projects into the vacant premises in Kilburn High Road and Kentish Town Road. This versatility has already been seen through the transformation of vacant premises into COVID-19 testing and
vaccination sites but may not be formally measured until the Camden Retail Survey 2022. Within the knowledge exchange it was also highlighted how goals to develop inclusive high streets within Camden and goals to develop the night-time economy might overlap or conflict with one another. However, the community assets data could be utilised to ensure that high streets have a certain proportion of premises which cater for the community and are open during the day, so that high streets are not left deserted during daylight hours.

7.4.3 Vacancy data and Online Property Portal
When evaluating the impact of the pandemic on Camden’s high streets, vacancy data can be used to assess resilience as well as to identify areas that are experiencing decline. One source of vacancy data is the Retail Frontage Survey data. When the dataset is joined with the London Borough of Camden boundary there were 381 vacant premises recorded at the time of survey, although the time period is unknown. In comparison, while the LDC dataset has less vacancies recorded during 2019 (only 335), the live and updated recordings range from vacant properties first checked on 15-01-2005 to first becoming vacant on 13-12-2019 and validated in June of 2021. Both the LDC and retail survey data has been aggregated using Uber’s (2018) h3 index at a resolution of 10. The data has been aggregated as the LDC’s dataset is subject to commercial sensitivity restrictions; therefore, counts within each h3 cell below 10 have been omitted.

Figure 7. 12: LDC store location data (2019) within the Location Planning Centres boundaries aggregated using an H3 index to resolution 10 and associated vacancy percentage.
Figures 7.12 and 7.13 display a comparison between the vacant stores recorded in 2019 from the LDC data and the Camden retail survey. The coverage and distribution of vacant premises between the two datasets is similar. This is arguably a good indicator that the LDC’s national coverage is similar in accuracy to the work conducted by researchers hired by local councils, although the contracted researchers likely have the advantage of local knowledge and intentions of informing policy. Nevertheless, even yearly updates of vacant property locations from the LDC can be costly and may not be the most beneficial form of data to alert local councils to newly available locations for meanwhile use and community projects.

While the Retail Frontage Survey data does provide a granular depiction of vacant stores, the long time period between surveys led participants in the Knowledge Exchange to explore the possibility of augmenting them by extracting data on commercial properties for rent from an online property portal.

Rightmove is the UK’s largest property listing website that contains information on commercial and residential property listings with their address and rent prices. The Rightmove website enables searches for properties by London borough and has a unique code for each; the code for Camden was obtained in the address bar and is ‘5E93941’. The Rightmove website only allows for the data scraping of up to page 42, irrespective of how many listings there are. Therefore, to gain the most relevant listings in a specific high street, smaller areas can be scraped such as Tottenham Court Road and the properties within a defined distance periphery, in this case 1km. Due to Rightmove displaying a
maximum of 42 pages, an index was created that started at 0 and added 24 for each page that was scraped. If the index is greater than the number of results, the loop breaks. The ‘BeautifulSoup’ package was used in Python to parse the data. The address of each listing was found in the “propertyCard-link” section of the HTML code (Medium, 2022). The commercial properties up for rent were scraped for January 2022 as an indicator of landlords looking for new occupiers within the Tottenham Court Road area. The addresses for the properties were then geocoded so that they could be mapped.

Figure 7.14 displays both the 2019 data from the Camden Retail Frontage Survey and the geocoded address locations of data sourced from January 2022.

Figure 7.14 displays the disparity between the online property portal data from January 2022 and the 2019 Camden Retail Survey, with for example an increased number of
recorded vacant premises surrounding Goodge Street station between 2019 and 2022. Consequently, harnessing data from online property portals of newly vacant spaces, might provide early indications of change within high streets.

7.4.4 Table and Chair Permit Data and additional sources
The restrictions imposed between March 2020 - July 2021 meant that for much of this period, people could only dine or drink at pubs and restaurants outside. In addition, consumer habits changed as outdoor venues became preferential to those concerned about COVID-19 transmission. As a result, some businesses adapted by investing in outdoor seating. This was facilitated by a new ‘Pavement Licence’ that was conceived as a temporary change to the ‘Tables and Chairs Permit’, but which has been extended to 30th September 2022. While the Pavement Licence is capped at a cost of £100, the Tables and Chairs Permit for Camden is £486.67 for an annual licence plus £45 per chair. In order to gauge which areas already had outdoor seating provisions before the pandemic, permit data has been used. While the permit data does not cover the use of tables and chairs on private land, it does cover tables and chair placement on public highways or city walkways. It is hoped that the Pavement License will become the primary legislation in due course as this is less onerous, but it is likely that the current approaches will be rolled over for another year. Figure 7.12 displays the location of Table and Chair Permits from 2016-2021 in Kilburn High Road, Kentish Town Road and Tottenham Court Road.
Figure 7.15 shows few permits in Kilburn High Road between 2016-2021, whilst Kentish Town Road had an increase in permits from 4 to 18. In the Tottenham Court Road area there was a substantial cluster of new permits in 2020-21 opposite Goodge Street station, which coincides with what we saw in the FHRS data of an increase in new restaurants. While the Table and Chair Permit data can be used to provide an indication on the expansion of outdoor seating provisions, it would be more beneficial to combine the data with the Pavement Licence data if available in order to gain the full picture of outdoor seating use during the pandemic. A full data insight would be especially important when evaluating the impact of outdoor seating on high street resilience following the lockdown restrictions that enforced outside dining.
Additional data sources were explored and mapped at high street level within the Data for Future High Streets report, including crime data sourced from Police.uk (Figure 10.10 and 10.11 in the appendices). However, throughout the knowledge exchange it was acknowledged that the recorded crime data could only be used as a rough proxy for crime occurrences and its impact on high streets due to the lack of information on the time of day of an incident, inconsistencies in location recordings, and changing laws. In particular, it is important to note that during the periods of lockdown restrictions, some COVID-19 related infringements may have been recorded as anti-social behaviour.

Overall, despite the potential benefits of the datasets explored within this section, there are limitations to the insights they can provide. On one hand, private and frequently updated datasets provided by LDC, or an online property portal are costly prompting disputes over whether funds are more useful elsewhere in the council’s services. Other costly datasets include the collection of data as part of the Camden Retail Survey, which while accurate is rarely updated leading to out-of-date insights. Therefore, alternative and pre-existing datasets, specifically the FHRS may provide a compromise for regular but a more cost-effective solution to mapping the store composition of Camden’s high streets. While the FHRS recordings may be fit for its intended purpose, small changes including checking the data upon input could optimise its accuracy to enable policy informing GIS analysis. Such changes include business case comparison when inputting data to check for consistency in recordings, checking of spelling errors, checking geographic location recordings and an element of ground truthing. These changes are particularly important given the more numerous limitations of other open-source datasets to inform analysis on high street composition such as OSM.

7.5 Discussion

7.5.1 Knowledge exchange insights
The knowledge exchange between UCL and Camden Council stemmed from the Camden Future High Streets Action Group with the aim of developing the Data for Future High Streets report. This effectively involved conducting a data audit of the available data sources relating to Camden’s high streets. The report underpinned all three of the action group challenges, with a particular focus being given to the ways in which pre-existing data could be used to show changes over time and to distinguish between high streets in order to inform local policy. The report enabled both imaginative thinking on possible applications of pre-existing data sources and critical engagement with the data.

Throughout the knowledge exchange there were a number of challenges and compromises that occurred. One example in particular was the complications that surround the sharing of data. From the offset, Camden council had a goal to mobilise collaboration between large players in the data field such as Google and Arup. Due to commercial sensitivity, however, the drawing up of legal contracts to enable data sharing are often complex and time consuming, hindering fast-paced analysis to inform policy. This was the case when obtaining the legal rights to a dataset obtained by CACI on pay cheque information at postcode level. By the time the contract was amended to allow UCL access to the data, the report was near competition and the data was not viewed as
a valuable asset to the existing information once viewed. A similar bureaucracy-induced time delay occurred when obtaining access to the high street boundaries developed by Ordnance Survey, with UCL needing to agree to a Public Sector End User Licence. This caused some delay at the start since it was vital to determine the exact boundaries used by Camden council to develop policy.

By implementing the methodology of engaged scholarship this thesis was able to research two main areas that would otherwise have been absent from a purely quantitative study. Firstly, through discussions with the Camden data team, insight was gained into what data they have access to, its integrity, and Camden’s data capabilities. Secondly, through dialogue the questions they wished to address using the data were made clear. More specifically, Camden council was able to gain access to the data part of the GLA’s ‘High Street Data Partnership’ which includes access to a number of commercial data sets: O2 footfall data, Strategic Coordination Group origin/destination data and Mastercard spend data.

The council were particularly eager to use the Mastercard spend data. However, the dataset had some inherent disadvantages, including the exclusion of physical cash or data from other companies, and a lack of scaling to account for other payment tenders. Such data is used by the GLA to calculate measures of resilience. However, a central focus on spend data arguably contradicts Camden council’s initial goal for its high streets to be inclusive spaces in which some of its goals cannot be quantified by cash flow (for example, its vision of high streets as places to “share knowledge and skills”, “learn” and “play”). It is therefore important to consider how new sources of data – particularly commercial sets and big data – might act as a distraction as well as a benefit to achieving policy goals. It is therefore vital for large commercially generated datasets to be scrutinised in terms of their validity, generalisability and representation of the communities that policymakers are trying to help.

In relation to the second research area, this thesis has been able to insight into the data priorities of a local council when informing high street policy. Those priorities included information on the key players in the commercial data market and their limitations. The council pressed for stronger recommendations that included deeper assessment of resourcing, costs and monitoring in relation to the commercial data it did not have access to. This perhaps suggests that the local council does not conduct much in-house analysis on the validity and reliability of external data sources, but instead relies on third parties or data providers/brokers such as the GLA to assess their potential applications. There was also observation of fragmentation between the high streets team and GIS and data analysis department suggesting that the council could utilise their pre-existing internal resources to conduct a more thorough investigation of the data being purchased for high street projects.
7.5.2 Knowledge exchange recommendations and outcomes
The overarching theme of the recommendations provided to Camden council at the end of the knowledge exchange was that single sources of data can only provide information about one aspect of high streets, but that a more in-depth understanding can be acquired by combining and triangulating different data sources. Through a holistic data approach Camden council can attempt to address their wide-ranging objectives to improve people’s experience of high streets as well as monitoring retail patterns.

The report found that the availability and quality of data varied for different high streets and between data resources. The spatial extent of each data source also varied as high street boundaries were defined in different ways depending on the dataset. The main example was that a high street boundary may refer to building frontages or may be defined as the general commercial area surrounding a street. This challenge carries particularly important implications when datasets are combined or when data sources are extracted geographically. Overall, it was therefore suggested that to improve the accuracy of future high street projects that leverage different data sources, the interoperability of different data sources should be increased. In particular, emphasis was placed on data sources collected by Camden, since it was within their control to improve the quality and regularity of data collection. Such improvements can improve the utility of data sources for downstream users and help detect trends through time. The FSHR data analysed within this chapter provides a fair example of how maintaining a standardised format allows for cases to be tracked historically.

It was also recommended that future data collection by Camden should be more granular, with additional attention placed on ensuring consistent data collection methodology over time. Finally, it was suggested that Camden council needs to increase the usability of existing publicly available data sources by allocating more time to the creation of detailed metadata describing the attributes, update frequency and data collection methodology of each dataset. Making the council’s publicly available data more useable could help it achieve its goals of increased engagement from the local community and external stakeholders. A more detailed overview of the six recommendations from the report has been displayed in Figure 10.6.

The final results of the knowledge exchange consisted of Camden Council responding to the recommendations set out in the Data for Future High Streets report. Table 7.7 summarises these responses.
<table>
<thead>
<tr>
<th>Recommendations</th>
<th>Defining terms: High streets and town centres</th>
<th>Improving data collection</th>
<th>Critical analysis of internal and external datasets</th>
<th>Better use of in-house data and judicious use of external data providers</th>
<th>Engender creative data sourcing</th>
<th>Develop a community of practice</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Explanation</strong></td>
<td>There is more than one definition, but needs to be consistent and definitions well-articulated.</td>
<td>Data collection and metadata that provides information about other data – working together across the council to ensure consistency and interoperability.</td>
<td>To establish utility and added value to better understand Camden’s high streets. Assess the real strengths and weaknesses of data suppliers</td>
<td>Added value of using in house data better and targeted commissioning of data service providers.</td>
<td>It may generate novel insights previously overlooked and chance to experiment without constraints of tightly defined tasks/outcomes.</td>
<td>This process has demonstrated the value of talking about data openly and between teams, forming an important community of practice that would be good to sustain.</td>
</tr>
<tr>
<td><strong>Outcomes</strong></td>
<td>Redefining what a high street and town centre is with a view to consistency across council services.</td>
<td>Better understanding of the extent of vacancy and monitor change.</td>
<td>Get better value and functionality to support high streets functions and planning.</td>
<td>Produce a set of metrics (which define what is to be measured) for high streets.</td>
<td>Continue to innovate around data sourcing – maybe art of community of practice.</td>
<td>Collaborative and open discussions should continue.</td>
</tr>
<tr>
<td></td>
<td>Map FSA data as an ongoing data set.</td>
<td>Develop ability to monitor change without excessive costs, officer time or resourcing.</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>Map data that supports high streets aims.</td>
<td></td>
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<tr>
<td></td>
<td>Use business bulletin to reflect high streets.</td>
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</tr>
<tr>
<td></td>
<td>Link community assets and</td>
<td></td>
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</tbody>
</table>
7.5.3 The feasibility of local growth policy

Whilst it is clear that there is a need for quantifiable analysis of high street intervention strategies and use of public funds, this chapter has found that local councils do not necessarily have the means or expertise to analyse and interpret large commercial datasets effectively.

Therefore, in order to facilitate and ensure the effectiveness of the devolution of power for high street policy, local councils should still predominantly rely on data sources which have been collected with a transparent and rigorous methodology. For example, the census is portrayed as a gold standard dataset as its inherent purpose is to capture the whole population; however, it is only carried out every 10 years. In addition, the data analysts at Camden expressed explicit concerns about the data collection issues for the 2021 census. They suggested that the census data for London underestimates the true population. This is due to the data collection being during the COVID-19 pandemic meaning many students, workers or international residents returned to live with family members in other parts of the UK or in other countries. This poor temporal granularity and issues with quality assurance creates the need for supplementary datasets in order to obtain an updated view of the population. A similar case can be made for high street related data, whereby rigorous methods using local knowledge such as the retail survey can be used and periodically supplemented by commercial sources.

Nevertheless, in order to meet the central government’s call for a well-directed spatial strategy to address the market failures affecting both ‘left behind’ and well performing areas, the spatial accuracy and consistency of data collected by local authorities needs to be improved. Improved spatial granularity will help to identify those individual high streets that need particular funding attention. Yet, the question is raised as to whether
funding bid strategies allocate resources to broad thematic areas fitting in with the political agenda as opposed to the geographical areas that are most in need. Consequently, Camden’s local policies should be focused on unleashing opportunity and stimulating allocative efficiency rather than the redistribution of funding between high streets.

When discussing the feasibility of Camden council implementing local growth policy to improve its high streets, it is also important to question the potential power the council has to shape and change its high streets. Fern and Jones (2017) state that in Camden there was a significant number of premises owned by the council which were sold to fund its Community Investment Programme, exemplifying the financial pressures and increased privatisation faced by high streets. Such practices by local authorities are noted by Hallsworth and Coca-Stefaniak (2018) to be national, where the power of retailers run up against the decreasingly powerful planner. In addition, while retail planning regulations still focus on land use decisions, the actual influence of planning itself has declined.

One example where a data driven approach could be essential for assessing the intersection of national and local policy on high street performance is for the opening of the Elizabeth Line, which opened in May 2022. The new transport link goes through the Camden high street of Tottenham Court Road, which will potentially lead to a transformation of the area. Before the opening of the new line, Camden council carried out a number of initiatives to make the high street more attractive and accessible (Camden, 2018). Through combining a number of data sources such as those outlined within this chapter, a holistic measurement of the impact of the opening of the Elizabeth Line on Tottenham Court Road could be developed, including possible changes in high street composition, footfall, uptake of outside dining, and adaptive resilience.

7.6 Chapter Summary

This chapter has offered an insight into the use of data within local authorities to inform high street policy. In particular, the chapter discusses the use of an engaged scholarship approach to conduct a knowledge exchange with the London Borough of Camden. Specifically, the knowledge exchange aimed to explore the breadth of data that can be used to inform Camden’s Future High Streets Programme. While a single source of data can provide knowledge about one aspect of a high street, triangulating and combining different sources of data allows the development of a much richer understanding. Using a multifaced data approach offers many more opportunities to monitor the factors that influence people’s interactions with high streets as well as to capture patterns of retail and area change.

Within this chapter, three different areas of data were explored: high street boundaries, retail, and community assets. Throughout this thesis the reliability of pre-existing high street boundaries that span the whole of Britain have been assessed and prioritised based on their accessibility and accuracy. Nevertheless, through engagement with Camden Local Authority it was learnt that all of their high street level analysis used the Local Plan’s “Centres Boundaries”, which have been developed by the Strategic Planning and Implementation Team. These boundaries cover town centres as well as “Central
London Frontages”. Despite the boundaries being universally useful from an internal planning perspective, the boundaries for high streets such as Tottenham Court Road were confined to the area of the frontage of ground floor use. These boundaries created problems when joining them to additional data sources as they did not provide a sufficient buffer to conduct valid analysis. Within this thesis a new manually estimated Tottenham Court Road boundary was used. However, the method is not applicable across all of the areas defined by “Central London Frontages”, so a standardised method of buffering the boundaries should be developed.

Secondly, retail data from the Food Standards Agency, Local Data Company and OpenStreetMap was compared alongside the Camden Retail Survey and Table and Chair Permits. These data sources were used to gain an understanding of changing retail occupancy and use. The Camden Retail Survey provides an in-depth granular picture of the retail premises across the whole of the borough, including vacant premises. However, the last available data was from 2019 with new survey data not being published until the summer of 2022.

Therefore, in order to supplement the outdated retail survey, FSA location data and Rightmove data were explored. The FSA data was validated against the commercial LDC dataset and opensource OSM data. While there were multiple errors in the consistency of the recordings within the FSA data, more vigilant checks at the data input stage would allow the data to act as a good proxy for the opening of food-related businesses on high streets. The data has the benefit of being internally generated, facilitating and reducing the cost of modifying recording practices. The Table and Chair Permits data also served as a good free resource to evaluate the impact of government policy on outdoor dining during the pandemic and its relationship with high street resilience.

The final subset of data explored was community asset and vacancy data sourced from the Camden Retail Survey. The retail survey data from 2019 was used to gain an understanding of the impact of pre-existing local community assets available within Camden’s high streets. The COVID-19 pandemic presented opportunities for new uses of vacant premises to meet community demands. For example, some vacant premises were used as vaccination and testing centres. Consequently, even after COVID-19 ceases to dominate policymaking, it would be beneficial to continue ‘meanwhile’ use projects and capitalise on local assets which could become hubs for community outreach projects. In order to gain an up-to-date picture of possible vacant premises for projects, the retail survey was not sufficient. Therefore, live Online Property Portal data was accessed to provide a description of the current available commercial properties for rent, their locations and prices. Accessing Online Property Portal data periodically through an API may therefore be a cost-efficient solution for local councils to maintain knowledge on vacancy between more granular surveys.

Upon reflection of the methodological approach taken in this chapter, it is important to highlight the key implications of conducting the knowledge exchange on the rest of this thesis. In particular, throughout the rest of the chapters, the CDRC retail boundaries were used as a basis for a spatial definition of a high street yet, this chapter has outlined how
local authorities predominantly use land use boundaries. While the CDRC boundaries were selected as they are one of the only open-source retail boundaries that span across the whole of Britain, this research may have benefited from a more in-depth comparison between the two sets of boundaries throughout. Access to the land use boundaries used in this chapter were granted by the London Borough of Camden as part of the knowledge exchange however, richer insights may have been developed through collaboration with more local authorities as a way of validating case study findings. Through presenting case study findings using the same boundaries and format as local authorities the results may have had greater value for stakeholders.

By using an engaged scholarship approach to investigate how local authorities use data to inform policy, an in-depth understanding of the challenges, strategies and available resources was developed. In light of the current challenges faced by British high streets, local councils are setting out wide and encompassing goals to make high streets all-embracing, inclusive, and hubs of everyday life. Despite the ambiguous nature of these goals, central government is increasingly pressing the benefits of good quality data to monitor and evaluate deliverable valuable outcomes. This has arguably led to an increased desire among local councils to purchase large commercial datasets. However, such datasets are often in need of critical analysis and interpretation. One of the most important findings in this chapter was the need for total quality management of data collection by councils. The food hygiene data served as a strong example of lax data collection and maintenance procedure that hamper the development of major data assets. Local councils can capitalise on pre-existing data that is generated in-house, ensuring that it remains reliable and consistent. This will help reallocate funds according to policy goals.
Chapter 8

Discussion, Applications and Research Prospects

8.1 Introduction

Previous high street research has either focused exclusively on quantifying high street success or focused on producing frameworks through qualitative collaborations with stakeholders. Consequently, the aim of this thesis has been to implement a mixed methods approach to firstly explore the measurement of high street success across Britain using a unique consumer dataset, and secondly to understand how data is used within local authority policies aimed at improving the vibrancy and resilience of high streets. In order to carry out the majority of this thesis’ analysis, initial investigation was required into the validity and limitations of the primary data source – the Local Data Company’s dataset on retail type, address and vacancy.

In addition, definitive decisions were made regarding the specific high street boundaries used throughout as a result of critical engagement with a variety of different data sources including the Consumer Data Research Centre, Geolytix and Ordnance Survey. This identified that, while the LDC’s dataset is granular with new data being generated at frequent intervals, it does have some recording issues that requires data cleaning prior to analysis - including differentiating between different premises and occupiers within shopping centres. In addition, it was discovered that local authorities often have their own high street boundaries derived from planning boundaries, which makes it difficult to compare high streets across the whole of Britain. However, it was shown that a combination of the CDRC retail boundaries, the OS definition of a high street and the LDC locations of stores could be combined to delineate uniform boundaries.

Despite the recognition of the inherent limitations of the LDC dataset, following the data cleaning process outlined in Chapter 3, the following chapters have aimed to utilise the dataset to create measures of high street success. The analysis in Chapters 4 to 7 was warranted by the gaps in the literature outlined in Chapter 2, specifically relating to the development of a politically neutral quantitative tool to identify high streets within Britain that are struggling the most in light of socio-economic shock. This can be used to inform funding allocations and policy decisions. While a primarily quantitative measurement of success arguably excludes important aspects of community life and local opinions, the analysis within this thesis has aimed to ground the findings within local context and acknowledge whether supply side retail composition meets consumer needs. Chapters 5 and 7 in particular demonstrate how new consumer datasets can supplement more traditional data sources covering demographic and social factors at a more aggregated scale. When these sources of data are combined, they provide a more holistic and in-depth picture of high streets than is possible using a single data source.
This final chapter aims to reinforce the academic impact and wider contributions this thesis offers. In the first sub-section the mixed methods approach used within this research is evaluated alongside relevant limitations. Next, the possible applications and implications of this research are explored with reference to the use of commercial datasets to inform high street policy, and more generally in relation to the datasets used by local councils. This thesis concludes by outlining prospects for further research.

8.2 Reflection on Methods

Due to the granularity of the data used within this research, including the LDC and FHRS datasets, there was the need for a mixed methods approach to validate and ‘ground-truth’ the results. The part of this thesis that most required qualitative validation was in Chapter 2, where the LDC data required extensive data cleaning. During this stage, patterns within the data were cross-referenced with multiple qualitative sources including news outlets and picture sources in order to uncover local conditions, including the presence of shopping centres, mergers, and expansions of premises. The same process was required in the previous chapter, where novel validity testing was conducted between the FSHR, LDC and OSM data. While this qualitative approach is manual and time-consuming, it was considered the most appropriate solution to capture the fundamental local context.

The main aim of this thesis was to measure the vibrancy and resilience of British high streets between 2017-2021. The research implemented a variety of methods to show how there is often a need for different heuristics depending on the rationale, users, and repeatability. Consequently, each of the analytical chapters called for a new decision on the method that would result in the best outputs for the intended use and research questions. The numerous options were selected via an iterative approach followed by ground truthing.

Each method had its own limitations, which have been discussed throughout. Each chapter’s method has a number of possible ways in which they can be improved. Nevertheless, when reflecting on the selected methods it is apparent that the most appropriate clustering methods were chosen for each research question. For example, Chapter 4 adopted a k-means clustering approach to defining the retail composition of high streets. In this instance, k-means was preferable to a hierarchical algorithm as it produces tighter clusters and tightly defined categories. The method also ensured that information about the problem domains was available, making modifications to improve the accuracy of the clusters a straightforward process.

However, in other chapters a more informative structure was required; for example, Chapter 6 uses hierarchical clustering, which is more explanatory than the unstructured clusters produced using k-means. This was particularly important as the optimal number of clusters could be selected from the model itself, minimising human interference with selection of resilience categories. Chapter 5 also used hierarchical clustering alongside a modified DBSCAN clustering method. In this instance, it was the most valuable method as it enabled the identification of noise data, or shops located away from the main high street. The use of Pavlis et al.’s (2018) modified DBSCAN clustering method meant that
smaller clusters could be derived within a specific distance relating to the high street literature. The DBSCAN method also meant that each subgraph was used to select clusters with a point density close to the overall high street study area.

The second main techniques used within this thesis were aimed at contextualising high street trends and discussing wider policy conditions and implications. While these external conditions were discussed throughout, Chapter 7 was particularly policy focused and adopted an engaged scholarship approach. While the research method required significant time and effort in developing relationships with stakeholders, it added a human touch to the research process. Engaged scholarship was the ideal method for exploring how data analysis can be implemented for high street research within local councils as it allowed for openness regarding preconceptions of priorities and even the overhaul of initial research questions. The method was also the most appropriate for engendering wider acceptance of the research conducted within this thesis within local policy and by local stakeholders. Through stakeholder engagement and learning from local government, the benefits of engaged scholarship are apparent, as it develops more valid, compelling and informative analysis.

The additional methods used throughout the thesis are mostly based on descriptions of the data sources. For example, in Chapter 4 the most frequent occupier changes were calculated using the LDC data and described in relation to their general trends and geographic patterns. In the same chapter, descriptive statistics were created to measure the vacancy and occupier turnover of each high street. These statistics were used in conjunction to quantify 'retail vibrancy', and a variation of these same metrics were then used throughout – for an index on commuter town high street resilience (Chapter 5), a Britain-wide measure of high street resilience (Chapter 6), and to validate open data sources (Chapter 7). While the development of descriptive statistics was a simple process apart from the data cleaning stage, as was outlined in the literature review there is a need for research which includes performance statistics that can be accurately compared across all of Britain’s high streets. The descriptive statistics developed in this thesis demonstrate how large commercial datasets can be aggregated to high street level to provide essential insights.

8.3 Limitations

This thesis has provided a multitude of unique insights into quantitative measures for retail vibrancy and resilience, and also in terms of how commercial data can be used to inform local high street policy. Nevertheless, this piece of work is still subject to limitations. These predominantly concern uncertainties within the main data source which was provided by the LDC.

One of the reoccurring limitations that are present throughout this thesis is uncertainty resulting from the inability to compare the commercial LDC dataset to a reference dataset. Data quality issues were raised in Chapter 3, where unquantifiable errors were identified. Such errors included incorrect coordinates of stores, issues surrounding the merging of properties, and errors and infrequent recordings for the timestamps of some premises.
During the data cleaning process in Chapter 3 a series of steps were taken to minimise the errors. However, uncertainties are intrinsic in this type of big data, and it is too time consuming to check every store location over such a large time period.

There was also uncertainty in the open data sources used in Chapter 7, in particular the FHRS dataset. The data was compared to the LDC data and OSM data to check for errors; however, since there were errors in both data sources it was difficult to measure the validity of both datasets. Nevertheless, the FHRS data was found to have more sources of errors. For example, the main issue was spelling errors of business names, leading to an inability to conduct precise string matches and an over-representation of occupier change. Despite the LDC data in particular following well-known and recorded trends and enabling the exploration of Britain’s high street retail landscape, the issue of errors within the data restricts the breadth of inferences that can be made regarding comparisons between high streets. Other additional issues with the FHRS data that have been discussed in Chapter 8 include a lack of metadata, which is particularly problematic in situations where the same business has been recorded as a different category on different occasions when it has been recorded. While this was picked up on the case study of Camden for the FHRS data, the same issue was not identified within the LDC data, suggesting that it was a more accurate source of retail composition.

The datasets used within this thesis also had issues of representativeness. Unlike other situations in traditional social science research where standardised protocols are in place to address biases in data, there are limited resources for measuring biases in the LDC data – specifically, whether the sample of shops within the LDC dataset is representative of whole high streets. Throughout the thesis and in particular Chapters 3 and 8, the LDC data was linked to other open sources and government statistics. Nevertheless, as outlined in Chapter 3 it is difficult to compare high street statistics when the boundaries usually differ from source to source. Chapter 3 also outlined how in some cases the sample of shops in the LDC data was clearly not representative of the whole high street and had to be omitted entirely. One example is the overrepresentation of vacant stores within a high street and the underrepresentation of other occupiers, drastically influencing the analysis outputs. While these errors were dealt with using case-wise deletion, it highlights the need to conduct future analysis using other granular commercial datasets that have different samples of shops within high streets to compare the patterns of vibrancy and resilience.

An additional limitation faced throughout this research is the uneven distribution of data across British high streets a result of differing sizes of high streets and uneven data collection. The result is that not all high streets have equal representation in relation to the true supply of shops and number of high streets. While a decision was made to use the OS and ONS definition of a high street and to only include retail areas with a minimum of 15 stores, this could have excluded some high streets that were not represented by the LDC data. While the LDC database is large and contains over 500,000 store locations across the UK, it may include less stores within smaller rural high streets.
A final important consideration regarding the data is irregularities in the time intervals that the premises are checked for new occupiers with urban areas possibly having more up to date and accurate recordings of retail composition. While the majority of premises were regularly updated and had been checked during the latest output in June 2021, which provided a large sample for longitudinal analysis between 2019-21, more frequent checks to sites could increase the accuracy of the findings.

Of particular importance is the fact that a small proportion of the data had not been checked following the lifting of the lockdown restrictions, meaning that some businesses that did not re-open after being temporarily closed might not be captured in the data. This is a particularly important consideration due to Chapters 6 and 7 aiming to measure the impact of the COVID-19 pandemic on high streets. Consequently, further analysis on data that was collected at the end of 2021 might have improved the analysis and captured the longer-term effects of the lockdowns.

This is particularly important for previously successful towns and cities that took longer to recover but would return to their original state with a return in footfall, something that was perhaps not captured in Chapter 6’s analysis. Nevertheless, access to the LDC data has provided a unique resource to measure pre-pandemic retail vibrancy and the short-term impact of the pandemic on high streets through the execution of new heuristics and qualitative validation.

To summarise, this research has identified the scope for implementing commercial datasets into spatial and temporal analysis of high street success that can be used to inform local policy. The results from the analysis are predominantly conditional on the validity and generalisability of the data being used, which could restrict the quality of the outputs and their ability to inform decision making.

8.4 Applications and Implications

Even in light of the discussed limitations, this thesis has still managed to produce multiple unique and valuable insights for the application of commercial store location data in academic and local government research on high streets. The first important contribution was made in Chapter 3 in relation to the in-depth exploration of the LDC data set and how to overcome its data quality issues. Prior to this research, studies using data generated by the LDC have focused more on producing commercial or academic applications. This thesis has gone one step further to consider if the data is both useable and representative enough to inform policy. Therefore, Chapter 3 has produced clear guidance on how the data can be transformed to produce quarterly metrics and useable variables, creating a valuable framework for those wishing to use it to map vibrancy and resilience. In addition, this research could help to improve other models of resilience though the inclusion of supply side variables such as store composition, which can be obtained from this data.

These findings could also be used to suggest how the LDC data could be applied to other social problems as touched upon in Chapter 7, including easy identification of vacant properties for community projects or vaccination centres. Even for these other uses of the data, it is important to have an understanding of the validity and accuracy of the data. In
the case of being limited to open-source data such as the FHRS, OSM and property portal data, it must be considered that the use of these sources in isolation misses a large proportion of businesses and properties within the high street. This underlines the importance of cross-validating them with other sources, including commercial data, and using them in conjunction with each other to gain a more robust depiction of British high streets.

Consequently, this thesis has highlighted the need for more formal audits within local councils on the data they collect, have pre-existing access to, and have purchased from commercial sources. Chapter 7 in particular has laid a roadmap to establishing linkages between various high street related datasets and comparing their accuracy both geographically and informatically. Access to such information offers academic and commercial insights and is invaluable to policy makers. Information regarding the biases within high street related commercial datasets would be useful to local councils so they can recognise and address current limitations, and critically reflect on if they will add value to their internal analysis.

Furthermore, this thesis has laid the foundation for future resilience measures that link together these multiple data sources to gain a more complete picture of high street case studies. In particular, Chapter 7 was built upon a knowledge exchange with Camden Council that aimed to compile a complete audit of the high street data available to them. This data audit, combined with Chapter 3, has provided an in-depth assessment of the available data sources and their limitations. While the majority of available datasets are open source and predominantly aggregated to local authority level, collaborations between commercial providers, academia and local governments create new opportunities to use granular commercial data to supplement open-source high street data. The LDC’s data makes a significant contribution to the mapping of high street composition, and therefore to retail vibrancy and resilience. While open data sources such as Camden Council’s retail survey and the FHRS data can provide a snapshot of some of the businesses in high streets at specific points in time, they do not allow for Britain-wide analysis that captures longitudinal information. When these datasets are not supplemented by more frequently updated commercial data, they are unlikely to successfully produce metrics regarding all store types in British high streets.

On balance, while there is scope for future research, this thesis has provided a strong case for the implementation of commercial shop location datasets in local authority high street analysis to produce measures of resilience. Using commercial data can help to fill in the important time gaps between time-consuming retail surveys, such as the 3-year gap in Camden council’s survey in which the true impact of the COVID-19 pandemic could not be measured. However, one main issue highlighted in Chapter 7 was that of data linkage resulting from the high street boundaries used by local councils – it was suggested that in some cases the planning boundaries did not have a sufficient buffer from the retail frontage polygons to produce sufficient data linkages. In fact, Camden council reflected on the analysis outlined in this thesis and is in the process of re-evaluating the delineation of its high street boundaries.
From a theoretical standpoint, this research has provided sufficient results suggesting that commercial store location data can produce and supplement a variety of different high street success measures. Throughout this thesis the potential benefits of such data have also been discussed, including greater granularity and more frequent updates than traditional sources. By quantifying latent concepts such as vibrancy and resilience, this study shows how existing research on the geographic distribution of retail success can be enhanced by implementing these processes.

One illuminating example is the Britain-wide measurement of the impact of the COVID-19 pandemic on high streets, where it was discovered that there were geographical clusters of similar resilience characteristics. The resilience characteristics varied between high streets based on the proportion of stores that were allowed to remain open during lockdowns, vacancy, and occupier change. There were significant differences between the resilience of high streets based on their prior success and their number of essential stores, indicating that the pandemic exacerbated pre-existing trends. In addition, the implementation of geographic constraints to account for underlying factors, including the strength of regional supply chains and linked consumption patterns, revealed strong geographic clusters. Therefore, this thesis produced quantitative evidence to suggest that there are geographic differences in factors relating to vibrancy, in particular the distribution of essential stores and vacancy. These measurements are important to identify politically neutral heuristics that can unveil geographical disparities across British high streets. An all-encompassing understanding of high street resilience is of interest to stakeholders aiming to regenerate high streets including retailers, BIDs and local authorities.

The main aim of this thesis was to provide an academic contribution to the measurement of high street success within the social sciences. Nevertheless, this study has also made a notable contribution to local policy firstly through an in-depth audit of data sources available to Camden Council relating to their high streets, including unique insights into the limitations and usability of commercial data sources. This exchange of knowledge aided the Camden Future High Streets team in understanding how they can use existing datasets to map characteristics of their high streets, while critically reflecting on their quality. The detailed assessment of some datasets, in particular the FHRS data, led to in-depth descriptions of errors in the recordings of stores, data cleaning strategies to rectify the errors, and suggestions to minimise the errors during the recording process. Secondly, this research provided impartial insights into the uses and limitations of commercial datasets to help local authorities to reassess their current uses of purchased data and possible future uses purchases. For example, following demonstration of how property portal data can be scraped to map current commercial vacancies, Camden Council is considering purchasing a property portal API to supplement its infrequent retail survey.

In addition, findings from the high street performance measures capturing vibrancy and resilience contributed to discussions surrounding whether there is a shift in narrative in the way academics, retailers and policy makers talk about high street success. By providing analysis from 2019 in a pre-COVID era, to the short-term impacts of the pandemic in 2021, this study was able to engage with current policies at the time of...
research and integrate policy priorities. In particular, in the pre-pandemic era retail vibrancy was denoted as high streets that were somewhat all encompassing, with a mix of leisure and convenience alongside pop-up shops and meanwhile spaces. Yet, when analysing the short-term impact of the lockdown restrictions it became apparent that high street success was more heavily reliant on the proportion of ‘essential’ stores which enabled greater resilience to economic and cultural shock.

The final and broader implication of this research is a contribution to debates surrounding access to unique and granular commercial data. In order for the majority of the analysis in this thesis to be conducted, either a strong relationship with a commercial data provider or a costly data purchase is required. Consequently, this work has highlighted a need for commercial companies to work with academics to explore the potential societal benefits of their data. This thesis has added to existing studies that show how commercial data sources such as that provided by the LDC can not only benefit and be sold to retailers, but also contribute to public good, while maintaining and accounting for commercial sensitivities.

Such collaborations between academics and commercial data providers create the possibility of a symbiotic relationship. For example, this thesis has highlighted and reinforced the LDC’s position in the market as having one of the most granular, high precision and wide-ranging datasets for retail store location. In addition, the previous chapter in particular discussed, impartially and in detail, the needs of a potential client - giving an outside perspective not driven by profit maximisation. The time allotted to testing the validity of the LDC data and producing outputs throughout this thesis was also arguably longer than that permitted by commercial analysts due to time constraints and KPI targets. Nevertheless, with academic endeavours that aim to create in-depth understandings of high streets by linking together multiple data sources, there are issues surrounding the possible disclosure of store names and location, which challenges the viability of commercial businesses. Therefore, future research should also remain wary of the risk of commercial disclosure and follow the precautions taken within this thesis in relation to aggregation methods. However, with thoughtful data presentation practices commercial data represents a largely untapped asset to academic researchers and local policy makers.

8.5 Future Prospects and Closing Remarks

While the potential of commercial data within academic studies is becoming more well-known, there are still minimal insights into the use of such data to inform high street planning, policy, and intervention strategies at a national and local level. From engagement with Camden Council, it has been shown how in many ways local authorities are only at the start of their journey towards fully understanding the uses and limitations of commercial data at high street level.

Two main suggestions have arisen from this thesis regarding future research avenues. Firstly, the importance of selecting high street boundaries that provide enough geospatial coverage to allow for data linkage, have a unified methodology for de-lineation across the
whole study area, and are in-line with wider planning policy. Secondly, future research should continue to challenge the integrity and reliability of commercial and open data sources which will lead to the development of datasets with less errors and useful metadata to produce data-linkage and analysis that measures the performance of high streets. With more detailed information regarding how the data was collected, processed and presented, richer analysis measuring the vibrancy and resilience of high streets might be developed. For example, the ability to check the validity of the FHRS data against the LDC data was limited due to recording issues in the FHRS leading to weak character string matches. The methods to produce metrics on vibrancy and resilience were also limited to specific application in the LDC data as a viable open data source was not found to produce outputs with the same granularity. Access to a greater variety of commercial data sources could facilitate a more reliable assessment of the accuracy of the LDC data, and therefore of the models produced within this thesis. However, such a comprehensive comparison of high street data sources would be costly or reliant on relationships with commercial providers.

Within the general context of retail location data, a potential area of future research is linked to the engaged scholarship and policy engagement aspect of this research. For example, the main aim of this thesis was to create measurements of retail vibrancy and resilience; ultimately, however, researching the possible implementation of such methods into local policy was equally as important as providing an academic contribution to social science. Engagement with social policy and policy makers was essential to this research due to lack of practical policy intervention knowledge and the relatively new practice of challenging the integrity of using commercial data sources to inform high street intervention strategies.

Using this research as a foundation, future studies should focus on implementing measures of high street success in macro-level policy, adding to the policy context of the Britain-wide measures developed in this research. For example, it may be beneficial to develop a comparison between the high streets that were hardest-hit by the pandemic based on measurements using commercial data and the town centres and high streets that actually received funding and additional government support. This would ultimately indicate whether commercial data that is more frequently updated could inform national planning policy and provide wider societal benefits. This thesis has aimed to produce a starting point for discussions regarding the role of commercial data in conjunction with more traditional sources to enable high-quality national analysis in response to the social and economic challenges and shocks faced by high streets.

To bring this thesis to an end, it can be surmised that commercial sources of data can act as a valuable supplement to existing traditional data sources to give insight into the composition and performance of British high streets. While the potential uses of commercial data have been evidenced, further comparisons are needed with additional data sources with the same granularity and frequency of updates, in order to fully understand their possible contribution to informing policy. This includes consideration of their limitations and also an acknowledgement that high street analysis is often subject to political agendas. Attention should therefore be paid to the existing resources, goals and
needs of local authorities if commercial research is going to have practical applications. It is also important to consider the usability of such data sources if they are to replace or supplement existing sources, including consideration of the scale of aggregation required to produce both commercially acceptable and informative outputs. As of yet, commercial datasets can only be used as a supplementary resource for local councils to build a more up to date and holistic picture of their high streets. Nevertheless, this thesis has presented a unique insight into the geographical disparities across Britain's high streets and into their hyperlocal nature and has highlighted the potential applications of commercial data in informing high street regeneration policy.
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**Appendix**

Figure 10. 1: CDRC Data Service User Guide, version 6.0.
Introduction

The Consumer Data Research Centre (CDRC or Centre) is an academic led, multi-institution laboratory which discovers, mines, analyses and synthesises consumer-related datasets from around the UK. The CDRC forms part of the ESRC-funded Big Data network and offers a data service aimed at providing researchers with access to a wide range of consumer data to address many societal challenges. CDRC’s key areas of interest include retail, transport, health, crime, housing, energy, mobility and sustainable consumption. We support the acquisition and analysis of data in these areas and others to achieve benefits for the ‘public good’.

The purpose of this guide is to describe the Centre’s data services and how researchers can access them. It identifies the different types of data the Centre holds and the service tiers through which these data sets are available. For data that are not publicly available, the guide details how researchers can register or apply for access and the kinds of support that is available to them.

CDRC Data Services

The CDRC provides data with three different levels of access. These correspond to the data levels described in the UK Data Service’s three tier access policy:

- **Open data**: data which are freely available to all for any purpose. Data includes open datasets where CDRC have added value and non-sensitive and aggregated data and derivative products produced by the CDRC. Examples might include geodemographic data derived from the Census. Open data are accessed through the CDRC service via basic registration and download.

- **Safeguarded data**: data to which access is restricted due to licence conditions, but where data are not considered ‘personally-identifiable’ or otherwise sensitive – an example might include data from retail companies on store turnover. Access to safeguarded CDRC data is via a remote service that requires users to submit a project proposal. This proposal must receive approval from the Centre’s Research Approvals Group (RAG) (see below) before access to the data will be authorised. Users are able to retrieve data after authentication and authorisation by the service.

- **Controlled data**: data which need to be held under the most secure conditions with more stringent access restrictions, including data which are ‘personally-identifiable’ and therefore subject to Data Protection legislation or are considered commercially sensitive. Examples might include data on individual consumer purchases. Access to CDRC controlled data is provided through the CDRC-secure service. This service requires that individuals gain project approval through the RAG and visit one of our secure facilities at either the University College London, University of Leeds or University of Liverpool.

Finding Data

All data available through the CDRC are accompanied by metadata that enable both attributes and geography to be searched.
Research Approvals Process

Access to both safeguarded and controlled data requires a process by which individuals submit project proposals for assessment and approval. The approval process is overseen by an independent Research Approvals Group (RAG) which comprises representation from the Data Partner(s) and the social science academic community. The Group may also draw upon the expertise from a social science ethics practitioner. The CDRC Senior Management Team provides comment on resource implications of a proposal. The composition ensures that the RAG has expertise in research design, analysis and impact, while also considering any commercial sensitivities a project may have. The RAG review process is overseen by the Chair of RAG.


Criteria for Approval
These criteria align with CDRC objectives and cover the following:

- **Scientific advancement** – how the project has the potential to advance scientific knowledge, understanding and/or methods using consumer data;
- **Public good** – how the project has the potential to provide insight and/or solutions that could benefit society;
- **Privacy and ethics** – the potential privacy impacts or risks, and wider ethical considerations relating to the project;
- **Project Design and Methods** – how the project will be conducted and who will be involved with a focus on demonstrating project feasibility;
- **Cost and resources issues** – what impact the project is likely to have on CDRC resources, including CDRC staff time and use of infrastructure, as well as any data acquisition costs. Resource requirements should be justified.

The RAG typically considers applications remotely and is designed to be lightweight but robust, enabling timely decisions on user applications.

Approval will not be granted without evidence that the user has acquired ethical approval for the research through their institution, or supplied evidence that it is not applicable. For non-academic projects, where there is no approval process in place the CDRC will assist the user with acquiring this.
Safe Researcher Training and Development

Safe Research Training

Users, both academic and non-academic stakeholders, wishing to access controlled data and on occasion safeguarded data are required to have completed a safe researcher course, as offered by the Administrative Data Research Network (ADRN), HM Revenue and Customs (HMRC), Office for National Statistics (ONS) or the UK Data Service (UKDS). Evidence of valid accreditation for the duration of access to the data will be required. If the user has not previously completed such training the CDRC will offer access to training courses.

Training and Development

In addition to providing data services, the CDRC has a range of training courses and materials available. Many of these will be of benefit to those who wish to use our facilities, as they are aimed at enhancing capacity in data analytics and data visualisation methods. Full details of the training available can be found at data.cdrac.ac.uk/tutorial. Our programme includes training in the following areas:

- Working on Big Data: introductory courses that explain the growing importance of Big Data; the importance of analytics and protocols; and standards for data management.
- Introductory and advanced courses in data analysis and visualisation, including courses in R.
- Introductory and advanced courses in Geographical Information Systems, including ArcGIS and Q-GIS.
- Advanced courses in microsimulation and geo-temporal demographics.
- Courses on how insights from Big Data analytics can enhance business.
- Visualisation.

Charges for CDRC Services

While a service will be provided to the academic community and stakeholders free of charge, researchers may need to apply for funding to cover the costs of additional data acquisitions, or be charged for access to certain, licensed software.
CDRC Services Overview and User Journey

Open Data Service
- Register to download
- Download open data
- Unrestricted research

Confidential Data Service
- Researcher registration
- Proposal development, assessment & approval
- Data Researcher Training (where required)
- Confidential data available for secure download
- Create summary of findings
- Publish & archive as appropriate
- Send to CDRC
- Inform CDRC

Secure Data Service
- Researcher registration
- Proposal development, assessment & approval
- Data Researcher Training
- Access to approved controlled data at secure CDRC sites
- Perform analysis at secure sites and submit to Researcher approval
- CDRC review, analysis and confirm if to be in with project approval
- Analysis released to researcher
- Create summary of findings
- Publish as appropriate
- Send to CDRC
- Inform CDRC
CDRC Website: A Single Point of Entry into the CDRC Data Services
The CDRC website, [www.cdrac.ac.uk](http://www.cdrac.ac.uk), is designed to provide a single point of entry into our services and these are clearly linked from the homepage.

CDRC Data
Our data portal, CDRC Data, provides a complete listing of data available through the three tiers of the service and enables the dissemination of open data and application for access to safeguarded and controlled data.

Accessing data from CDRC Data [data.cdrac.ac.uk](http://data.cdrac.ac.uk)

Open Service:
Access to the Open Service requires:

1) Registration
Users will be required to provide contact details including a valid email address prior to download. This is to enable the CDRC to monitor the use of the resource. Data will then be available to the user to download for unrestricted use.

Safeguarded Service:
Access to the Safeguarded Service requires that users to obtain formal approval.

1) Initial Proposal
An approach is made to the CDRC by the user through completion of an online form, [www.cdrac.ac.uk/data-services/using-our-data/](http://www.cdrac.ac.uk/data-services/using-our-data/). This initial proposal is processed and assessed by the Senior Management Team to see if it fits within the remit of the Centre. If not, the proposal may be referred to another Centre in the Big Data Network. Proposals that do not fit into either of these categories will be turned down at this stage.

2) Proposal Development
If the initial proposal fits within the Centre's remit, the user is supplied with the 'Safeguarded Data Project Proposal Form', and assigned to a CDRC data scientist who can advise on the technical aspects of the formal application. The aim is to co-produce an acceptable project proposal. Proposals will comprise:

a) Research motivation and purpose
b) Research impact
c) Planned outputs
d) Research team
e) Data requested
f) Data linkage
g) Duration of access
h) Ethical approval from user’s institution

3) RAG Assessment and Approval
Once an application has been completed it is considered by the RAG against agreed criteria that are published on our website, www.cdrc.ac.uk/data-services/using-your-data/. The number of rejected approvals will be minimised through initial interaction with the data scientists. Where approval is withheld, applications are referred back to the user for revision, and clear guidance will be given regarding those areas requiring clarity. If such amendments are agreeable by RAG, approval will be given. If minor, the user may be asked to make further revisions, however, if issues are still considered to be major the RAG may decide to make a final decision to reject the proposal. Following approval, the user and their institution are required to agree to the CDRC User Agreement, including stipulations made by the Data Partner(s) and RAG.

4) Data Access
Access to a secure download of the agreed data is made available. This process requires that users telephone the CDRC to obtain a further password to unlock the encrypted download files. Once the user has downloaded the encrypted file, they are solely responsible for the data and its analysis.

5) Outputs
Users can use results of their analyses in publications, reports and presentations provided they abide by the terms and conditions with particular reference to the data partner publication terms. There is no screening of outputs by CDRC staff.

6) Completion, Reporting and Acknowledgement
Users are required to deposit copies of working papers, peer-reviewed journal articles, logs of impact and other publications for access with the CDRC site whenever copyright permits. Where this is not possible, full references to research outputs are required for CDRC audit purposes. Please email publications@cdrc.ac.uk when publications are ready for deposit or logging. The commitment to produce specified outputs is normally a condition of the data approval process. The terms of service require that published outputs include an acknowledgement stating: “The data for this research have been provided by the Consumer Data Research Centre, an ESRC Data Investment, under project ID CDRC xxx, ES/L011840/1; ES/L011891/1”. The acknowledgement will make further reference to the use of specific datasets according to the wishes and needs of individual data partners. After the project end date is reached, the CDRC will contact the user to confirm the destruction of the data and to document any outputs to date. The CDRC will contact users normally at 6 and 12 months after the project end date to request a log of any further publications or impact logs.

If the user’s institution does not have a system for data protection and ethics approval then the CDRC will assist with gaining ethical review if required.
7) Undergraduate and Postgraduate Student Applications

Undergraduate and Masters Students requesting access to data will be required to submit a proposal in the normal way including their academic supervisor as a named applicant.

CDRC Secure Service
Access to CDRC controlled data is via our Secure Service at one of three secure facilities located at University College London, the University of Liverpool and the University of Leeds. Independent analysis of secure data can be undertaken at all of our secure facilities. If users require bespoke guidance and support with analytics, this service is provided at the University of Leeds only.

Use of the CDRC-Secure service requires registration and project approval, with an additional step of booking into one of the secure facilities and meeting any site specific secure facility requirements. The user will be informed of these once the site to be visited has been selected.

Accessing data from CDRC secure sites
Access to this service requires that users obtain formal approval.

1) Initial Proposal

An approach is made to the CDRC by the user through completion of an online form, www.cdrc.ac.uk/data-services/using-our-data/. This initial proposal is processed and assessed by the Senior Management Team to see if it fits within the remit of the Centre. If not, the proposal may be referred to another Centre in the Big Data Network. Proposals that do not fit into either of these categories will be turned down at this stage.

2) Proposal Development

If the initial proposal fits within the Centre’s remit, the user is supplied with the ‘Controlled Data Project Proposal Form’, and assigned to a CDRC data scientist who can advise on the technical aspects of the formal application. The aim is to co-produce an acceptable project proposal. Proposals will comprise:

a) Research motivation and purpose
b) Research impact
c) Planned outputs
d) Research team
e) Data requested
f) Data linkage
g) Access requirements
h) Ethical approval from user’s institution

3) RAG Assessment and Approval

2 If the user’s institution does not have a system for data protection and ethics approval then the CDRC will assist with gaining ethical review if required.
Once an application has been co-produced it is considered by the RAG against agreed criteria that are published on our website [www.cdr.ac.uk/data-services/using-our-data/](http://www.cdr.ac.uk/data-services/using-our-data/). The number of rejected approvals will be minimised through initial interaction with the data scientists. Where approval is withheld, applications are referred back to the user for revision, and clear guidance will be given regarding those areas requiring clarity. If such amendments are agreeable by RAG, approval will be given. If minor the user may be asked to make further revisions, however if issues are still considered to be major the RAG may decide to make a final decision to reject the proposal. Following approval, the user and their institution are required to agree to the CDRC User Agreement, including stipulations made by the Data Partner(s) and RAG.

4) Data Access

Following approval, the allocated CDRC data scientist arranges access for the registered user. Dates are booked to use the secure facility at either UCL, University of Liverpool or University of Leeds. Users will receive a document informing them of site specific secure facility requirements and instructions of use.

5) Data Analysis

The user works on the data only within the secure environment. If users wish to combine controlled data with other less sensitive data (open or safeguarded), then it will be necessary to have obtained consent for this from RAG as part of the project proposal. This supporting data will then be made available to the user in the secure facility. The same applies to software required for analysis. CDRC staff provide limited support through the advanced analytics service. At the University of Leeds, a supported analytics service is available which provides the user with bespoke guidance and support in both accessing and analysing data.

6) Outputs

All outputs that the user wants to take out of the secure environment must be vetted and cleared by the CDRC before they can be released. Source data do not leave the secure facility. Users can take results of their analyses for use in publications, reports and presentations provided they abide by the terms of the User Agreement and with particular reference to the data partner publication terms.

After completion of analysis the user informs the data scientist that the analysis is complete and that their files are now ready for vetting. For full details of the output process please see the CDRC site specific ‘Secure Lab Data Import/Export Procedures’.

a) Outputs will be checked by two CDRC data scientists to ensure that they conform to CDRC control criteria.

i. Outputs requested should be ‘finished outputs’ i.e. the finished statistical analyses that you intend to present to the public, must be easy to read and interpret and how they are to be used explained and must be non-disclosure.

ii. The CDRC team will ensure that the outputs are the same specification as those agreed in the approved project proposal.
iii. The user is informed of the outputs vetting outcome within 5 working days and if 
successful with details about how the data extracts or analysis will be returned to 
them.
iv. Extracts that match approval are transferred by the CDRC team to a secure server 
from where outputs can be downloaded under the same arrangements as 
safeguarded data or transferred to the user on an encrypted USB/hard drive.
v. Where extracts are deemed not to match the required criteria, the user is informed. 
i. Where there are issues with a part of the output, if feasible the user will be 
allowed to revisit the secure facility to rectify the problem.
ii. Major transgressions may be permanently deleted and the remaining output 
is returned to the CDRC approver pool.
vi. Once the user has completed all their analysis or their agreed lab access time has 
been reached all passes or electronic fobs are returned and access to the secure 
facility is immediately revoked.

7) Completion, Reporting and Acknowledgement
Users are required to deposit copies of working papers, peer-reviewed journal articles, logs of 
impact and other publications for access with the CDRC site wherever copyright permits. Where 
this is not possible, full references to research outputs are required for CDRC audit purposes. 
Please email publications@cdrac.ac.uk when publications are ready for deposit or logging. The 
commitment to produce specified outputs is normally a condition of the data approval process. 
The terms of service require that published outputs include an acknowledgement stating "The 
data for this research have been provided by the Consumer Data Research Centre, an ESRC Data 
Investment, under project ID CDRC xxx, ES/L011840/1; ES/L011891/1". The acknowledgement 
will make further reference to the use of specific datasets according to the wishes and needs of 
individual data partners. After the project end date is reached, the CDRC will contact the user to 
confirm the destruction of the data and to document any outputs to date. The CDRC will contact 
users normally at 6 and 12 months after the project end date to request a log of any further 
publications or impact logs.

8) Undergraduate and Postgraduate Student Applications
Undergraduate and Masters Students requesting access to data will be required to submit a 
proposal in the normal way including their academic supervisor as a named applicant.

9) Request for data not currently available through CDRC
It is possible to request access to data variables or datasets not currently available through the 
CDRC. To submit a request please complete an initial proposal form cdrc.ac.uk/data-
services/initial-proposal-form/ and we will contact you to discuss further.
Table 10.1: The number of high street boundaries in regions in Great Britain, 2021.

<table>
<thead>
<tr>
<th>Region</th>
<th>Count</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>East Midlands</td>
<td>229</td>
<td>5.98</td>
</tr>
<tr>
<td>East of England</td>
<td>286</td>
<td>7.47</td>
</tr>
<tr>
<td>London</td>
<td>883</td>
<td>23.07</td>
</tr>
<tr>
<td>Northeast</td>
<td>171</td>
<td>4.47</td>
</tr>
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<td>Northwest</td>
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<td>13.56</td>
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<td>Scotland</td>
<td>202</td>
<td>5.28</td>
</tr>
<tr>
<td>Wales</td>
<td>146</td>
<td>3.81</td>
</tr>
<tr>
<td>West Midlands</td>
<td>290</td>
<td>7.58</td>
</tr>
<tr>
<td>Yorkshire and The Humber</td>
<td>353</td>
<td>9.22</td>
</tr>
<tr>
<td>Southwest</td>
<td>291</td>
<td>7.60</td>
</tr>
<tr>
<td>Southeast</td>
<td>458</td>
<td>11.96</td>
</tr>
</tbody>
</table>
Table 10.2: The composition of high streets in Great Britain 2017-21.

<table>
<thead>
<tr>
<th>Category</th>
<th>Year</th>
<th>Percentage (%)</th>
<th>Category</th>
<th>Year</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clothes &amp; Fashion</td>
<td>2017</td>
<td>7.25</td>
<td>Pubs, Bars &amp; Clubs</td>
<td>2017</td>
<td>3.56</td>
</tr>
<tr>
<td>Clothes &amp; Fashion</td>
<td>2018</td>
<td>6.53</td>
<td>Pubs, Bars &amp; Clubs</td>
<td>2018</td>
<td>3.60</td>
</tr>
<tr>
<td>Clothes &amp; Fashion</td>
<td>2019</td>
<td>5.93</td>
<td>Pubs, Bars &amp; Clubs</td>
<td>2019</td>
<td>3.55</td>
</tr>
<tr>
<td>Clothes &amp; Fashion</td>
<td>2020</td>
<td>5.90</td>
<td>Pubs, Bars &amp; Clubs</td>
<td>2020</td>
<td>3.53</td>
</tr>
<tr>
<td>Clothes &amp; Fashion</td>
<td>2021</td>
<td>5.02</td>
<td>Pubs, Bars &amp; Clubs</td>
<td>2021</td>
<td>3.43</td>
</tr>
<tr>
<td>Events &amp; Attractions</td>
<td>2017</td>
<td>0.83</td>
<td>Restaurants</td>
<td>2017</td>
<td>5.16</td>
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<tr>
<td>Events &amp; Attractions</td>
<td>2018</td>
<td>0.85</td>
<td>Restaurants</td>
<td>2018</td>
<td>5.11</td>
</tr>
<tr>
<td>Events &amp; Attractions</td>
<td>2019</td>
<td>0.85</td>
<td>Restaurants</td>
<td>2019</td>
<td>5.01</td>
</tr>
<tr>
<td>Events &amp; Attractions</td>
<td>2020</td>
<td>0.84</td>
<td>Restaurants</td>
<td>2020</td>
<td>4.99</td>
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<tr>
<td>Events &amp; Attractions</td>
<td>2021</td>
<td>0.85</td>
<td>Restaurants</td>
<td>2021</td>
<td>5.10</td>
</tr>
<tr>
<td>Food &amp; Drink</td>
<td>2017</td>
<td>17.28</td>
<td>Shops &amp; Amenities</td>
<td>2017</td>
<td>28.41</td>
</tr>
<tr>
<td>Food &amp; Drink</td>
<td>2018</td>
<td>17.01</td>
<td>Shops &amp; Amenities</td>
<td>2018</td>
<td>27.31</td>
</tr>
<tr>
<td>Food &amp; Drink</td>
<td>2019</td>
<td>16.67</td>
<td>Shops &amp; Amenities</td>
<td>2019</td>
<td>25.39</td>
</tr>
<tr>
<td>Food &amp; Drink</td>
<td>2020</td>
<td>16.60</td>
<td>Shops &amp; Amenities</td>
<td>2020</td>
<td>25.25</td>
</tr>
<tr>
<td>Food &amp; Drink</td>
<td>2021</td>
<td>17.19</td>
<td>Shops &amp; Amenities</td>
<td>2021</td>
<td>23.48</td>
</tr>
<tr>
<td>Health &amp; Beauty</td>
<td>2017</td>
<td>14.21</td>
<td>Vacant Properties</td>
<td>2017</td>
<td>10.73</td>
</tr>
<tr>
<td>Health &amp; Beauty</td>
<td>2019</td>
<td>15.74</td>
<td>Vacant Properties</td>
<td>2019</td>
<td>15.05</td>
</tr>
<tr>
<td>Health &amp; Beauty</td>
<td>2020</td>
<td>15.71</td>
<td>Vacant Properties</td>
<td>2020</td>
<td>15.40</td>
</tr>
<tr>
<td>Health &amp; Beauty</td>
<td>2021</td>
<td>16.24</td>
<td>Vacant Properties</td>
<td>2021</td>
<td>17.84</td>
</tr>
<tr>
<td>Home &amp; Garden</td>
<td>2017</td>
<td>7.68</td>
<td>Other</td>
<td>2017</td>
<td>4.38</td>
</tr>
<tr>
<td>Home &amp; Garden</td>
<td>2018</td>
<td>7.30</td>
<td>Other</td>
<td>2018</td>
<td>4.78</td>
</tr>
<tr>
<td>Home &amp; Garden</td>
<td>2019</td>
<td>6.80</td>
<td>Other</td>
<td>2019</td>
<td>4.49</td>
</tr>
<tr>
<td>Home &amp; Garden</td>
<td>2020</td>
<td>6.77</td>
<td>Other</td>
<td>2020</td>
<td>4.48</td>
</tr>
<tr>
<td>Home &amp; Garden</td>
<td>2021</td>
<td>6.49</td>
<td>Other</td>
<td>2021</td>
<td>3.86</td>
</tr>
<tr>
<td>Hotels</td>
<td>2017</td>
<td>0.51</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hotels</td>
<td>2018</td>
<td>0.54</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hotels</td>
<td>2019</td>
<td>0.53</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hotels</td>
<td>2020</td>
<td>0.52</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hotels</td>
<td>2021</td>
<td>0.49</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 10. 3: List of the categories of occupier types within the Local Data Company data set on retail premises location. The store categories have been deemed as essential due to their ability to remain open during the retail related lockdown restrictions in England, Wales and Scotland during March 2020 to May 2021.

<table>
<thead>
<tr>
<th>Essential stores and services</th>
<th>Discount store</th>
<th>Laser eye treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accident compensation</td>
<td>Doctors surgeries</td>
<td>Laundries and launderettes</td>
</tr>
<tr>
<td>Accountants</td>
<td>Dry cleaners</td>
<td>Letting agents</td>
</tr>
<tr>
<td>Advice centres</td>
<td>Electricians</td>
<td>Livery companies</td>
</tr>
<tr>
<td>Alternative and complementary medicines</td>
<td>Estate agents</td>
<td>Locksmiths</td>
</tr>
<tr>
<td>ATM lobby</td>
<td>Farmers markets</td>
<td>Minicabs</td>
</tr>
<tr>
<td>Bakers shops</td>
<td>Fast food delivery</td>
<td>Mobility services</td>
</tr>
<tr>
<td>Banks and other Financial institutions</td>
<td>Fast food takeaway</td>
<td>Mortgage companies advisors</td>
</tr>
<tr>
<td>Builders</td>
<td>Financial advisors</td>
<td>MOT testing centres</td>
</tr>
<tr>
<td>Builders merchant</td>
<td>Fish and chip shops</td>
<td>Newsagents</td>
</tr>
<tr>
<td>Building societies</td>
<td>Fishmongers</td>
<td>Nursing homes</td>
</tr>
<tr>
<td>Bureaux de change</td>
<td>Funerary directors and monumental masons</td>
<td>Opticians</td>
</tr>
<tr>
<td>Butchers</td>
<td>Garage services</td>
<td>Painting and decorating supplies</td>
</tr>
<tr>
<td>Coffee shops</td>
<td>Garden and patio furniture</td>
<td>Pet shops and pet supplies</td>
</tr>
<tr>
<td>Café and tearoom</td>
<td>Garden centres</td>
<td>Petrol filling stations</td>
</tr>
<tr>
<td>Community centres</td>
<td>Gas log and coal fires</td>
<td>Pizza takeaway</td>
</tr>
<tr>
<td>Car and van hire</td>
<td>Gas suppliers</td>
<td>Plumbers</td>
</tr>
<tr>
<td>Car accessories and parts</td>
<td>Gourmet food</td>
<td>Plumbers merchants</td>
</tr>
<tr>
<td>Car body repairs</td>
<td>Greengrocers and fruit sellers</td>
<td>Post office services</td>
</tr>
<tr>
<td>Car breakdown and recovery service</td>
<td>Grocers</td>
<td>Postal, packing and shipping</td>
</tr>
<tr>
<td>Car parking and garaging</td>
<td>Halal butchers</td>
<td>Property consultants</td>
</tr>
<tr>
<td>Car wash and valet services</td>
<td>Halls</td>
<td>Recruitment agencies</td>
</tr>
<tr>
<td>Cash and carry</td>
<td>Hardware merchants and ironmongers</td>
<td>Royal mail delivery offices</td>
</tr>
<tr>
<td>Central heating- installation and servicing</td>
<td>Health centre</td>
<td>Safe deposit boxes</td>
</tr>
<tr>
<td>Chartered surveyors</td>
<td>Health clinics</td>
<td>Shoe repairs</td>
</tr>
<tr>
<td>Cheese shops</td>
<td>Health clubs</td>
<td>Solicitors</td>
</tr>
<tr>
<td>Chemists and toiletries</td>
<td>Health foods and products</td>
<td>Storage and removals</td>
</tr>
<tr>
<td>Cheque cashing</td>
<td>Hearing aids</td>
<td>Street markets</td>
</tr>
<tr>
<td>Child care</td>
<td>Herbalists</td>
<td>Student unions</td>
</tr>
<tr>
<td>Chinese fast food takeaway</td>
<td>Hire centres</td>
<td>Supermarkets</td>
</tr>
<tr>
<td>Chocolatiers</td>
<td>Household services</td>
<td>Take away food shops</td>
</tr>
<tr>
<td>Citizen advice bureaux</td>
<td>Household stores</td>
<td>Taxis and private hire</td>
</tr>
<tr>
<td>Confectioners</td>
<td>Housing association</td>
<td>Tea and coffee merchants</td>
</tr>
<tr>
<td>Convenience stores</td>
<td>Hydroponics</td>
<td>Translation agencies</td>
</tr>
<tr>
<td>Cosmetic dentistry</td>
<td>Indian takeaway</td>
<td>Tyre dealers</td>
</tr>
<tr>
<td>Cosmetic surgery</td>
<td>Indoor markets</td>
<td>Uniforms and staff wear</td>
</tr>
<tr>
<td>Council services</td>
<td>Information centre</td>
<td>Universities and colleges</td>
</tr>
<tr>
<td>Credit unions</td>
<td>Insurance agents</td>
<td>Veterinary surgeons and practitioners</td>
</tr>
<tr>
<td>Cycle shops</td>
<td>Ironmongers</td>
<td>Wholesalers</td>
</tr>
<tr>
<td>D.I.Y</td>
<td>Job centres</td>
<td>Wine making and brewer supplies</td>
</tr>
<tr>
<td>Delicatessen</td>
<td>Joiners</td>
<td>Wines, spirits and beers</td>
</tr>
<tr>
<td>Delivery services</td>
<td>Landscape gardeners</td>
<td></td>
</tr>
<tr>
<td>Dentists</td>
<td>Language schools</td>
<td></td>
</tr>
</tbody>
</table>

Figure 10. 2: Elbow plot displaying the optimum number of clusters for the high street typology.
Figure 10.3: Plots of the typology data clustered into either 2, 3, 4, 5, 6, 7 or 8 clusters.
Figure 10. 4: Radar plots displaying the characteristics of each high street cluster.
Figure 10.5: Elbow plot displaying the optimum number of clusters for the high local authority typology.
Figure 10. 6: Plots of the typology data clustered into either 2, 3, 4, 5, 6 clusters.
Figure 10. 7: Radar plots displaying the characteristics of each local authority cluster.
Figure 10.8: London Borough of Camden letter of support for a knowledge exchange between University College London and Camden’s Future High Streets program.
Mrs Mariana Trejo
Knowledge Exchange Manager
UCL Innovation & Enterprise
90 Tottenham Court Rd
London W1T 4TJ

Dear Mrs Trejo

As co-chairs of Camden’s High Street Board at London Borough of Camden, we are writing to confirm that Camden supports the proposal outlined in the attached application.

Camden’s high streets play a crucial role in community life. They are the places where residents, workers and visitors shop, work, socialise, and access culture and services. They provide a range of jobs and employment opportunities and have an important role in supporting the health and well-being of our communities. However, Camden’s high streets, along with those up and down the country, have been facing a range of challenges, trends and changing consumer habits, which have been compounded by the extraordinary impact of the Covid-19 pandemic. In response Camden Council has commenced the Camden Future High Streets programme, to support high streets through the pandemic and into a robust recovery and re-imagined future.

We have identified three challenge areas: vacancy, the night-time economy and digital high streets. We see data – a better understanding of what is available and how it might be used to inform our work – as a crucial articulating theme of all three challenges. So we are delighted to be working with UCL’s Consumer Data Research Centre to conduct this vital underpinning piece of work together.

Camden Council has a long-established track record of collaborating with UCL. In December 2020, we launched a new step in our strategic relationship by signing a joint Memorandum of Understanding (MoU). This collaboration would be closely aligned to the principles and ambitions outlined in the MoU.

Therefore we would enthusiastically welcome the opportunity to work on the attached project. We believe that this funding has a significant potential to support our work at the Council, as well as drive academic research with substantial impact. We very much hope that this proposal succeeds.
We confirm our commitment to liaise with the PI and UCLB and/or the Research Contracts Office where applicable to put a collaboration agreement in place to protect and maximise the value of UCL’s IP.

We very much look forward to working with UCL.

Yours sincerely,

David Burns

[Redacted]

Director of Economy, Regeneration and Investment

Richard Bradbury

[Redacted]

Director of Environment and Sustainability
Table 10.4: Table of data sources relating to Camden high streets taken as an extract from the ‘Data for Future High Streets’ report.

<table>
<thead>
<tr>
<th>Type of data</th>
<th>Data Source</th>
<th>Aggregation Level</th>
<th>Information</th>
<th>Link</th>
<th>Data License</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boundaries</td>
<td>Greater London Authority, ‘GLA High Street Boundaries’</td>
<td>High street as defined by Ordnance Survey (2022)</td>
<td>Boundaries of high streets as developed by the Regeneration Team at the Greater London Authority. They reflect the wider uses of high streets including community, public and cultural, in addition to concentrations of retail units.</td>
<td><a href="https://data.london.gov.uk/dataset/gla-high-street-boundaries">https://data.london.gov.uk/dataset/gla-high-street-boundaries</a></td>
<td></td>
</tr>
<tr>
<td>Boundaries</td>
<td>Greater London Authority, ‘Town Centre Boundaries’</td>
<td>Town centre as defined by Ordnance Survey (2022)</td>
<td>There are five broad types of town centres according to their scales and roles: International centres, Metropolitan centres, Major centres, District centres and Neighbourhood and more local centres.</td>
<td><a href="https://data.london.gov.uk/dataset/town_centre_boundaries">https://data.london.gov.uk/dataset/town_centre_boundaries</a></td>
<td></td>
</tr>
<tr>
<td>Boundaries</td>
<td>High street land ownership table</td>
<td>High street as defined by the GLA</td>
<td>Extracts of the Land Registry ownership boundaries, from the National Polygon Service where they overlap with GLA High Street Boundaries.</td>
<td><a href="https://data.london.gov.uk/high-street-data-service/partnership-data/">https://data.london.gov.uk/high-street-data-service/partnership-data/</a></td>
<td></td>
</tr>
<tr>
<td>Neighbourhood planning forum boundaries</td>
<td>Neighbourhood planning forum boundaries</td>
<td>A Neighbourhood Area is the geographical boundary within which your Neighbourhood Plan, including all its policies, will apply. Most parish councils opt to designate the whole of their parish as a Neighbourhood Area, and this approach is generally seen as the 'default' position.</td>
<td></td>
<td><a href="https://opendata.ca/Planning/Neighbourhood-Planning-Forum-Boundaries/aniv-pmidw">https://opendata.ca/Planning/Neighbourhood-Planning-Forum-Boundaries/aniv-pmidw</a></td>
<td></td>
</tr>
<tr>
<td>Wards</td>
<td>Camden 2022 Wards</td>
<td>Wards</td>
<td>A new ward structure comes into effect from 1 January 2022. Data from the 2011 Census has been ‘best fit’ to the new wards to give some idea about the demographics for the new areas. The file includes a map of the areas and is indexed by the names of the 20 new wards.</td>
<td><a href="https://opendata.ca/OpenData/People-Places/2011-Census-Profiles-for-Camden-2022-Wards/qur5-v5ix">https://opendata.ca/OpenData/People-Places/2011-Census-Profiles-for-Camden-2022-Wards/qur5-v5ix</a></td>
<td></td>
</tr>
<tr>
<td>Mobility</td>
<td>Greater London Authority, ‘Google Mobility by Borough’</td>
<td>Borough, categorised mobility data</td>
<td>Google collects location data shared by users of Android smartphones, and compares the time and duration of visits to locations to the median values on the same day of the week in the five weeks from 3 Jan 2020. The activity levels are grouped into 6 different categories: Retail and Recreation, Grocery and Pharmacy, Parks, Transit Stations, Workplaces Percent and Residential.</td>
<td><a href="https://data.london.gov.uk/dataset/google-mobility-by-borough">https://data.london.gov.uk/dataset/google-mobility-by-borough</a></td>
<td></td>
</tr>
<tr>
<td>Mobility</td>
<td>Apple ‘Mobility Trends Reports’</td>
<td>City level, categorised mobility data</td>
<td>This data is generated by counting the number of requests made to Apple Maps for directions in select countries/regions, sub-regions and cities. Data that is sent from users’ devices to the Apple Maps. The availability of data in a particular country/region, sub-region or city is based on a number of factors, including minimum thresholds for direction requests per day.</td>
<td><a href="https://covid19.apple.com/mobility">https://covid19.apple.com/mobility</a></td>
<td></td>
</tr>
<tr>
<td>Source</td>
<td>Level</td>
<td>Data Description</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>--------</td>
<td>-------</td>
<td>------------------</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local Data Company, ‘SmartStreetSensor Footfall Data’</td>
<td>Retail centre or sensor level</td>
<td>The LDC SmartStreetSensor footfall data produced in partnership with the CDRC includes details of passive WiFi signal probing from a sensor network across Great Britain. These data are used as a proxy for estimating footfall at retail locations. <a href="https://data.cdrc.ac.uk/dataset/local-data-company-smartstreetsensor-footfall-data">https://data.cdrc.ac.uk/dataset/local-data-company-smartstreetsensor-footfall-data</a></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OpenTable ‘Restaurant reservation data’</td>
<td>City level</td>
<td>Seated diners from online, phone, and walk-in reservations <a href="https://www.opentable.com/state-of-industry">https://www.opentable.com/state-of-industry</a></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TFL ‘Public Transport Journeys by Type of Transport’</td>
<td>City level</td>
<td>Number of journeys on the public transport network by TFL reporting period, by type of transport. <a href="https://data.london.gov.uk/dataset/public-transport-journeys-type-transport">https://data.london.gov.uk/dataset/public-transport-journeys-type-transport</a></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Santander Bike Sharing</td>
<td>Precise docking station location</td>
<td>Daily updated data on the maximum simultaneous usage numbers for the larger UK bikeshare systems. <a href="https://data.cdrc.ac.uk/dataset/bikeshare-activity">https://data.cdrc.ac.uk/dataset/bikeshare-activity</a></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>O2 Footfall data</td>
<td>MSOA</td>
<td>Anonymised and Aggregated data by O2. The People Counts shows the number of people dwelling in each MSOA area per hour, split by: Resident – based on where the user has spent most of their evening and night time in the latest historical month available. Worker – based on where the user has spent most of their working hours predominantly based on February 2020 where available. Visitor (at least 30mins in location). <a href="https://data.london.gov.uk/high-street-data-service/partnership-data">https://data.london.gov.uk/high-street-data-service/partnership-data</a></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vivacity</td>
<td>Street level on pedestrian, cycle and motor traffic flow and patterns</td>
<td>Camden Transport team are about to commission – it would entail the capture of classified counts and ‘path data’ in two spots on Kilburn High Road over a 5-year period. Information on people numbers, and where they are moving to and from and crossing the road. <a href="https://vivacitylabs.com">https://vivacitylabs.com</a></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Camden cycle counters</td>
<td>Street level on cycle lanes</td>
<td>Count of cyclists along cycle routes. <a href="https://opendata.ca/Openmden.gov.uk/Transport/Camden-Cycle-Counters-Phase-2/it3h-agpf">https://opendata.ca/Openmden.gov.uk/Transport/Camden-Cycle-Counters-Phase-2/it3h-agpf</a></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parking suspensions</td>
<td>High street</td>
<td>Location of parking spaces in Camden as well as if they're currently suspended or will be in the future and why. <a href="https://opendata.ca/Openmden.gov.uk/Transport/Camden-Parking-Suspensions/av3b-8tg">https://opendata.ca/Openmden.gov.uk/Transport/Camden-Parking-Suspensions/av3b-8tg</a></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TFL Annual entry/exit station counts per quarter hour</td>
<td>Station</td>
<td>Individual TFL managed rail modes (London Underground, London Overground, Docklands Light Railway and TFL Rail) The data coverage can be the entry / exit of the station (that may include one or more modes) or boarding / alighting for a specific mode in the station. <a href="http://crowding.data.tfl.gov.uk/">http://crowding.data.tfl.gov.uk/</a></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Demand by Station Type shows how daily activity— in terms of entry and exit taps at ticket barriers—for each underground station has changed since around the start of the year.

The dataset contains location data derived from in-app mobile-phone usage across Great Britain. Mobile phone applications seek user’s consent for recording and storing a mobile device’s GPS location when the app is in use. The total number of unique devices and the total number recorded locations are aggregated in unique tiles. Aggregated counts of less than 10 are censored to preserve individual privacy.

This data shows registered land and property in England and Wales owned by UK companies. The data does not show land or property owned by: private individuals, overseas companies or charities.

Annual estimates of paid hours worked and earnings for UK employees by sex, and full-time and part-time, by home-based region to local and unitary authority level.

Card data from Mastercard aggregated to high street town centre level to show how spending patterns have changed over time. Including total spend and number of transactions.

<table>
<thead>
<tr>
<th>Dataset Name</th>
<th>Source Type</th>
<th>Description</th>
<th>URL</th>
</tr>
</thead>
<tbody>
<tr>
<td>TFL Demand by Station Type</td>
<td>Station</td>
<td>Demand by Station Type shows how daily activity— in terms of entry and exit taps at ticket barriers—for each underground station has changed since around the start of the year.</td>
<td></td>
</tr>
<tr>
<td>Huq mobility data</td>
<td>Custom</td>
<td>The dataset contains location data derived from in-app mobile-phone usage across Great Britain. Mobile phone applications seek user’s consent for recording and storing a mobile device’s GPS location when the app is in use.</td>
<td><a href="https://huq.io/">https://huq.io/</a></td>
</tr>
<tr>
<td>Land registry: UK companies</td>
<td>Address</td>
<td>This data shows registered land and property in England and Wales owned by UK companies. The data does not show land or property owned by: private individuals, overseas companies or charities.</td>
<td><a href="https://use-land-property-data.service.gov.uk/datasets/ccod">https://use-land-property-data.service.gov.uk/datasets/ccod</a></td>
</tr>
<tr>
<td>Land registry: overseas</td>
<td>Address</td>
<td>This data shows registered land and property in England and Wales owned by UK companies. The data does not show land or property owned by: private individuals, overseas companies or charities.</td>
<td><a href="https://use-land-property-data.service.gov.uk/datasets/ocod">https://use-land-property-data.service.gov.uk/datasets/ocod</a></td>
</tr>
<tr>
<td>ONS ‘Earnings and hours worked’</td>
<td>Local Authority</td>
<td>Annual estimates of paid hours worked and earnings for UK employees by sex, and full-time and part-time, by home-based region to local and unitary authority level.</td>
<td><a href="https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningandworkinghours/datasets/placeofresidencebylocalauthoritylevel/yashetable8">https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningandworkinghours/datasets/placeofresidencebylocalauthoritylevel/yashetable8</a></td>
</tr>
<tr>
<td>Mastercard ‘Spend data’</td>
<td>High street</td>
<td>Card data from Mastercard aggregated to high street town centre level to show how spending patterns have changed over time. Including total spend and number of transactions.</td>
<td><a href="https://data.london.gov.uk/high-street-data-service/partnership-data/">https://data.london.gov.uk/high-street-data-service/partnership-data/</a></td>
</tr>
<tr>
<td>Source</td>
<td>Type</td>
<td>Details</td>
<td>URL</td>
</tr>
<tr>
<td>--------</td>
<td>------</td>
<td>---------</td>
<td>-----</td>
</tr>
<tr>
<td>Camden Non-Domestic Rates – Rateable Values</td>
<td>Local authority</td>
<td>A list of properties in the rating valuation list since 1 April 2010, including transitional relief allowed for each year.</td>
<td><a href="https://opendata.ca/OpenData/comm/mtden.gov.uk/Business-Economy/Camden-Non-Domestic-Rates-Rateable-Values/jumr-tymj">https://opendata.ca/OpenData/comm/mtden.gov.uk/Business-Economy/Camden-Non-Domestic-Rates-Rateable-Values/jumr-tymj</a></td>
</tr>
<tr>
<td>Community Infrastructure Levy Projects In Camden</td>
<td>Local Authority</td>
<td>details of infrastructure projects which have been funded from the 'local' proportion of the Community Infrastructure Levy - can show investment going into an area</td>
<td><a href="https://opendata.ca/OpenData/comm/mtden.gov.uk/Planning/Community-Infrastructure-Levy-Projects-In-Camden/ugsq-q3ga">https://opendata.ca/OpenData/comm/mtden.gov.uk/Planning/Community-Infrastructure-Levy-Projects-In-Camden/ugsq-q3ga</a></td>
</tr>
<tr>
<td>CACI Equivalised Paycheck Directory</td>
<td>Postcode</td>
<td>Equivalised pay check directory at postcode level.</td>
<td>Already licensed to Camden</td>
</tr>
<tr>
<td>Retail</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local Data Company 'Retail type, vacancy and address data'</td>
<td>Store location</td>
<td>Retail Type and Vacancy data tables include: Shop name, Shop use, Classification, Category, Subcategory (inc. Retail Type/Vacancy). Retail Address data table includes: Unit, Building, Street No, Street, Town, Postcode, Latitude, Longitude.</td>
<td><a href="https://www.localdatacompany.com/">https://www.localdatacompany.com/</a></td>
</tr>
<tr>
<td>Office of National Statistics 'High street employment, land use and resident population'</td>
<td>Local authority area</td>
<td>Mapping the location and characteristics of high streets in Great Britain, working with experimental Ordnance Survey High Street extents and Office for National Statistics data.</td>
<td><a href="https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/highstreetemploymentandpopulation">https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/highstreetemploymentandpopulation</a></td>
</tr>
<tr>
<td>Food Standards Agency food hygiene ratings</td>
<td>Store location</td>
<td>The data provides the food hygiene rating or inspection result given to a business and reflect the standards of food hygiene found on the date of inspection or visit by the local authority. Businesses include restaurants, pubs, cafes, takeaways, hotels and other places consumers eat, as well as supermarkets and other food shops.</td>
<td><a href="https://data.cdrc.ac.uk/dataset/food-hygiene-rating-scheme-fhrs-ratings">https://data.cdrc.ac.uk/dataset/food-hygiene-rating-scheme-fhrs-ratings</a></td>
</tr>
<tr>
<td>Dataset</td>
<td>Scope</td>
<td>Description</td>
<td>Source</td>
</tr>
<tr>
<td>----------------------------------------------------------------------</td>
<td>----------------------------------------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td><strong>Camden retail survey</strong></td>
<td>Local authority</td>
<td>The retail frontage survey is not a complete survey of all shopping frontages in the borough. The survey area covers the Local Development Framework Town Centres, Neighbourhood Centres, Central London Frontages and some frontages in the Central London Local Areas.</td>
<td><a href="https://opendata.ca/Openmden.gov.uk/Planning/Camden-Retail-Frontages-Survey/2j3jTnbw">https://opendata.ca/Openmden.gov.uk/Planning/Camden-Retail-Frontages-Survey/2j3jTnbw</a></td>
</tr>
<tr>
<td><strong>Table and chairs licence</strong></td>
<td>Longitude and Latitude</td>
<td>If businesses want to place tables and chairs outside on a public street they must apply to their local authority. The license needs renewing each year.</td>
<td><a href="https://opendata.ca/Openmden.gov.uk/Your-Council/Table-And-Chair-Applications/8ixcjf73/data">https://opendata.ca/Openmden.gov.uk/Your-Council/Table-And-Chair-Applications/8ixcjf73/data</a></td>
</tr>
<tr>
<td><strong>Social and demographic</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment Claimant Count</td>
<td>Local Authority</td>
<td>DWP Claimant Count unemployment measure, combining Jobseekers Allowance (JSA) claimants and Universal Credit claimants who are actively seeking work.</td>
<td><a href="https://opendata.ca/Openmden.gov.uk/Business-Economy/Unemployment-Claimant-Count-LATEST/g3p6usd3">https://opendata.ca/Openmden.gov.uk/Business-Economy/Unemployment-Claimant-Count-LATEST/g3p6usd3</a></td>
</tr>
<tr>
<td>Income estimates for small areas, financial year ending 2018</td>
<td>MSOA</td>
<td>Total annual household income; Net annual household income; Net annual household income (equivalised) before housing costs; Net annual household income (equivalised) after housing costs</td>
<td><a href="https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/datasets/smallareaincomeestimatesfrommiddlelayeroutputareasenglandandwales">https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/datasets/smallareaincomeestimatesfrommiddlelayeroutputareasenglandandwales</a></td>
</tr>
<tr>
<td>Data Type</td>
<td>Location/Description</td>
<td>Details</td>
<td>Source</td>
</tr>
<tr>
<td>---------------------------------</td>
<td>--------------------------------------------------------------------------------------</td>
<td>--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Police Crime data</td>
<td>Crime location</td>
<td>These CSV files provide street-level crime, outcome, and stop and search information, broken down by police force and 2011 lower layer super output area (LSOA).</td>
<td><a href="https://data.police.uk/data/">https://data.police.uk/data/</a></td>
</tr>
<tr>
<td>Public Conveniences in Camden</td>
<td>Precise location</td>
<td>This dataset contains public conveniences in the London Borough of Camden. Attributes include the address and geographic coordinates of each facility; these are largely taken from Camden’s Local Land and Property Gazetteer and published under the OS Presumption To Publish process.</td>
<td>[<a href="https://opendata.ca/Openmden.gov.uk/Peop">https://opendata.ca/Openmden.gov.uk/Peop</a> le-Places/Public-Conveniences-In-Camden/4b2v-65nr](<a href="https://opendata.ca/Openmden.gov.uk/Peop">https://opendata.ca/Openmden.gov.uk/Peop</a> le-Places/Public-Conveniences-In-Camden/4b2v-65nr)</td>
</tr>
<tr>
<td><strong>Sustainability</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Air quality</td>
<td>Street – level</td>
<td>Measured via ‘diffusion tubes’ for NO2 levels and also with automatic electronic sensors which measure NO2 and PM. As of June 2021 there were 200 diffusion tubes and six automatic monitoring sites throughout the borough.</td>
<td><a href="https://opendata.ca/Openmden.gov.uk/stories/s/Camden-Air-Quality-Monitoring/bnrm-k7pv/">https://opendata.ca/Openmden.gov.uk/storie s/s/Camden-Air-Quality-Monitoring/bnrm-k7pv/</a></td>
</tr>
<tr>
<td>Camden Parking Suspensions</td>
<td>Precise location</td>
<td>This dataset contains the location of parking spaces in Camden as well as if they’re currently suspended or will be in the future.</td>
<td><a href="https://opendata.ca/Openmden.gov.uk/Transport/Camden-Parking-Suspensions/av3b-8trq">https://opendata.ca/Openmden.gov.uk/Transport/Camden-Parking-Suspensions/av3b-8trq</a></td>
</tr>
<tr>
<td>Electric charging points</td>
<td>Street level</td>
<td>Camden currently has 307 on-street electric vehicle charging points (EVCP).</td>
<td><a href="http://CamdenCouncil">Electric vehicles - Camden Council</a></td>
</tr>
</tbody>
</table>
Figure 10. 9: An insert from the Data for Future High Streets report outlining examples of data which relate to Camden high streets and associated academic studies.

**Supporting Data Audit**

This document supports the *Data for Future High Streets* report prepared by UCL for Camden Council and should be read alongside that. It is designed to be an indicative list of datasets that may be of use in the council’s analysis going forward. It is not definitive nor does it endorse one source of data over another and much of the information is extracted as is from supplier websites. For further information please email jamee.cheshire@ucl.ac.uk.

**Economic data**

**Data:** Office for National Statistics, Income Estimates for Small Areas, England and Wales

**Date:** April 2017- April 2018

**Aggregation:** Middle layer Super Output Area

Information: Estimates of annual household income for the four income types for Middle layer Super Output Areas, or local areas, in England and Wales. The four income types include: total annual household income, net annual household income, net annual household income before housing costs and net annual household income after housing costs. Total annual household income is the sum of the gross income of every member of the household plus any income from benefits such as Working Families Tax Credit. Net annual household income is the sum of the net income of every member of the household. It is calculated using the same components as total income, but income is net of: income tax payments; national insurance contributions; domestic rates/council tax; contributions to occupational pension schemes; all maintenance and child support payments, which are deducted from the income of the person making the payments; and parental contribution to students living away from home. Net annual household income before housing costs (equivalised) is composed of the same elements as net household weekly income but is subject to the OECD’s equivalisation scale.

Net annual household income after housing costs (equivalised) is composed of the same elements of net household weekly income but is subject to the following deductions prior to the OECD’s equivalisation scale being applied: rent (gross of housing benefit); water rates, community water charges and council water charges; mortgage interest payments (net of any tax relief); structural insurance premiums (for owner occupiers); and ground rent and service charges.

Participants: The data is based on the Family Resources Survey due to it being the largest sample that includes suitable questions on income.
Application: The granularity of the data allows for a more accurate estimation of income for the population surrounding the individual high streets within the borough of Camden.

Limitations: In common with any ranking based on estimates, when ranking MSOAs by income, care must be exercised in interpreting the ranking of the MSOAs. One needs to take into account the variability of the estimates when using these figures. Although these model-based estimates can be used to rank MSOAs by income they cannot be used to make any conclusions on the distribution of income over the MSOAs. The estimation procedure will tend to shrink estimates towards the average level of income for the whole population so estimates at each end of the scales tend to be over or under estimated. Nevertheless estimates can be used to make inferences such as the average weekly household income for MSOA A is greater than the value for MSOA B (if the appropriate confidence intervals do not overlap).

Citations:


Data: Office for National Statistics, Earnings and Hours Worked

Date: 05/04/2020- 05/04/2021, each tax year since 2021

Aggregation: Local authority: Camden

Information: Annual estimates of paid hours worked and earnings for UK employees by sex, and full-time and part-time, by home-based region to local and unitary authority level. Hourly and weekly estimates are provided for the pay period that included a specified date in April. They relate to employees on adult rates of pay, whose earnings for the survey pay period were not affected by absence. Estimates for 2020 and 2021 include employees who have been furloughed under the Coronavirus Job Retention Scheme (CJRS). Annual estimates are provided for the tax year that ended on 5th April in the reference year. They relate to employees on adult rates of pay who have been in the same job for more than a year.

Participants: The data set covers employee jobs in the UK. Indicative counts for the number of jobs are provided alongside all estimates. These are intended to provide a
broad idea of the numbers of employee jobs but they should not be considered accurate estimates.

Application: Looking at the average earnings of individuals living in the borough of Camden compared to other boroughs in London. The data can be used to see the annual percentage change in annual pay.

Limitations: It does not cover the self-employed or employees not paid during the reference period. ASHE is based on a 1% sample of jobs taken from HM Revenue and Customs’ Pay As You Earn (PAYE) records. Consequently, individuals with more than one job may appear in the sample more than once. Estimates with a Co-efficient variance greater than 20% are suppressed from publication on quality grounds, along with those for which there is a risk of disclosure of individual employees or employers. Estimates of the change from the previous year are provided for the median and mean. It is important to note that these are not adjusted to account for changes in the composition of the labour market during that period. Such factors can influence the apparent change in medians or means independently of changes in individuals’ earnings. For example, when there are more low-paying jobs in the labour market in one year compared to the previous year, this acts to decrease the median. Consequently, care should be taken when drawing conclusions about changes in pay for individuals over time.

Citations:


Data: Office for National Statistics, Housing affordability ratios for Middle layer Super Output Areas

Date: Year ending March 2018

Information: Ratio of median house prices to net annual household income (equivalised) before housing costs, by property type, for Middle Layer Super Output Areas in England and Wales, 2018. Affordability ratios for Middle Layer Super Output Areas (MSOAs) are calculated by dividing house prices by net annual household income (equivalised) before housing costs. House prices are taken from our House Price Statistics for Small Areas, and refer to year ending March 2018. Income data is taken from the Income estimates for small areas, which are model-based estimates for financial year ending 2018. By producing these estimates for MSOAs in England and Wales, we can fulfil users’ requirements for more granular income and house
price information on a consistent geography. Net annual household income (equivalised) before housing costs are model-based estimates taken from the Income estimates for Small Areas. Net household income is the sum of the net income of every member of the household. It is calculated using the same components as total income but income is net of: income tax payments; national insurance contributions; domestic rates/council tax; contributions to occupational pension schemes; all maintenance and child support payments, which are deducted from the income of the person making the payments; and parental contribution to students living away from home.

Limitations: Some values are suppressed due to being fewer than 5 house sales and the data is 3 years old, house prices could have been impacted by the COVID-19 pandemic.

**Data: Office for National Statistics. Median house prices for administrative geographies: HPSSA dataset 9**

Date: December 1995-March 2021

Aggregation: Local authority: Camden

Information: Median price paid for residential property in England and Wales, by property type and administrative geographies. Annual data, updated quarterly.

Participants: Homeowners who purchased a residential property within the time bracket.

Application: Compare property prices to other boroughs in London, to see affordability out housing.

Limitations: Limited to Local authority level and is not high street specific.

Citations:


**Data: Ministry of Housing, Communities and Local Government Weekly Rents**

Date: 1991-2020

Aggregation: Local Authority: Camden

Information: The Ministry of housing provides information on average rents for both local authority housing and private registered rent levels.
Local authority rent levels: Information on how much local authorities charge for their properties is collected through the housing revenue account subsidy claim form up until April 2012. Following the move to housing revenue account self-financing, local authorities are no longer required to complete the subsidy claim form. To ensure that key data on rent levels and stock composition are still collected, the local authority housing statistics (LAHS) return captures this information for the first time in 2011 to 2012. This provides an overlap in the local authority rent data collected.

Participants: Individuals who rent local authority housing.

Application: Comparing rent prices to other London local authorities, to ensure retail is matched to residents and purchasing behaviour.

Limitations: It excludes private sector rent levels which are only available at regional level.

Citations:


Morphet, J. and Clifford, B.P., 2017. *Local authority direct provision of housing*. UCL.

Data: Office for National Statistics, *High street employment, land use and resident population*.

Date: March, 2020

Aggregation: Local Authority: Camden

Information: This data set maps the location and characteristics of high streets in Great Britain, working with experimental Ordnance High Street extents and Office for National Statistics data. The proportion of addresses on the high street are broken down by land use category, into retailing, offices, community, leisure and residential at local authority level.

Application: Understanding the composition of high streets in Camden local authority high streets.

Participants: The dataset is high street specific and originates from the Ordnance Survey and Office for National Statistics. The data bounds retail clusters using street naming and aims to deliberately exclude other retail functions like retail parks, industrial estates, and isolated shopping centres. To be included in the dataset, a
High street must be a named street predominately consisting of retailing, defined by a cluster of 15 or more retail addresses within 150 metres.

Limitations: Care should be taken when considering the relevance of these statistics for rural and isolated areas, where smaller high streets may not be captured in the current definition. Similarly, the fact that the definition uses a minimum retail address threshold means that some traditional high streets which are locally important may not be captured. Note that the geographic coverage (both the Ordnance Survey extents and the joining to ONS employment survey data) are experimental.

Citations:


Mobility data

Data: Google Mobility by Borough

Date: 15/02/2020-04/11/2021 (cont.)

Aggregation: Local Authority: Camden

Intention: Measure the change in mobility as a consequence of the COVID-19 pandemic. The data can be used to show how visits and length of stay at different places change compared to a baseline.

Information: The data is split into 6 different categories: Grocery & Pharmacy (Mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies.), Parks (Mobility trends for places like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens.), Transit stations (Mobility trends for places like public transport hubs such as subway, bus, and train stations.), Retail and recreation (Mobility trends for places like restaurants, cafes, shopping centres, theme parks, museums, libraries, and movie theatres.), Residential (Mobility trends for places of residence.) and workplaces (Mobility trends for places of work.)
The changes in visits and length of stay are compared to the baseline. The baseline is the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. The datasets show trends over several months with the most recent data representing approximately 2-3 days ago—this is how long it takes to produce the datasets.

Participants: The data depends on user settings, connectivity, and whether it meets Google’s privacy threshold. When the data doesn’t meet quality and privacy thresholds, there are empty fields for certain places and dates. Participants are users who have opted-in to Location History for their Google Account, so the data represents a sample of Google’s users. As with all samples, this may or may not represent the exact behaviour of a wider population.

Application: Viewing the mobility patterns in the borough of Camden and the impact of COVID-19. Seeing which areas of mobility were most resilient. Comparing the recovery of mobility patterns of Camden to other London boroughs.

Limitations: As time passes and the data moves further away from the baseline period, populations might vary due to relocation or new regional and remote working options. Google’s understanding of categorized places might also change. For example, the same value today and in April 2020 might not indicate the same behaviour or adherence—it might be that Google has updated information about shops and restaurants in the region or that fewer people live there now. These differences could shift the values up or down over long time periods, so we recommend using some caution when analysing data from longer time intervals (6+ months).

Citations:

Google LLC "Google COVID-19 Community Mobility Reports." https://www.google.com/covid19/mobility/


Data: Apple Mobility Trends Reports

Data: 13/01/2020- 07/11/2021 (Cont.)

Aggregation: City level: London

Information: Apple Maps is a web mapping service developed by Apple Inc. It is the default map system of iOS, macOS, and watchOS, and provides directions and
estimated times of arrival for automobile, pedestrian, and public transportation navigation.

In April 2020, Apple released “Apple Mobility Index” reports that are published daily and reflect the changes in the requests for directions in Apple Maps during the COVID-19 pandemic. The data is generated by counting the number of requests made to Apple Maps for directions in select countries/regions and cities. The mobility index is calculated separately for requests made for driving, walking and transit and the mobility index is defined as the percentage relative to the number of requests made on 13 January 2020.

Participants: Location data sent from users’ devices to the Apple Maps service is associated with random, rotating identifiers so Apple doesn’t have a profile of users’ movements and searches and cannot make any statements about the representativeness of this data against the overall population.

Application: Viewing the mobility patterns in the city of London and the impact of COVID-19. Comparing the recovery of London mobility to 13 other cities in the UK such as Birmingham, Bristol, Leeds, London, Liverpool, Manchester, Edinburgh, Glasgow, Cardiff and more.

Limitations: The geographical boundary definition used by Apple is not publicly documented. Data availability in a particular country/region or city is subject to several factors, including minimum thresholds for direction requests made per day.

Citations:


Data: Open Table

Date: 18/02/2020- 07/11/2021 (Cont.)

Aggregation: City level: London

Information: OpenTable is an online restaurant-reservation service company. OpenTable currently services 47,000 restaurants in 20 countries and seats over 1.5 million diners per week. In response to the COVID-19, OpenTable published two
indexes to show the state of the restaurant industry. First index shows the average reduction in seated diners at a sample of restaurants in 48 metropolitan areas across the world (with the threshold of a minimum of 50 restaurants per metropolitan area on the OpenTable network). The second index aims to track the recovery of the restaurant industry. In both cases the index show the year-over-year comparisons of the covers by day comparing the same day of the week from the same week in the previous year. The volume of covers are aggregate across all the channels and include online reservations, phone reservations, and walk-ins.

Participants: Individuals who book a restaurant through OpenTable to be seated diners.

Application: Measuring the recovery of restaurants in London and the impact of government restrictions on seated dining.

Limitations: The second index sample includes only restaurants that have chosen to reopen in a given market with the threshold market size of at least 500+ restaurants on OpenTable network (for metropolitan areas, this index is available for only London and New York). The index is based on seated diners and not use of restaurant for takeaways.

Citations:


Data: Department for Transport and Transport for London

Date: 01/03/2020 01/11/2021

Aggregation: City level: London

Information: The Department for Transport is the government department responsible for the English transport network and a limited number of transport matters in Scotland, Wales and Northern Ireland that have not been devolved and Transport for London (TfL) is a local government body responsible for the transport system in Greater London, England. In response to the COVID-19 pandemic, Department for Transport has started to release statistics the reductions on road traffic, rail passenger journeys, bus travel and cycling in Great Britain and reduction in tube and bus usage in Greater London. London tube and bus data is provided by
Transport for London (TfL). This is operational data, based on contactless card use, considered fit for purpose for reporting changes in trends in usage. The usage is measured by entry/exit data from tube stations and bus boarding taps. This is then compared to equivalent data from a year ago to gauge the extent to which travel has been reduced. Where a bank holiday occurs, this year or last year, then the comparison is to the nearest similar day (so a bank holiday is not compared to a non-bank holiday).

Participants: Individuals travelling by car, light commercial vehicles, heavy goods vehicles, National Rail, TFL, bus and bike.

Application: Can see how different types of public transport use in London was impacted by the COVID-19 pandemic, National Rail levels might give an indicator to levels of tourism in London, following the easing of restrictions.

Limitations: Due to middle door bus boarding policy earlier in the pandemic, there is a period for which they did not receive the same high-quality data.

Citations:


Data: Bike Sharing (Consumer Data Research Centre)

Date: 01/03/2020- 08/11/2021 (Cont.)

Aggregation: City level: London

Information: Bikeshare Activity in London captures usage levels between 6 am and midnight in Santander Cycles (Central London only) and Freebike bike share systems. The data is provided in the raw format where daily activity peaks are expressed as the highest number of simultaneous users during this date. Besides Greater London, the data is also available for some larger cities in the UK (Cardiff, Edinburgh, Glasgow, Liverpool, Brighton, Bournemouth, Watford and Hereford) where the bike-sharing systems remained open throughout the first lockdown.

Participants: Users of specific bike sharing systems in London.
Application: Monitoring the use of bike sharing systems in London and comparing the levels to other cities. Determining if the COVID-19 had an impact of bike share usage.

Limitations: Only at a citywide level therefore usage in Camden or specific docks cannot be determined.

Citations:


Social and demographic data

Data: Office for National Statistics, Annual personal well-being estimates

Date: 2015-2021

Aggregation: Local authority: Camden

Information: Annual estimates of life satisfaction, feeling that the things done in life are worthwhile, happiness and anxiety in the UK. Personal well-being is assessed through four measures: Life satisfaction, feeling the things done in life are Worthwhile, Happiness, and Anxiety. To collect this data, Office for National Statistics (ONS) asks people in the UK to rate their well-being on an 11-point scale. Data for personal well-being estimates are sourced from the Annual Population Survey (APS), which is the UK’s largest household survey containing the ONS personal well-being questions. Personal well-being data are presented as both average means and thresholds (very low/low, medium, high/very high); the mean averages provide an overall estimate of personal well-being and the thresholds allow us to look at the distribution of the scores. Personal well-being estimates and accompanying datasets are published quarterly, based on the most recent year’s worth of data from the APS.

Participants: The achieved sample size of the APS is approximately 122,000 households (or around 320,000 respondents) on each annual APS dataset. However, of these 320,000 respondents only around 150,000 provide valid personal well-being responses. This difference is due to personal well-being questions having
to be answered in person and respondents of the personal well-being questions having to be over the age of 18 years. Non-response is also a factor.

Application: Comparing the well-being of Camden residents to other London borough in order to evaluate if high street resources can be harnessed to improve life satisfaction of local residents.

Limitations: If using local authority data, the most appropriate comparisons to make are progress over time within the same local authority, or across local authorities that share a similar demographic composition to one another; simply ranking local authorities by their numerical scores can be misleading due to several reasons including sample sizes and mode effects.

Citations:


Data: Office for National Statistics Census 2011, Ethnic group

Date: 2011

Aggregation: Output areas

Information: The Output Areas and Small Areas list contains 232,296 areas of the following constituent geographies: 171,372 Output Areas in England. Ethnic group classifies people according to their own perceived ethnic group and cultural background. This topic contains ethnic group write-in responses without reference to the five broad ethnic group categories, e.g. all Irish people, irrespective of whether they are White, Mixed/multiple ethnic groups, Asian/Asian British, Black/African/Caribbean/Black British or Other ethnic group, are in the 'Irish' response category. This topic was created as part of the commissioned table processing. Due to question and response category differences in the country-specific ethnic group question asked in the 2011 Censuses of the UK, some responses are not directly comparable. The UK output on ethnic group is therefore presented using a high-level classification as recommended by the ONS 'Primary Standards for Harmonised Concepts and Questions for Social Data sources'.

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Application: The information the census provides granular data that can be corresponded to the ethnicity of the individuals who live within a specified walk-time to each high street in Camden.
Limitations: Data from over 10 years ago.

Data: Office for National Statistics, Census 2011, Age

Date: 2011
Aggregation: Output areas

Information: The Output Areas and Small Areas list contains 232,296 areas of the following constituent geographies: 171,372 Output Areas in England. Age is derived from the date of birth question and is a person's age at their last birthday, at 27 March 2011. Dates of birth that imply an age over 115 are treated as invalid and the person's age is imputed. Infants less than one year old are classified as 0 years of age.

Participants: Every ten years since 1801 the nation has set aside one day for the census - a count of all people and households. It is the most complete source of information about the population that we have. The latest census was held on Sunday 27 March 2011. Every effort is made to include everyone, and that is why the census is so important. It is the only survey which provides a detailed picture of the entire population, and is unique because it covers everyone at the same time and asks the same core questions everywhere. This makes it easy to compare different parts of the country.

Application: The information the census provides granular data that can be corresponded to the age of the individuals who live within a specified walk-time to each high street in Camden.

Application: The information the census provides allows central and local government, health authorities and many other organisations to target their resources more effectively and to plan housing, education, health and transport services for years to come.

Limitations: Data from over 10 years ago.

Citations:


**Data: Office for National Statistics, Estimates of the population for the UK, England and Wales, Scotland and Northern Ireland**

Date: 1981-2020

Aggregation: Local authority: Camden

Information: National and subnational mid-year population estimates for the UK and its constituent countries by administrative area, age and sex (including components of population change, median age and population density). The mid-2001 to mid-2019 detailed time-series contains the latest available mid-year population estimates and components of change from mid-2019 back to mid-2001. Two boundary sets: In April 2021, changes were made to the administrative geography of the UK. This spreadsheet uses the boundaries after that point, which are the bodies that existed at publication. An accompanying version presents data on the boundaries before that point i.e. for the bodies that existed at the data reference period.

Participants: Usual residence definitions: the estimated resident population of an area includes all those people who usually live there, regardless of nationality. Arriving international migrants are included in the usually resident population if they remain in the UK for at least a year. Emigrants are excluded if they remain outside the UK for at least a year. This is consistent with the United Nations definition of a long-term migrant. Armed forces stationed outside of the UK are excluded. Students are taken to be usually resident at their term time address.

Application: Able to get an understanding of the age, gender and population in Camden borough to know who the high streets within the local authority should be catered for.

Limitations: When comparing mid-year population datasets please be aware that while they are broadly comparable, different data sources and methods are used to create the estimates for England and Wales, Scotland, and for Northern Ireland. Differences can also occur between years. Please see the Quality and Methodology Information (QMI) report linked below for more information. Rounding: estimates are presented both rounded to the nearest hundred and unrounded. Unrounded estimates are published to enable and encourage further calculations and analysis. However, the estimates should not be taken to be accurate to the level of detail provided. More information on the accuracy of the estimates is available in the Quality and Methodology document (QMI). Small counts: the estimates are produced using a variety of data sources and statistical models, including some statistical
disclosure control methods, and small estimates should not be taken to refer to particular individuals.

Citations:


Crime data

High crime areas discourage business development through deterring potential customers, high insurance premiums and high-risk of theft and property damage costs, making for an undesirable retail development (Bowes, 2007). Therefore, Police UK data has been used to map the locations of specific crime categories during the year of 2019, before the pandemic and compared to 2021. It is anonymised and aggregated to street intersections.

Figure 13 compares the occurrence of violent and sexual offences along Kilburn High Road, where it can be seen that outside Brondesbury station there was an increase in recorded occurrences. Figure 13 can be used to display a rise in recorded anti-social behaviour directly outside Warren Street station on Tottenham Court Road when comparing 2019 to 2021. Figure 13 also shows an increase in the number of recorded shoplifting cases in Kentish Town Road, particularly near the location of a Co-op. Nevertheless, the recorded crime data can only be used as a rough proxy for crime occurrences and its impact on high streets due to lack of information on the time of day of an incident, inconsistencies in location recordings and changing laws. In particular it is important to note that during 2021 when there were periods of lockdown restrictions, some COVID-19 related infringements may have been recorded as anti-social behaviour.
Figure 10. 11: The timing and location of crimes in high streets in Camden. The location of different categories of crime in 2019 (left) and 2021 (right) for different high streets in Camden.
Figure 10. 12: An insert from the Data for Future High Streets report outlining the 6 recommendations as an outcome of the analysis conducted within the report.

1. More closely aligned definitions and standards for commonly used – and fundamental – terms and concepts. “High street”, for example, means different things both in terms of policy but also in the way it is and can be encoded within the many datasets used here. A single definition may not be desirable, but the working definition within each use context needs to be clear and well-articulated.

2. Improvements in data collection and metadata. For example - and as set out above - the FHRs dataset has proven useful for monitoring the changing composition of food outlets but suffers from misspellings preventing linkage of the same outlet across years. Better data entry standards here (although probably acceptable for the purpose of inspection) would enable easier linkage and cleaning in analysis. The same applies for metadata in order that when datasets are passed between teams their contents are properly articulated and interpretable.

3. A culture of critical analysis and interpretation of data should be fostered to establish the utility and added value that the range of data on offer brings to better understanding Camden’s high streets. Data suppliers should be transparent about their data’s strengths and weaknesses and due diligence undertaken by Camden prior to data being used in analysis.

4. Related to recommendation 3, thought should be given to the added value that Camden can generate in-house vs the value that needs to be outsourced to data providers. For example, the likes of the Huq mobility data would not be a viable option in its raw form (given it’s volume and complexity) and so might lend itself to commissioning higher level insights/ analysis, whilst the FSA data appear more manageable and could be integrated within existing analysis functions at no extra cost.

5. Creative data sourcing is to be encouraged since it may generate novel insights previously overlooked. Those with the skills to work with data should therefore be given the chance to experiment where appropriate without constraints of tightly defined tasks/ outcomes.

6. Collaborative and open discussions should continue. This process has demonstrated the value of talking about data openly and between teams, forming an important community of practice that would be good to sustain.
Table 10. 9: British high street level vacancy for 2019. Estimation method: Robust OLS

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*Note: *Sig. <0.05 **Sig. <0.01 (two-tailed)*