OFFENDER RESIDENTIAL CONCENTRATIONS: A LONGITUDINAL STUDY IN BIRMINGHAM, ENGLAND.

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Abstract

The overarching aim of this thesis is to advance understanding into the geographic distribution of offender residences, that is, where known offenders live. Although this strand of research emerged amidst the earliest studies in spatial criminology, contemporary research has since favoured the examination of offences, much at the expense of offender residences. This shift has occurred despite there being strong theoretical and empirical reasons for studying both. To revive interest into offender residences, and achieve the aim of this thesis, three key themes are identified through a comprehensive review of existing literature, relating to spatial scale, longitudinal stability and explanation. From these, three research questions are posed, the answers to which constitute the original contribution of this thesis. Firstly, what is the most appropriate spatial scale to study offender residential concentrations? Secondly, to what extent do offender residential concentrations demonstrate stability over time? Thirdly, how can we explain the longitudinal (in)stability of offender residential concentrations? To answer these research questions, analysis is conducted on longitudinal police recorded data of known offender residences in Birmingham between 2007 and 2016, supplied by West Midlands Police Force, and census data under Open Government Licence. The methods deployed are largely inspired by the (considerably more advanced) offence strand of research, and include descriptive statistics, extensive (spatial) visualisations, multilevel variance partitions, novel longitudinal clustering techniques and spatially lagged multivariable regression models. Findings suggest that small ('micro') spatial scales are most suitable for studying the geography of offender residences. The degree to which concentrations demonstrate longitudinal (in)stability varies by the methods deployed, but findings suggest a reasonable degree of volatility over time, some of which is due to the individual-level residential mobility of offenders. Longitudinal trends can be explained by a number of demographic characteristics, including deprivation, ethnic diversity and housing tenure. Discussions emerge from these findings which have implications for methodology, theory and policy, opening prospect to generate avenues for future research.

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Chapter 1

Introduction

For many researchers in social science the topic of this thesis might appear unorthodox. The title itself conjures up all kinds of images, theories, topics and debates for academics and non-academics alike. Criminologists might immediately think of *individuals* and their life-courses, from onset through to desistence, and the individual characteristics or events that drive or deter deviant behaviour. Why are a large proportion of all crimes committed by a such a small percentage of the populous? Why do some people begin offending in the first place, and why do many tend to cease offending in early adulthood? Such research has proved highly influential, with findings having significant implications for the way in which the criminal justice system, and society as a whole, views and addresses criminality.

In contrast to the individual-level approach, this thesis is in the spirit of 'environmental' or 'spatial' criminology. This subfield takes a different perspective, focusing instead on the *spatial* distribution of crime, victimisation and offenders. Rather than using individuals as the unit of analysis, spatial criminologists examine *places*, from cities, down to neighbourhoods, streets, and even specific buildings or locations. Are people more likely to be victimised in city centres compared to the suburbs? Why do a disproportionate number of known offenders live in particular areas? How do these patterns emerge and evolve over time, and why? In this sense, whilst there are many parallels to individual-level research, spatial criminology has just as much in common with geography as it does with criminology.

As we will see, the field of spatial criminology emerged amidst the work of European statisticians and cartographers in the 19th Century, and was subsequently formalised by American academics in the early 20th Century. These influential bodies of research largely examined the spatial distribution of offender residences, that is, *where known offenders lived*. They demonstrated that some neighbourhoods tended to house a disproportionately large number of offenders, and that these concentrations tended to persist even over lengthy periods of time. As the field developed, interest in offender residences waned, and instead researchers began focusing increasingly on the distribution of offences, that is, *where crimes occur*. Indeed, this is largely the focus of spatial criminology to this day. Consequently, as this thesis will demonstrate, many contemporary advances in data and methods are yet to be exploited to examine offender residences, despite there being strong theoretical and empirical reasons for doing so. This motivates the principal aim of this thesis: to advance understanding into the geographic distribution of offender residences, and to bring it back up to speed with the (now more developed) offence strand of research.

1.1 Key research questions

In pursuit of this aim, a number of key themes are identified. These are areas in which the offence strand of research has made considerable progress, but in doing so, the field has neglected offender residences, leaving a number of shortcomings which demand rectification. The first theme relates to the choice of *spatial scale*. When investigating the geographic distribution of known offender residences, what is the most appropriate unit of analysis, theoretically and empirically, for conducting the study? The second theme addresses *longitudinal stability*. This deals with the temporal element of offender residence concentrations, and interrogates the extent to which the spatial patterning of where known offenders reside changes, or remains stable, over time. The third is that of *explanation*. Given the longitudinal (in)stability observed, how might we begin to explain these patterns?

In light of these research interests, and the overarching aim of the thesis, the following key research questions are posed.

- RQ1: What is the most appropriate spatial scale to study offender residential concentrations?
- RQ2: To what extent do offender residential concentrations demonstrate

longitudinal stability over time?

- RQ3: How can we explain the longitudinal (in)stability of offender residential concentrations?

1.2 Original contributions

In answering these research questions, this thesis makes a number of original contributions which can be summarised into five dimensions. Firstly, the study provides compelling justification for a revival of the offender residence strand of research through extensive literature reviews and empirical demonstration. Secondly, in pursuit of the most theoretically and empirically suitable geographic unit of analysis, this thesis provides a comprehensive (longitudinal) demonstration of the impact of spatial scale when studying offender residence concentrations. Thirdly, by exploiting contemporary developments in data and methods, findings shed new light on to the degree of longitudinal stability in offender residence concentrations at fine-grained spatial scales. Fourthly, and relatedly, a new longitudinal clustering method is introduced which showcases the merits of using bespoke approaches to unpicking temporal stability in offender residence concentrations. Finally, fresh insight is gained into potential explanations for the stability of these concentrations, using both individual-level and aggregated data.

1.3 Structure of thesis

In an effort to make these original contributions in a manner which has clarity and flow, the thesis structure reflects that of a substantive research paper. The research questions outlined above, relating to spatial scale, longitudinal stability and explanation, could have formed individual chapters, each with their own literature reviews, methodological outlines, findings and discussions. However, given the sequential nature of questions, and the dependency of these topics on one another, a decision was made to consider the three in unison, even though it represented a greater challenge in writing-up. With this in mind, the thesis has the following structure.

1.3.1 Chapter 2 - Offenders and offences in spatial criminology

Chapter 2 traces a historical narrative of spatial criminology, since pioneering research conducted in the 19th Century to the present day. In doing so, the purpose is not to provide a comprehensive review of the entire field, but rather, to provide an account of how research into the field's two primary strands, namely, offender residences and offences, has developed along the themes of spatial scale, longitudinal stability and explanation. It is demonstrated how, despite focus initially being placed on the examination of offender residences, academic endeavour has increasingly favoured the investigation of offences. Consequently, the offender residence strand of research has benefited little from modern advances in data and methods, leaving a significant gap in existing research along these three themes. This has occurred despite there being strong theoretical and empirical reason for reviving interest in the spatial patterning of offender residences, largely due to the relationship between where offenders live and where offences are committed. Following this account of existing literature, and in an effort to remedy these shortcomings, the three primary research questions, as stated above, are posed.

1.3.2 Chapter 3 - Considerations of data and method

In light of this, Chapter 3 sets about reviewing the relevant data and methods in an effort to establish the most appropriate approach, theoretically and empirically, to answer our three research questions relating to spatial scale, longitudinal stability and explanation. In doing so, particular weight is given to state-of-the-art research in the offence strand of spatial criminology, as the significantly more advanced subfield. That said, methods are reviewed critically, with a number of areas being ear-marked for tailoring and improvement when deployed on offender residence data, especially longitudinal clustering methods, commonly used to investigate longitudinal stability. Specific attention is paid to offender residence literature when appropriate, for instance when discussing issues of measurement and aggregation, which are specific to studies examining the spatial patterning of where offenders live. In providing this review, the chapter provides clarity on the appropriate methods and data required to effectively answer the research questions posed.

1.3.3 Chapter 4 - Data, methods and analytical strategy

These considerations feed directly in to Chapter 4, informing the data, methods and analytical strategies deployed in this thesis. In the first section, the data available for the study, provided by West Midlands Police Force, is outlined in detail, including discussions on bias, integrity, variables and ethics. Specific attention is then paid to the study area, Birmingham. Census data used under Open Government Licence, largely for answering the research question of explanation, is then detailed, including the selection of appropriate theoretically-driven variables, and the complications arising from census boundary changes and causation. The second section outlines the methods deployed, and associated analytical strategies, for answering the three key research questions relating to spatial scale, longitudinal stability and explanation. In doing so, attention is paid to the introduction of a new method for examining longitudinal stability, designed as part of this thesis. An additional plan is outlined to provide a initial demonstration of the empirical distinction between offender residence and offence locations in Birmingham, to augment the theoretical arguments made in Chapter 2.

1.3.4 Chapter 5 - Results: scale, instability and explanation

Following the implementation of the analytical strategies detailed in Chapter 4, Chapter 5 reports on the findings. To begin with, an account is provided on the empirical distinctions between offender residence and offence concentrations in Birmingham during the study period, using descriptive statistics and visualisations. Attention then shifts to answering the three key research questions. First, findings are reported on the suitability of different spatial scales when studying offender residence concentrations using descriptives, visualisations and multilevel variance partitions (RQ1). This then informs the choice of spatial scale for subsequent analysis. With a suitable unit chosen, findings relating to the question of longitudinal stability are then outlined (RQ2), which includes a systematic comparison of longitudinal clustering methods used to examine stability, including the new, bespoke method designed as part of this thesis. The final section details the results from analysis which explain the (in)stability observed, including individual-level offender residential flow patterns, and theoretically-driven explanatory models derived from social disorganisation theory (RQ3). In their totality, these findings answer the three main research questions posed, and in turn, generate a number of discussion points for the next chapter.

1.3.5 Chapter 6 - Discussion: implications and future research

Beginning with a re-cap of key findings, the discussion points which arise from the results are then detailed in terms of their implications for theory, methodology and policy, along with comments on how the data and methods deployed may have impacted on the results. Theoretically, focus is placed on the wider implications for spatial criminology, in particular, how explanations for offender residences and offence concentrations are distinct, but reconcilable, along with the support for expectations derived from social disorganisation theory. In terms of methodology, findings highlight the importance of spatial scale, effective visualisation and the sensitivity of findings to the methods deployed and measurements used. Policy-wise, the findings hold significance for West Midlands Police, showcasing the insight gained from examining the spatial patterning of where offenders live in Birmingham, and the implications this might have for their own work. More generally, results also hold significance for the estimation of crime-based police demand and associated funding calculations. In recognising the limitations of examining the three key research questions using quantitative methods, a discussion is also provided on the explanatory power of (unmeasured) housing policy and urban development in Birmingham. The chapter concludes with final comments on the shortcomings of the study, which links to suggestions for future research.

1.3.6 Chapter 7 - Conclusion

The concluding chapter provides a short summary of the thesis. It gives an overview of the study aims, and in doing so, reiterates the key research questions and re-caps on the contents of each chapter, including the major findings and discussion points. The thesis is brought to a close with a final comment on the original contributions of the study.

1.4 Key findings

A number of key findings emerge from the thesis. Firstly, the preliminary theoretical and empirical investigation into the distinction between offender residences and crime concentrations suggest that the two are indeed distinct (but related) phenomena. In Birmingham, offenders tend to commit crime relatively close to where they reside, but not in the immediate vicinity of their local area. Secondly, in answering RQ1, findings suggest that fine-grained spatial units of analysis unmask greater variance in offender residence concentrations compared to larger scales, prompting the use of so-called 'micro' units of analysis. Thirdly, in addressing RQ2, although there is some evidence of stability in concentrations over time, there is also non-uniformity in longitudinal trends, with many local areas experiencing relative increases in known offender residences, even amidst widespread persistency or decline. The introduction of a novel longitudinal clustering technique demonstrates that these findings are somewhat sensitive to the methods deployed. Individual-level population flow analysis also uncovers underlying instability, with many repeat offenders moving to and from particular areas throughout the study period. Fourthly, emerging from RQ3, neighbourhood demographic characteristics including deprivation, ethnic diversity and residential instability are shown to play a key role in determining the longitudinal trends observed. Although findings are largely consistent with expectations from social disorganisation theory, there is a clear need for a contemporary twist on traditional explanations of offender concentrations, informed by the suburbanisation of poverty and local housing regeneration initiatives.

1.5 West Midlands Police Force collaboration

The overarching aim of this thesis, along with the research questions posed and analyses conducted, was guided through a collaboration with West Midlands Police Force. As detailed in later chapters, the data used for the project was provided through a data sharing agreement with the Force. Findings were presented to personnel including geospatial analysts, offender management leads and evidence-based practice specialists on three occasions between 2016 and 2019, with the discussion points and feedback raised iteratively feeding back into subsequent analysis. This has ensured that the scope of this thesis, and consequently the findings and discussion points, have practical relevance to policing in the West Midlands, not just the academic literature. The input and conversations with personnel from the Force are referred to periodically throughout the thesis. As noted, a comprehensive discussion on the implications of findings for policing in the West Midlands is returned to in Chapter 6.

Chapter 2

Offenders and offences in spatial criminology

2.1 Introduction

This chapter traces a historical narrative from the origins of spatial criminology to the present day. Focus is placed on two key research strands, namely, examinations into *where offenders reside* ('offenders') and *where crimes occur* ('offences'). It is demonstrated how, despite the pioneers of the field primarily studying the spatial patterning of offender residences, sometimes in parallel with offences, contemporary research has focused almost exclusively on the latter. Consequently, the field has made significant advances into our understanding of where crimes occur, and in doing so, has largely neglected the topic of where offenders reside, despite there being strong theoretical and empirical reason to examine both phenomena.

In tracing this narrative chronologically, three key themes are highlighted. The first is the geographic unit of analysis. Broadly, the *spatial scale* at which offender residence and offence concentrations have been examined has decreased over time. However, as we will see, progress in this domain has slowed considerably for offender residences, even as major advancements have been made in the offence strand. Secondly, there has been an ever-growing acceptance that spatial criminology should be developmental rather than static, permitting comments on *longitudinal stability.* This view emerged during the Chicago School era, through both theoretical reasoning and empirical observations about the longitudinal stability of offender residence concentrations. Interest has been revived in contemporary research, but only for offences. Thirdly, there has always generally been some form of attempt at *explaining* the longitudinal stability observed, through theoretical reasoning or statistical modelling. As we shall see, these attempts have become less common in recent years, with even many contemporary offence-based papers becoming largely atheoretical.

Informed by this narrative, the chapter concludes by deriving three key research questions relating to the themes of spatial scale, longitudinal stability and explanation, specifically for offender residences. In posing and answering these questions, the overarching aim of this thesis, to advance understanding into the geographic distribution of offender residence concentrations, can be achieved.

2.2 Origins: the 19th Century scholars

The spatially-sensitive approach to studying criminal phenomena, and the emergence of two distinct strands of research into offences and offenders, can be traced back to scholars active in Western Europe during the 19th Century (e.g. Quetelet, 1831/1984; Glyde, 1856; Guerry, 1833; Balbi & Guerry, 1830; Rawson, 1839; Fletcher, 1850; Mayhew 1851/1862). These researchers concerned themselves with mapping the variation of offender residences or offences across space. Their contributions have been the subject of much review (see Morris, 1957; Kenwitz, 1987; Melossi, 2008; Weisburd, Groff & Yang, 2012). Two of our key themes make appearances here already: discussions around the most suitable spatial scale, and attempts to explain the spatial patterning observed.

The first key contribution was made by Adriano Balbi and Andre-Michel Guerry (1830; Guerry, 1833) who used judicial statistics to map out concentrations of offences[1] across the administrative districts of France. The authors observed not only that crime tended to concentrate in particular districts of the country, but that these concentrations were associated with other variables, such as demographic

[1] As Morris (1957) points out, the use of judicial statistics which recorded where offenders were *charged* makes Balbi and Guerry's study one of offence concentrations, rather than one examining where offenders lived. That said, around 70% of charges occurred in the same area in which the offender resided. As we will see, the degree to which offender residences and offence locations are empirically similar can vary by the spatial scale used. In Balbi and Guerry's study, these scales were large, with only 86 districts representing the whole of France.

characteristics. Other studies using French district data at the time, most notably by Quetelet (1831/1984), also found that crime levels were associated with population characteristics such as poverty. The significance of these studies cannot be understated. Guerry and Balbi, along with Quetelet, demonstrated what has become a truism and a key explanandum in criminology: the non-random distribution of crime across space. They did this using *spatial* units of analysis, for which measures of crime concentration were constructed from individual data. The authors also made some of the first attempts to measure the association between social characteristics and crime at these aggregated scales. Whilst the statistical evidence of causality was limited, the authors clarified how such mechanisms could be justified through argumentation (Morris, 1957). Already, then, some key themes were being introduced, that of spatial units of analyses for studying crime (in this case, large administrative regions), and that of explaining the non-random distributions observed.

Contemporary researchers have widely acknowledged the influential role of these scholars in establishing the offence strand of research (see Weisburd, Bruinsma & Bernasco, 2009). However, not so widely acknowledged is that the 19th Century scholars were also examining the spatial distribution of offender residences, sometimes in concert with that of offence locations. In the United Kingdom, Henry Mayhew was examining offender residence concentrations at a nationwide level, but he was also compiling an extensive catalogue of information about the spatial patterning of offender residences *and* offences in London, collecting anecdotal and quantitative data at much more fine-grained spatial scales than the likes of Guerry and Balbi, who largely mapped out 'macro' units at the regional level.

Mayhew noted that specific areas of London were home to a disproportionately large volume of offenders. He demonstrated this using 'micro-level' units of analysis, such as town squares, streets and buildings. Lodging houses in particular were identified as problematic, as they tended to house individuals who were criminally active. It became clear that the region-wide maps generated by Mayhew's predecessors (and often Mayhew himself) were masking underlying variation occurring at more localised scales. In conducting ethnographic and descriptive statistical analyses at scales lower than regions and cities, Mayhew also found that the areas of the city where offenders resided were not always those in which offences tended to be committed. He recognised that the factors generating criminal propensity amongst residents were distinct from those factors which lead to offending in particular areas[2].

Soon after, John Glyde, from the Statistical Society of London, published work on the concentration of offender residences in Suffolk (Glyde, 1856). Like Mayhew, Glyde provided a novel insight into concentrations of criminality at fine-grained spatial scales. Within Suffolk, the number of known offenders housed in each local area ("Union") varied considerably, but even within these areas, Glyde argued that each town and village were "not equally favourable or unfavourable" (1856, p. 103). In other words, he confirmed what Mayhew had found, which was that greater variation is unmasked when examining offender residence concentrations at localised spatial scales, rather than large, administrative districts. It is clear then, that even amidst the earliest mapping of offences and offenders, researchers were mindful of the benefits of selecting an appropriately fine-grained spatial scale.

Whilst contemporary academics have acknowledged the importance of these 19th Century works, little retrospective attention has been paid to the offender residence and offence distinction outlined by scholars like Henry Mayhew. Recent in-depth reviews by authorities in the field of spatial criminology have given no consideration to the fact that Mayhew was interested not just in where crimes occurred, but also where offenders lived (see Weisburd et al., 2009; Weisburd et al., 2012). Whilst Mayhew's work lacked a formal reconciliation of the two strands of research, there is sufficient evidence to argue that the two were beginning to emerge during this period, thanks to his efforts, and those of his peers in Britain and mainland Europe. Collectively, their research outputs generated a number of key themes. Firstly, the non-random spatial distribution of crimes and offender residences was demonstrated and visually reported through cartography. As such, these scholars can be credited for pioneering the field of spatial criminology. Secondly, the importance of spatial scale was introduced, with the variation unmasked using fine-grained data showcasing the merits of using localised spatial scales, rather than macro-level aggregations. Thirdly, sociological explanations for why crimes and offenders tended to concentrate in particular areas were discussed and tested.

It would be the Chicago School, decades later, who would revive this research

[2] Mayhew's work also represented an important retort to lines of thought at the time about the role biological factors (e.g. physical features) played in determining criminal propensity. Such theories would later be brought to prominence by Cesare Lomborosso. Instead, Mayhew advocated sociological and environmental explanations for criminal propensity.

for specific urban areas in North America. In doing so, the Chicago School took significant steps forward with two of the themes already identified, spatial scale and explanation, but it would also introduce a new theme, namely, longitudinal stability.

2.3 The Chicago School

2.3.1 Clifford Shaw

In the 1920s, a group of sociologists from the University of Chicago embarked on a series of fresh projects examining the criminality of the city, which would continue for several decades. These studies built on the two traditions of spatially-orientated criminological research which had been informally established by the 19th Century scholars, namely, the distribution of offenders residences and offence locations across the urban landscape. Nonetheless, their focus was on documenting, describing and explaining specifically where offenders lived. The impact of these studies, and the theoretical frameworks that were developed to explain what was observed during this period, have had a profound impact on contemporary research. Studies being carried out at the cutting edge of the field will typically frame their research around the theories and discussions ignited by the Chicago School, although as we will see, they tend to adopt them for offence concentration research, rather than offender residences.

Whilst continuing to deal with the two themes already introduced, spatial scale and explanatory mechanisms, the Chicago School made two important additions. Firstly, they expanded upon the loose explanations provided by the 19th Century pioneers by formulating formal theoretical frameworks to explain what was being observed. Secondly, the Chicago School can be credited for viewing the spatial patterning of criminality through a developmental lens. Geographic areas were not just examined one snapshot in time, but over many years, which permitted a demonstration and discussion on the extent of *longitudinal stability* in offender residence concentrations.

Clifford Shaw (1929) replicated Mayhew's observation that certain areas of cities tended to generate a disproportionate number of offenders. Unlike his predecessors in mainland Europe, who tended to produce maps using large-scale administrative districts for entire countries, Shaw and his colleagues appeared to draw more from Mayhew and Glyde's work by using small spatial scales, mapping bespoke 'natural areas' with census tracts and square-mile units of analysis. These were commonly referred to as 'neighbourhoods'. Shaw and his colleagues labelled those areas with an especially high number of known offender residences, even after accounting for resident population numbers, as 'delinquency areas'. These were areas of the city where delinquents tended to *live* rather than strictly *where they offended*. That said, Shaw hinted that he considered the two to be closely related, even though the empirical and theoretical interest was certainly in where offenders lived. This interest echoed some of the earlier work of Breckinridge and Abbott (1916), also from the University of Chicago, who had mapped out the residential locations of young offenders in the city, noting that certain districts housed a disproportionately large volume of offenders. As discussed, similar observations had been made by Henry Mayhew (1851/1862) decades earlier in London, but Clifford Shaw formalised the 'delinquency area' as a phenomenon that demanded explaining through theoretical reasoning. A key component of this explanation was longitudinal.

Shaw thought that delinquency areas emerged over time as a result of urban growth, an explanation rooted within the ecological theories of other Chicago sociologists and the concentric zone model proposed by Robert Park, amongst others (Park, 1925/1967). This concentric model of urban areas was used to explain how urban growth resulted in a distinct urban structure, characterised by significant variation in social characteristics and physical features across space. The model mapped the growth of Chicago into four concentric zones which emanated from the central business district area. Each zone was said to contain neighbourhoods with particular land uses. Beginning from the central business district (the inner-most zone), moving outwards, these zones were labelled as (1) zone of transition, (2) working class zone, (3) residential zone, and (4) commuter zone. A key proposition of the model, and surrounding argumentation, was that the volume of known delinquents in any given neighbourhood would depend on the characteristics of the zone in which it was situated, and the distance of this zone from the centre of the city (Weisburd et al., 2009). The characteristics of the 'zone of transition' rendered it one especially prone to delinquency. The causal mechanism behind this relationship was formalised, and made a benchmark in spatial criminology and sociology, by Shaw's collaboration with Henry D. McKay some years later.

2.3.2 Clifford Shaw and Henry D. McKay

The initial steps taken to build on the concentric model would be expanded into Shaw and McKay's influential volume *Juvenile Delinquency in Urban Areas* (1942/1972). This expansive volume examined the social background and residential distribution of individual offender residences in Chicago, following on from preliminary work carried out by Shaw and his Chicago School colleagues in the preceding decades. The comprehensiveness of Shaw and McKay's study has made their 1942 volume a "magnum opus" in the criminology of place literature (Bottoms, 2007, p. 530).

Shaw and McKay mapped out the residential addresses of juvenile offenders to demonstrate clustering in space (e.g. Shaw & McKay, 1942/1972, p. 51). The concentric zone model was applied to maps of Chicago to calculate delinquency rates for each of the zones derived from the theoretical framework of Park and colleagues (e.g. Shaw & McKay, 1942/1972, p. 78). The authors observed a negative association between the distance from the city centre and delinquency rates. More profound, however, was the observation that areas characterised by high delinquency rates tended to remain that way over many decades, irrespective of the populations residing in these communities (Bursik, 1986). This was a key development on existing work, which had only described such areas at one point in time, and it had important implications. If the residential composition and associated demographic characteristics of areas change over time, and the criminality persisted, it was suggestive of environmental factors contributing to the propensity of individuals to commit crime. Statements on such stability can only be made with longitudinal data. The 19th Century scholars did not give thorough consideration to the persistence of concentrations over time, but Shaw and McKay made their theoretical contribution in attempting to "explain the existence and stability of these area differentials in delinquency" (Kornhauser, 1978, p. 62). As a consequence, the developmental dimension and interest in the longitudinal stability of offender residence concentrations became firmly established.

Another influence of Shaw and McKay's volume would stem from the explanation of why delinquency areas tended to persist over time. This was based on the notion of social disorganisation theory. From an ecological perspective, this theory was being discussed by the likes of William Thomas (1929/1966) and Ernst Burgess (1926/1968), but Shaw and McKay integrated social disorganisation as an explanatory mechanism for their unique observations about offender residences. It is widely accepted that Shaw and McKay did not suggest a *direct* causal mechanism between economic deprivation and delinquency (Kornhauser, 1978; Bursik, 1986), but the variation of economic deprivation across space is the root of their explanation. The 'zone of transition' was said to contain affordable housing due its proximity to industry, and therefore attracted residents of low socioeconomic status. These residents would leave as soon as they had the financial capability, and as a consequence, such areas would suffer from high residential turnover (Bursik, 1986). The affordability of these areas would also make them particularly attractive for new migrants. This, accompanied with the continuous flux in the resident population, would render those who lived in such areas a heterogeneous group. Shaw and McKay argued that these conditions would generate communities that were incapable of forming common values and enforcing self-regulation and social control (Kornhauser, 1978; Bursik, 1986). Delinquency was the inevitable consequence. Given that housing in the zone of transition was constantly held at a low cost, the mechanism generating social disorganised communities was considered to persist over time regardless of changes in population composition. Shaw and McKay argued that these "enduring social characteristics" were the cause of delinquency (Kornhauser, 1978, p. 63). The importance of housing in driving the spatial distribution of known offender residences was revived by the work of Anthony Bottoms and John Baldwin in the 1970s and 1980s. More attention is paid to this in the next section.

Shaw and McKay's work had such a significant impact for two principle and related reasons. Firstly, it raised the importance of considering offender residences and the longitudinal nature of communities *over time*, rather than taking snapshots at one particular point. Secondly, the authors adopted a formal theoretical framework, social disorganisation theory, to explain what was being observed. These elements would cement Shaw and McKay's (1942/1972) volume as a highly influential work in spatial criminology, and as we shall see, one that is still highly influential on contemporary research.

By the 1940s, then, three themes had emerged and been cemented by the Chicago School, some of which had drawn inspiration from the 19th Century pioneers. Firstly, the importance of examining offender residences and offences at fine-grained geographies was firmly established. This had empirical benefits, as it unmasked greater detail, but was also theoretically relevant, since social disorganisation was expected to manifest among relatively small neighbourhood communities, nested within cities. Secondly, observations about the persistency of delinquency areas in Chicago raised discussions about the longitudinal stability of offender residence concentrations over time. Thirdly, following this observation, a formal theoretical framework was introduced, social disorganisation theory, to explain why particular areas tended to house a disproportionately large numbers of offenders over time.

2.4 Where next?

Despite the novelty of *Juvenile Delinquency in Urban Areas*, the volume "was considered by many to be little more than an interesting footnote in the history of community-related research" decades later (Bursik, 1986, p. 36). This can retrospectively be attributed to three factors. Firstly, much of the research that followed (e.g. Allison, 1972; Beasley & Antunes, 1973; Boggs, 1965) simply "[presented] the correlates of a geographical distribution of delinquency at one point in time rather than investigate the dynamic processes underlying such distributions" (Bursik & Webb, 1982, p. 27). As such, the developmental dimension and associated interest in longitudinal stability was largely lost. Secondly, little attempt was made to replicate findings outside of North American cities, despite social disorganisation theory having global relevance (Kornhauser, 1978). Thirdly, subsequent research often failed to make the reconciliation between offence and offender residence concentrations. Whilst Shaw and McKay formalised interest in offender residences, there was no doubt that they "failed to give adequate consideration" to "the location of crimes as opposed to the location of offenders' homes, and the relationship between the two" (Morris, 1957, p. 93). As a consequence of this neglect, there were unanswered questions about offenders and offences in space. Were the geographic distributions empirically synonymous, as Shaw and McKay seemed to imply? Was there reason to believe that offender residences and crimes were at least theoretically distinguishable, as Mayhew had speculated? Most of the research that followed did not address these questions, and progress stagnated.

Nonetheless, there were notable exceptions. Terence Morris (1957) rectified two out of three issues by examining the relevance of the Chicago concentric zone model, and comparing offence and offender residence concentrations cross-sectionally in Croydon, England. Calvin Schmid (1960) stayed in the United States, but managed to incorporate the developmental element of the Chicago School. A group of researchers then built on Morris' work in England with a comprehensive cross-sectional comparison of offenders and offences in Sheffield, England (Baldwin & Bottoms, 1976). These are now discussed in turn[3].

2.4.1 Croydon

Terence Morris was particularly interested in the ecological research carried out by the Chicago School. He recognised that Shaw and his colleagues had failed to provide a simultaneous, comprehensive examination of the two distinct strands of research established by the 19th Century scholars. Morris visualised the distribution of both offences and offender residences at local Ward level (see Morris, 1957, p. 120-123). Specifically, Morris sought to test the concentric zone model on an urban area outside of the United States. He found that the model had "little relevance" to the growth of Croydon, aside from its expansion in the very early stages of its development (Morris, 1957, p. 116). It is therefore not a surprise that Morris found minimal association between land use and delinquency areas in Croydon, given that the explanatory power of the concentric model revolves around an understanding of land use in each zone (e.g. slums, low cost housing). This cast doubt on the relevance of social disorganisation as a way of explaining delinquency areas in England.

That said, by examining both strands of research simultaneously, Morris' work pointed to the geographically similar relationship between where offenders reside and where offences tend to be committed. Although he did not comprehensively demonstrate to what degree the two were distinct, the maps reported for each certainly have clear differences (1957, p. 120-123). Morris suggested that the two were empirically similar, but he also argued that the two could not be treated synonymously. Clifford Shaw had also argued this, although Morris notes that he did so only vaguely. Morris explicitly claimed that the mechanisms generating

[3] A handful of other studies took place in England, inspired the Chicago School, which were not as extensive as Morris (1957) but are worthy of acknowledgement. Wallis and Maliphant (1967) mapped out resident offender concentrations of London boroughs, Jones (1958) did similarly in Leicester and there was a comparable study in Liverpool (Castle & Gittus, 1957). These studies are rarely mentioned, if at all, in contemporary reviews, seemingly because they lacked the detail and comprehensive reviews of literature that Morris offered, although it is not immediately clear why they are not reviewed.

delinquency areas were distinct from those attracting offenders to target specific areas of the city. He did so with reference to findings from an earlier study in Egypt (see El-Saaty, 1946). Subsequent reviews have used Morris' study as an example of how offenders and offences in space should not be considered identical, either theoretically or empirically (Bottoms & Wiles, 1986). As such, amongst his wider contribution of testing the relevance of the Chicago concentric model in an English urban area, the simultaneous examination of offender residences and offences at localised spatial scales was an important exercise by Morris.

That said, he admits that a key shortcoming of his 1957 publication was that it failed to assess trends in offence and offender distributions over time. The developmental component to delinquency areas started by the Chicago School was therefore lost in Morris' study. In particular, the question over the stability of delinquency areas over time could not be addressed. Nevertheless, Morris continued to demonstrate the importance of using local units of analysis (rather than nationwide regions), and made a notable contribution to the relevance of explanatory mechanisms for offender residences and offences outside of the United States.

2.4.2 Seattle

The closest to a replication to the *longitudinal* dimension of Shaw and McKay (1942/1972) came from Schmid (1960) in Seattle. Not only did he recognise that "it is important to know… not only where 'delinquents' or 'criminals' live, but also where violations actually occur" (p. 675), but he also sought to examine what he referred to as the "constancy" of criminality over time (p. 669). As such, Schmid reported data on offender residences and crime locations jointly, noting that the two distributions had similarities but were by no means synonymous. He also (albeit briefly) reported on the longitudinal stability of crime over time, finding that offence concentrations tended to persist, even over many years. He did so using a combination of census tracts and 'natural areas' used by his predecessors in Chicago, continuing the trend of using fine-grained, local spatial scales. Schmid's work would go on to inspire a replication of Shaw and McKay's study by Bursik and Webb (1982) using offender residence data, which ultimately led to a number of key publications during the 1980s, covered extensively later in this chapter. As such, Schmid's contribution was significant.

2.4.3 Sheffield

A study some years later in Sheffield continued to emphasise the importance of examining both offender residence and offence concentrations simultaneously (see Baldwin & Bottoms, 1976). But, like Morris' research, it also continued to lack the dynamic element of the Chicago School that Schmid (1960) had briefly captured with offences. Nonetheless, Baldwin and Bottoms made important contributions by demonstrating that the two geographic distributions were distinguishable. The authors did so using enumeration districts as their unit of analysis, continuing the tradition formalised by the Chicago School of using smaller units of analysis compared to the large, countrywide regions of the 19th Century. In Sheffield, offender residence rate concentrations did not mimic those of offences, with only the latter conforming to the concentric circle pattern emanating from the city centre. Their findings have subsequently been used as evidence to support the examination of both offences and offender residences in space, rather than assuming the two are synonymous (Bottoms & Wiles, 1986).

Relatedly, the Sheffield study represented one the earliest attempts (following Turner, 1969/2017) at describing what subsequently became known as the 'journey to crime', by measuring the distance travelled from an offenders' home residence to the crime location. The relationship between 'origin' (residence location) and 'destination' (offence location) is fundamental to the geographic relationship between the two distributions. Crudely, if every offender committed their offences at home, or in their own street or neighbourhood, the two distributions would indeed be synonymous, and empirically indistinguishable using aggregated data. Baldwin and Bottoms found that offenders do not exclusively offend near to where they live, and instead often travel to commit crime. For instance, they reported that one in two lone-wolf offenders travelled over a mile to commit property crime. Although results tended to vary by crime type, the conclusions were clear. Even if the distributions were similar using aggregated data at geographic levels of analysis (such as the wards used by Morris in 1957), these patterns would merely be artefacts of underlying individual-level journeys to crime, and would not render offenders and offences indistinguishable.

Evidence suggesting that offenders were willing travel some distance to commit offences supported the notion that the mechanisms generating concentrations of each were distinct, just as Morris (1957) had claimed. It supported earlier assertions that certain residential areas housed a disproportionate volume of offenders, but that they were then attracted to offend in more commercial areas (El-Saaty, 1946). This was corroborated in studies which showed that offenders tended to travel away from residential areas with few suitable targets to those areas that had greater opportunity (Boggs, 1965; Phillips, 1980), and would be incorporated into contemporary theoretical frameworks and empirical studies relating to the journey to crime, discussed later.

Nevertheless, the irrelevance of the concentric zone model to urban areas outside of the United States, certainly regarding offenders, appeared to be replicated in Sheffield, as it had in Croydon by Morris (1957). To Baldwin and Bottoms, this provided further evidence to suggest that the ecological theories posited by the Chicago School were unsuitable when deployed to explain the urban landscape of Britain. Nonetheless, they were adamant about the importance of the housing market, which was a key component of the social disorganisation equation. As discussed, Shaw and McKay posited that cheap housing in the zone of transition was the root cause of the emergence of social disorganisation and the subsequent continuity of delinquent areas. The Sheffield study argued that areas with comparable social characteristics could still have starkly different offender residence rates, and that the housing market was the key to explaining this variation. A defining result was that delinquency areas were said to be characterised by a large proportion of rented and local authority housing. As such, although they could not replicate the findings from Chicago, largely due to a lack of longitudinal data, their theoretical explanations for delinquency areas had common ground in the importance of housing.

2.5 Themes emerging

By the mid-1970s, then, the field had made substantial progress since the early writings of Henry Mayhew and the 19th Century scholars in mainland Europe. Discussions were emerging about the distinction between offender residences and offence locations, with evidence suggesting that the two were empirically distinguishable, demanding unique theoretical explanations. The merits of examining offenders and offences using small spatial scales, nested within a specific urban area, were demonstrated, cementing the field's interest in the localised spatial patterning of criminality, as opposed to region-wide maps. Advancements in the availability of longitudinal data, although limited to only a small number of studies, meant that researchers were beginning to examine the stability of concentrations over time. Finally, the development of a formal theoretical framework to explain offender residences, social disorganisation theory, had emerged, including a recognition that explanations for offender residence concentrations were distinct from those explaining offence locations.

2.6 Lost years: the ecological fallacy

Despite these major steps forward, the immediate post-war era being discussed was not exactly a hive of activity for the field. This can be largely attributed (see Weisburd et al., 2012) to what is termed the 'ecological fallacy', a critique introduced in the *American Sociological Review* (Robinson, 1950). Robinson argued that ecological researchers were fundamentally interested in the behaviour of individuals, but lacked the individual-level data, and instead used what is available. The readily available data tended to be administrative (e.g. census) data, aggregated to small spatial scales which approximated neighbourhoods. He makes this point with reference to a number of classic studies, including that of Shaw and McKay on delinquency areas. Robinson demonstrated that correlations between aggregated data do not necessarily hold when using individual-level data (and in fact, can be reversed), and consequently, inferences drawn from such correlations can be spurious.

Robinson's demonstration did not automatically invalidate the work of the Chicago School, or indeed any subsequent research that used geographic units of analysis. In fact, this problem was openly acknowledged and investigated by Baldwin and Bottoms (1976), for example. Nevertheless, it was a strong critique of ecological researchers who claimed to have provided a valid substitute for individual-level research. In spatial criminology, researchers would have to take great care in interpreting their results, and the lack of punch that came with this caveat may have put researchers off such examinations. Contemporary research has used Robinson's critique to promote the use small-scale geographic units of analysis, which mitigates for this problem, as it is considered most acute at large spatial scales

(Andresen & Malleson, 2011). Not only was Robinson's work a key explanation for the quiet post-Chicago era in spatial criminology (as per Weisburd et al., 2012), but it can be retrospectively credited for furthering the abandonment of large, region-wide geographic units of analysis, and further motivating the pursuit of small-area analyses.

Despite the concerns raised by Robinson's contribution, and subsequent loss of momentum within spatial criminology in the immediate post-war era, a volume entitled *Communities and Crime* published in the 1980s would go some way in reviving interest in the field.

2.7 Emergence of the criminal career perspective

2.7.1 Background

With the emergence of themes relating to spatial scale, longitudinal stability and explanation, the publication of a special volume of Crime and Justice entitled *Communities and Crime* (1986) signalled an important moment in spatial criminology. The collection of papers in this volume, primarily from the United States, called for a renewed focus into the spatial patterning of offender residences and offences at fine-grained spatial scales, but in particular, demanded further examination of the *longitudinal* dimension, reviving Shaw and McKay's interests. Momentum had been building in the years preceding this publication following a study by Bursik and Webb (1982), which found reason to question the existing understanding, found by the Chicago School, that delinquency areas were stable over time.

Bursik and Webb managed to recover the original data used by Shaw and McKay, and even appended it with additional time periods. The earliest period of the study replicated the results of the original research: neighbourhood delinquency rates remained remarkably stable overtime. That said, the later time periods in Bursik and Webb's study found that delinquency areas might fluctuate in response to changes in the characteristics of the resident population. So, changes in the composition of some neighbourhoods might increase or decrease the number of known resident offenders. The implication for other research was clear: geographic areas were not static, but instead *dynamic* units of analysis that demanded longitudinal study. Inspired by these findings, the 1986 special volume was a call to develop the evidence-base of what was termed the 'criminal careers' of communities.

2.7.2 The parallel to individual-level research

Around the same time, academics were having a similar, but fiercer, debate on whether individual-level criminal propensity could be better understood when considered dynamically, as oppose to assuming continuity over time (for a full review see Soothill, Fitzpatrick & Francis, 2013). Advocates of the dynamic approach (e.g. Blumstein, 1986; Sampson & Laub, 1993) argued that a 'criminal career' approach, studying the life-course of offenders, was necessary to comprehend the onset and persistence of individual offending, and could ultimately lead to policy implications which encouraged desistence. Others felt that the individual propensity to commit crime was static, and that once it had emerged, it had remarkable continuity over the life-course, rendering dynamic approaches redundant (Gottfredson & Hirschi, 1986). A review of this individual-level debate is beyond the scope of this literature review, but the parallels are clear. The dynamic approaches to studying the life-course of offenders had a major influence on the methodologies used in place-based criminal career literature (e.g. Nagin & Land, 1993). This is expanded upon in the following chapter. For now, it is relevant only in that the 1980s saw a growing understanding that not only did individuals have criminal careers, characterised by "the longitudinal sequences of offences committed" (Farrington, 1992, p. 521), but so too did spatial units, characterised by explainable longitudinal fluctuations in offence and offender residence concentrations. In other words, "today's safe environment can become tomorrow's dangerous one" (Reiss, 1986, p. 2).

2.7.3 Communities and Crime

Back in the field of spatial criminology, the studies in *Communities and Crime* were generating similar debates around longitudinal stability, whilst continuing the focus on fine-grained spatial scales and explanatory mechanisms. There was also some discussion over the theoretical and empirical distinction between offender residences and offence locations, although as we will see, this discussion was not straightforward. The papers within this volume can be themed according to our three key dimensions: spatial scale, longitudinal stability and explanation.

Spatial scale

Firstly, each study used the 'community' as their spatial unit of analysis, defined as "any group of people in a designated social space who interact to produce a culture that then affects their life-style and life chances" (Bottoms & Wiles, 1986, p. 103). This was very much in the spirit of Shaw and McKay's study (1942/1972) in which a combination of square-mile areas and census tracts were used to form what they referred to as 'neighbourhoods'. In the field, this term tended to be used interchangeably with 'community' (e.g. Schuerman & Kobrin, 1986; Griffiths & Chavez, 2004). The ontological meaning behind the neighbourhood unit was fundamental for the explanatory mechanism of social disorganisation theory, since this was the spatial scale at which residents were theorised to realise common values and enforce self-regulating, delinquent-deterring behaviour. The papers in *Communities and Crime* which were inspired by Shaw and McKay's work defined their units of analysis as per this reasoning (e.g. Bursik, 1986; Schuerman & Kobrin, 1986). Other studies in the volume which examined different dimensions of crime also argued that these effects manifested at the neighbourhood level, including social control (McGahey, 1986), policing behaviour (Smith, 1986; Sherman, 1986) and fear of crime (Skogan, 1986). The volume was therefore a concerted push for using neighbourhoods as the appropriate spatial scale to study offender residences and offences, but also other criminological phenomena. It certainly confirmed that the era of macro-level units of analysis was well and truly over.

Longitudinal stability

Secondly, a number of key papers in the volume specifically advocated a longitudinal approach to studying neighbourhood criminality. As outlined above, this was largely due to the replication study by Bursik and Webb (1982) which questioned Shaw and McKay's long-held assumption of longitudinal stability in delinquency rates (1942/1972). In this spirit, the opening chapter of the volume offered a re-run of this analysis (Bursik, 1986), reconfirming the findings, and furthering the call for more work in the area. This work would subsequently be extended with a more methodologically advanced demonstration of how Chicago neighbourhoods are developmental, characterised by non-uniform longitudinal trajectories in offender residence rates (Bursik & Grasmick, 1992). The notion of 'community careers in crime' was formally proposed in Schuerman and Kobrin's chapter (1986;

see also Kobrin & Schuerman, 1981). Using offender residences as a proxy for crime, they demonstrated that high-crime neighbourhoods in Los Angeles could be categorised into three groups based on their longitudinal crime trajectories: emerging, transitional and enduring, each with distinct trends in neighbourhood characteristics such as unemployment, education and residential mobility. This expanded upon the findings and argumentation of Bursik and Webb (1982), and ultimately supported further examination into longitudinal stability. This effort to disentangle neighbourhood-level trajectories from the citywide trend would be become a highly influential research aim in contemporary research.

Although Schuerman and Kobrin's contribution to longitudinal stability was significant, the authors used offender residence data as a "surrogate measure of all crime because crime report data at the neighbourhood level were not available" (Schuerman & Kobrin, 1986, p. 69). This is justified as one would expect: the high correlation between the two distributions. Nonetheless, the concerns of El-Saaty (1946), Morris (1957), Schmidt (1960) and Baldwin and Bottoms (1976) were largely ignored. Schuerman and Kobrin's study appears to assume that the two distributions were both empirically and theoretically synonymous. This is non-trivial, as their work went on to inspire highly influential papers in *Criminology* discussed in the next section (see Griffiths & Chavez, 2004; Weisburd, Bushway, Lum & Yang, 2004), which can be retrospectively identified as the nail in coffin for applying the criminal career perspective to offender residence concentrations in the spirit of the Chicago School. Inevitably, this also had consequences for the way in which explanatory theories were utilised, which brings us to our third theme of explanation.

Explanation

The assumption that offender residence and offence distributions were analogous had an important implication: it inherently rendered social disorganisation theory capable of explaining both phenomena. This shift began to blur the lines between offender residences and offences, contrary to the arguments made in key British studies (e.g. Morris, 1957; Baldwin & Bottoms, 1976), and the emerging evidence that offenders were willing to travel outside of their resident area to commit offences (Rand, 1986; Suttles, 1968). The contemporary focus on offences, as detailed later in this chapter, can at least be partially attributed to this shift.

Nevertheless, studies in *Communities and Crime* yielded interesting findings generated from theoretical expectations. Enduringly high-crime (thus, in some cases, also high offender residence) areas were found to have the strongest trends towards abandonment, such as declines in housing and commercial units, and tended to lose residents with professional or skilled occupations and high education levels (Schuerman & Kobrin, 1986). Evidence also showed that changes in the housing market, specifically, the development of areas close to the city centre and subsequent gentrification, could alter the spatial patterning of offender residence concentrations (Bottoms & Wiles, 1986). This suggested that over time, the areas traditionally housing most known offenders, often around the city centre, might be pushed elsewhere. Gentrification was also shown to reduce crime rates through a developmental process of social organisation, although the evidence was presented as 'suggestive' rather than definitive (McDonald, 1986). Ideas ignited by the Chicago School regarding the inability of residents to enforce informal social control to deter delinquent behaviour also began to be expanded upon specifically for offences by Sampson (1986), which would later be developed for his paper on collective efficacy in Chicago neighbourhoods (Sampson, Raudenbush & Earls, 1997). As such, *Communities and Crime* represented a key contribution to proposing and testing theoretical expectations of criminality at the neighbourhood level, despite the lack of clarity over the distinction between offender residences and crimes.

Contribution

The argumentations made in *Communities and Crime*, and results reported, were non-trivial. Retrospectively, the 1986 volume can be said to have convinced the field that (1) neighbourhoods were a theoretically and empirically suitable spatial scale to study and explain offender residence and offence concentrations, (2) neighbourhoods were not stable as originally thought, but dynamic, demanding longitudinal examination, and (3) explanations for offender residence and offence concentrations manifested at the neighbourhood level, with social disorganisation and the housing market being a key determinant of the spatial patterning of offender residences. Around this time, explanations for offence concentrations at fine-grained spatial scales were also becoming more formalised, with discussions over the importance of opportunity incorporated into routine activities theory (Cohen & Felson, 1979). Thankfully, such developments occurred despite the likes of Schuerman and Kobrin (1986) reinforcing the assumption that offender residences and offence spatial patterns were empirically indistinguishable. In fact, a new field was about to emerge which specifically addressed the distinction between the two: the journey to crime.

2.7.4 Interlude: the journey to crime

The purpose of this chapter is to trace the two principal strands of enquiry in spatial criminology, namely, the geographic concentration of offences and offender residences, along themes of spatial scale, longitudinal stability and explanation. At this point, the focus is shifting away from offender residences to offence locations, largely as a result of the assumption that the spatial patterning of offender residences and offences were synonymous. In both offender and offence studies, *spatial scales* were increasingly being defined as 'neighbourhood' units nested within specific urban conurbations. Consistent with developments in individual-level life-course criminology, there was a growing acceptance that units of analysis should be studied *longitudinally* to capture the degree of stability over time. Social disorganisation remained a potentially key explanation for the persistency of high offender rate neighbourhoods over time, but in the UK, evidence was emerging suggesting that the housing market and gentrification were also key factors in determining the spatial patterning of known offenders. Opportunity theories like routine activities, and sociological theories like collective efficacy, were also beginning to make their mark in seeking to explain offence concentrations.

As such, following *Communities and Crime*, the gap between the two strands of research had opened, and the kind of lengthy, in-depth examinations of both offenders and offences, carried by Morris (1957) and Baldwin and Bottoms (1976), were less popular[4]. Nonetheless, 'journey to crime' literature was emerging, which focused on examining the relationship between where offenders resided and where their offences were committed. It is beyond the scope of this literature review to provide a complete overview of this field, but its contribution is worth noting: it provides further empirical and theoretical scrutinisation of the assumption that offender and offence distributions were indistinguishable, and supports assertions that each merit their own (albeit related) examination.

[4] An exception is Wikstrom's comprehensive account of offences and offender residences at the neighbourhood level in Stockholm, Sweden, which was published in 1991. This volume was very much in the spirit of the British scholars' work in Croydon and Sheffield, but again, lacked the longitudinal dimension, instead relying only on cross-sectional data.

Some of the research already discussed has touched on this topic in one way or another. For instance, Baldwin and Bottoms (1976) had found that offenders were willing to travel several miles to commit offences, although the distance travelled depended upon other parameters, such as age and whether offenders acted alone. Others had discussed the journey to crime theoretically, suggesting that the forces pulling offenders to reside in particular areas were very different from the forces attracting them to offend in others (El-Saaty, 1946; Morris, 1957). As part of a study in Stockholm, it would later be reported that the majority of offences were committed outside of the offender's resident neighbourhood (Wikstrom & Dolmen, 1990). And yet, the fact that some studies reported that offender residence and offence distributions were empirically similar often prevailed over theoretical reasoning and empirical findings. This can retrospectively be identified as a key reason behind many researchers abandoning interest in offender residence concentrations, or simply using it as a proxy for crime. To build on the claims of Morris (1957) and others, a formal theoretical conceptualisation and more robust evidence-base was needed. Even in circumstances where the two spatial distributions were comparable, evidence that offenders travelled outside of their own neighbourhood to commit crime would suggest that the similarity was largely an artefact of much more complex underlying mobility patterns, just as Morris (1957) and El-Saaty (1946) had claimed.

Although the evidence from 'journey to crime' literature is not straightforward, the message is clear: offenders do indeed travel outside of their local area to commit offences. Evidence has been reported to support the idea of a 'buffer zone' around where offenders live, to avoid the risk of recognition (Rossmo, 1999). This can be combined with the idea of a distance decay, whereby offenders try to minimise costs (including non-financial costs, such as exertion) by not travelling excessive distances from home (Rattner & Portnov, 2007). That said, there is still plenty of evidence to indicate that offenders prefer targets close by (e.g. Bernasco, 2010; Bernasco, Ruiter & Block, 2017), whilst still being willing to travel beyond their local area to commit crime (amongst others: Polisenska, 2008; Morselli & Royer, 2008; Rattner & Portnov, 2007), often incentivised by increased financial reward (Snook, 2004). In general, findings have tended to lean towards the idea of a buffer zone, whereby offenders are unwilling to commit their offences in the immediate vicinity of their home (Block, Galary & Brice, 2007). Some have found that distances from home to target can vary from around 3 to 5 miles depending on the crime type (Ackerman & Rossmo, 2015). The finding of a buffer zone does not render the two irrelevant to another, rather, it strongly suggests that offender residence concentrations can be a fundamental dimension when seeking to explain offence hotspots. It does, however, suggest that any evidence of similarity between the two potentially masks underlying offender mobility patterns. Moreover, aggregate correlations might be dictated by the grain of spatial scale used, which can vary considerably from study to study, as noted in Chapter 3.

The journey to crime was also conceptualised to extend the preliminary theoretical comments by the likes of Morris (1957). The theories that emerged served to formalise the idea that offenders search for suitable targets, rather than offending randomly or in the immediate vicinity of their home. Studies have demonstrated the worth of rational choice theory by examining the journey to crime of burglars, for instance, assuming that offenders seek out targets based on an appraisal of the costs and benefits of the options available (Langton & Steenbeek, 2017; Elffers, 2004; Vandeviver, Neutens, Van Daele, Geurts & Vander Beken, 2015). In their search, offenders are said to use a sequential, spatially structured thought process (Brantingham & Brantingham, 1978). That is, a suitable area within a city is first chosen, and then a specific target (e.g. residential home for burglary) is selected following an appraisal of the costs and benefits of the available options. Crime pattern theory tell us that these areas are most likely areas with which the offender is familiar ('knowledge spaces'), which makes searching less effortful, with targets tending to be near, or on the path to, their personal residence or common activity nodes, such as work or school (Brantingham & Brantingham, 1990). Routine activities theory is therefore highly relevant to the journey to crime, since, these nodes are defined by an offender's routine leisure or work activities, which determine the opportunities available to them, and the convergence with suitable targets. Local areas form part of individuals' routine activities, are within the knowledge space, and minimise the costs incurred. It is through these theoretical frameworks that researchers have tended to predict offence concentrations, and hypothesise that offence locations are geographically proximal, but distinct, to the offenders' residence location.

The emergence of the journey to crime literature provided a theoretical and empirical reason to distinguish between offender residences and offence concentrations in spatially orientated research. The mechanisms used to explain why offenders choose to commit crime in particular areas, drawing upon rational choice, routine activities and crime pattern theory, were distinct from those frameworks originally designed to explain why some areas housed a disproportionately large volume of known offenders, such as social disorganisation theory. Any existing evidence suggesting that the two distributions were synonymous was therefore likely to be masking more complex mobility patterns between the origin (offender residence) and destination (offence location), and be sensitive to the spatial scale chosen.

As we are about to see, the spatial criminal career field was about to gain significant momentum in examining the longitudinal stability of offences. Much of this work was inspired by Schuerman and Kobrin (1986), whose study was subject to the critiques noted above, and social disorganisation theory, despite its focus on where offenders live, not strictly where crimes occur. The journey to crime field was to thrive during the same era of these advancements, particularly after the methodological contributions of Bernasco and Nieuwbeerta (2005), but there was minimal return to the discussion. Research on offences was to make significant steps forward, and in doing so, would leave the examination of offender residences behind. This step forward has not been formally identified in existing literature, and thus is referred to here as the 'new wave'.

2.8 The post-2004 'new wave'

The impact of *Communities and Crime* (1986) is demonstrated in a 'new wave' of criminal career literature that emerged in 2004 following the two influential publications in *Criminology* briefly mentioned earlier (Griffiths & Chavez, 2004; Weisburd et al., 2004). These two studies, and those that followed, adopted some of the key components developed in the 1986 volume, but made further contributions along our three themes. Firstly, they furthered the use of fine-grained spatial scales, but also advocated the use of even smaller units termed 'micro-places', such as street segments. This revived some of the early observations of Henry Mayhew, but with all the advancements of modern-day data and computing. Secondly, studies in the new wave specifically sought to examine the longitudinal stability of offence concentrations over time. This was very much in the spirit of the Chicago School and subsequent work by Schuerman and Kobrin (1986), but by focusing exclusively on offences, this decision signalled a turning point away from examining offender residences, in favour of offence locations, in longitudinal research. Thirdly, explanations for the longitudinal stability observed became less theoretically-driven, as originally intended by Shaw and McKay, and more data-driven. As we shall see, usage of micro-place units of analysis had benefits, but theoretically-relevant independent variables were (and remain) rarely available at such fine-grained aggregations. For that reason, efforts by the new wave to explain what was being observed tended to be post-analysis, or atheoretical.

Each of these developments are addressed in this section, but first, specific attention will be paid to the two publications in *Criminology* which are identified as signalling the beginning of the new wave, both in terms of their theoretical and empirical contributions.

2.8.1 Griffiths and Chavez (2004)

Picking up where the contributors to *Communities and Crime* had left off, Griffiths and Chavez (2004) studied the longitudinal trajectories of violent crime rates in Chicago neighbourhoods. Whilst part of their contribution was methodological, discussed in the following chapter, a fundamental aim of the paper was theoretically orientated around explaining the extent to which neighbourhood-level crime trajectories were stable, and differed from the citywide trend. The degree of volatility within and between trajectories was used to adjudicate on the extent to which neighbourhoods remained stable over time. To explain what was observed, not only did the authors revisit the assumption of stability in social disorganisation theory, but they also drew upon the more contemporary routine activities theory. Both theories held explanatory power at the neighbourhood-level, and by running analysis at this spatial scale, there was continuity from the work carried out in *Communities and Crime*. In doing so, they sustained the focus on offences, rather than offender residences, adopting social disorganisation theory for use with the former.

In revisiting social disorganisation theory, Griffiths and Chavez (2004) further scrutinised the dynamic nature of communities, following the critique of stability by the likes of Bursik (1986) and Reiss (1986). The authors argued that social disorganisation could have reciprocal effects, whereby "crime undermines community participation and organisation, and communities without these controls are vulnerable to increased crime" (Griffiths & Chavez, 2004, p. 944). Theoretically, this was suggestive of a non-linear process whereby neighbourhoods might experience some degree of fluctuation, even amidst long-term declines. Griffiths and Chavez criticised research (i.e. Schuerman and Kobrin, 1986) which implicitly assumed gradual, unidirectional (i.e. increasing *or* stable *or* decreasing) and linear (i.e. sequential, consistent) change over time. Instead, neighbourhoods might experience "multiple and varied trajectories of community crime" due to the recursive effects of social disorganisation (2004, p. 944). Contrary to social disorganisation theory, the authors also argued that this change might occur rapidly. Evidence of short-term volatility would counter the claims made by some in *Communities and Crime*, whose developmental explanations were based on slowly changing structural variables like population density, in the spirit of social disorganisation theory.

To explain short-term volatility, Griffiths and Chavez (2004) drew upon opportunity theory, in the form of routine activities. Changes in routine activities over time were said to alter the convergence of suitable targets, motivated offenders and the absence of capable guardians, and in turn, dictate longitudinal crime trajectories (Cohen & Felson, 1979). Only one of these dimensions need shift for crime rates to increase and could occur amidst little to no change in wider demographic variables, and over short periods of time. For instance, if the structural conditions said to increase criminal propensity (e.g. residential mobility) remained stable, along with the number of suitable targets available (e.g. shops in a neighbourhood), a decline in capable guardians (e.g. police) would be enough for shoplifting rates to spike. The routine activities approach came about to explain the post-war increase in crime rates, which occurred during a widespread improvement in the structural conditions said to decrease criminal propensity. To Cohen and Felson, an alternative framework to social disorganisation theory was needed to explain these trends. Extensions of the routine activities approach added the 'facilitator' dimension (Clarke, 1995). Facilitators weaken the ability of guardians to protect targets (such as weapons, in this case) and can be become available quickly, explaining rapid fluctuations in crime rates. Griffiths and Chavez posited that variations of routine activities within neighbourhoods over time was an alternative explanation to the more gradual process of social disorganisation, which could only explain long-term trends. It raised the prospect that neighbourhoods were not just dynamic over many decades, but potentially subject to rapid change over just one or two years.

Findings were not explicitly in support of one theory or the other, but instead, there was evidence of both the stability expected from social disorganisation theory, and the volatility one might expect from routine activities theory. However, their conclusions was tentatively in favour of routine activities theory, since the volatile fluctuations in homicide rates during the study period could not be explained by the sluggish change in structural variables said to underpin the crime-generating processes of social disorganisation. Instead, the observed volatility provided evidence to support routine activities theory, which was more suitable for explaining short-term change. Specifically, in the case of violent crime, the rapid increase in street gun usage was found to be responsible for wider increases in homicide, lending support for the facilitator dimension of routine activities.

The paper made important contributions along three grounds. Firstly, it maintained and promoted the theoretical relevance of the neighbourhood, providing continuity from *Communities and Crime*. Secondly, the authors cemented the dynamic approach to studying geographic units of analysis by using longitudinal data on recorded crime. In doing so, the paper revived the developmental dimensions of the Chicago School, although at the same time, rejected the focus on offender residences. This had been done the year before, although less influentially (see Kubrin, 2003). Thirdly, the paper discussed the relevance of social disorganisation and routine activities theory simply by examining the stability of crime concentrations over time, without theoretically-relevant associative data (e.g. demographic characteristics). This approach would come to define the new wave literature.

2.8.2 Weisburd, Bushway, Lum & Yang (2004)

In the same year, David Weisburd and his colleagues published a comparable paper in *Criminology* examining longitudinal crime concentrations in Seattle. There were fundamental similarities between this paper and that of Griffiths and Chavez (2004). It too discussed the relevance of social disorganisation and routine activity theories in explaining the longitudinal stability of offences, and in doing so, continued the suspension of longitudinal offender residence-based research. The paper also claimed to offer a reasonable test of expectations derived from social disorganisation and routine activities theory simply by modelling the stability of crime concentrations over time, without the use of theoretically-relevant independent variables.

There were also key differences. Firstly, Weisburd and his colleagues shifted focus to a more fine-grained unit of analysis: the street segment. A convincing case was made for the suitability of this unit of analysis, both empirically and theoretically, which became a defining feature of the new wave to follow. Secondly, rather than finding competing theoretical explanations for longitudinal volatility in crime concentrations, Weisburd *et al* (2004) argued that routine activities theory could compliment the expectation of long-term stability made by social disorganisation theory.

The shift from the neighbourhood to more fine-grained spatial units was a move that had been stirring for some time. Empirically, Sherman and his colleagues (1989) had found that only 3% of addresses were responsible for 50% of calls for police service in Minneapolis. Since then, similar findings had been replicated elsewhere using street segments in the United States (e.g. Weisburd & Mazerolle, 2000; Weisburd, 2015). Street segments were defined as "two block faces on both sides of a street between two intersections" (Weisburd et al., 2004, p. 290). The idea was that large spatial scales such as neighbourhoods could mask underlying variation between micro-places like addresses or street segments. A high crime neighbourhood might simply be an artefact of one 'hot' micro-place, rather than the entire area.

Whilst this problem is largely methodological, and discussed as such in the next chapter, Weisburd and his colleagues also drew upon the theoretical relevance of the street segment as a meaningful unit of analysis. Crime-deterring mechanisms like informal social control were argued to manifest at street segments, with residents having homogeneous social norms and recognising the physical boundaries of the street (Taylor, 1997). This countered the claims made in *Communities and Crime* that mechanisms like social disorganisation manifested at the neighbourhood-level. The relevance of routine activities to micro-places had already been demonstrated (e.g. Eck & Weisburd, 1995; Smith, Frazee & Davison, 2000), so Weisburd and his colleagues had a robust argumentation for using street segments as an empirically and theoretically useful unit of analysis to study the longitudinal stability of crime. As we shall see, this argument was widely accepted and highly influential. It encouraged a host of fresh research into the developmental trends of micro-places, outstripping existing research into neighbourhoods.

Interestingly, whilst Griffiths and Chavez (2004) had found evidence of volatility in violent crime trajectories to counter the assumptions of social disorganisation and provide some support for routine activities theory, Weisburd's study concluded that street segments were largely stable over time. The finding itself is noteworthy, but it was the authors' theoretical explanation for this stability that proved particularly important. In agreement with Griffiths and Chavez (2004), the authors noted that long-term stability was consistent with social disorganisation theory, but it was also argued that this finding was consistent with routine activities. This appeared to conflict with the reasoning of Griffiths and Chavez (2004) who used the framework to explain rapid fluctuations in violent crime trajectories, and even conflicted with the original purpose of routine activities as a way of explaining longitudinal changes in crime rates (as per Cohen & Felson, 1979). The authors justified this conflict by arguing that the patterns dictating the convergence of motivated offenders, suitable targets and capable guardians were only subject to change if (1) acted upon by 'unnatural' conditions such as hotspot policing (e.g. Sherman & Weisburd, 1995), or (2) considered over a lengthy period i.e. many decades. One might view the sudden availability of handguns, as a facilitator of violent crime, as an 'unnatural' condition in Griffiths and Chavez's study. This would settle the apparent conflict in theoretical explanations and highlighted the importance of context. Nevertheless, their assertion that findings of stability supported routine activities theory would become influential and widely adopted, which became apparent as the 'new wave' took hold.

2.8.3 Contribution of the 2004 Criminology papers

The principal contributions of these two papers was fourfold. Firstly, both studies formalised research questions surrounding the longitudinal stability of geographic areas. The extent of instability became defined as the degree to which the crime trajectories of local spatial units (e.g. neighbourhoods, street segments) differed from the citywide trend. By disentangling these trajectories and assessing how fluctuations differed over time, definitive statements could be made about the longitudinal stability of crime concentrations. Secondly, and relatedly, both papers revived social disorganisation theory, and adopted routine activities theory, as frameworks for explaining the relative (in)stability of highly localised crime concentrations over time. As we have seen, discussions on whether the degree of volatility (short or long-term) supported the various theoretical frameworks was conducted *following* analysis, devoid of independent variables. Thirdly, in reviving interest in longitudinal stability within spatial criminology, along with social disorganisaton theory, these studies continued what *Communities and Crime* had started: focusing on offences instead of offender residences. Fourthly, the theoretical and empirical relevance of micro-place (street segment) units was demonstrated, building on earlier work by the likes of Sherman *et al* (1989). The following section will demonstrate how these contributions had a significant impact on the work that followed, which is labelled here as the 'new wave' of criminal career research. This will bring us to the present day.

2.9 The 'new wave' begins

The impact of the *Criminology* papers in 2004 was not immediate. In the two years that followed, aside from some drawing methodological inspiration (e.g. LaFree, Morris, Dugan & Fahey, 2006) the only evidence of comparable research being undertaken was by Elizabeth Groff in her master's dissertation (2005) under the supervision of David Weisburd. It would be several years before this work would gain momentum and be published (see Groff, Weisburd & Morris, 2009). Since then, 23 research outputs have been identified as having deployed a criminal career framework to examine crime concentrations (or related phenomena, such as calls-for-service), either at the neighbourhood or street segment level, in the spirit of the *Criminology* papers. These publications constitute what is termed here as the 'new wave' of developmental research, and are summarised in Table 2.1. Specifically, the studies were chosen because they adopt methodologies aimed at disentangling local variance in citywide crime trends, in the spirit of existing research examining longitudinal stability within a criminal career framework. The methodologies deployed are detailed in the next chapter. Given the commonalities existing between each paper, rather than being considered chronologically, this section will consider the 'new wave' under our three respective themes: spatial scale, longitudinal stability and explanatory frameworks. First, though, some consideration is given to the context of new wave studies, in terms of the geographic study areas and time periods examined. All studies referenced in this section are summarised in Table 2.1.

2.9.1 Study regions and time periods

One of the most salient observations from Table 2.1 is the overwhelming proportion of geographic study areas in North America. It is not unusual for the geographic study area in criminological research to be driven almost entirely by the data sources available. In fact, the city of Seattle was initially chosen due to the extensive data recorded in computerised format by the Seattle Police Department (Weisburd et al., 2004). As Table 2.1 demonstrates, Seattle became the primary source of data for many subsequent studies in the new wave. One of the key comparisons to Seattle, Vancouver, was selected due to its geographic proximity, similar climate, demographics and size, but also because the longitudinal data available was comparable to Seattle (Curman, Andresen & Brantingham, 2015). Others were chosen due to their dissimilarity to previous study areas, such as the case of Albany, New York (Wheeler, Worden & McLean, 2015), or because the city had not received much attention in previous research (Kikuchi & Desmond, 2010). Others offer no reasoning for their choice (Payne & Gallagher, 2016).

A number of studies make specific justification for the city under examination, which often goes hand-in-hand with the time period. For instance, during the 1980s and 1990s the city of Chicago experienced stark changes in its homicide rate, thought to be largely due to the emergence of crack cocaine markets and the escalating usage of handguns (Griffiths & Chavez, 2004). Given that this experience was true for many cities in the United States, a similar justification is made for examining gun violence in Boston (Braga, Papachristos & Hureau, 2010). Many studies also took place in the era of the crime drop (see Aebi & Linde, 2010). The specific aim is then to disentangle local variance in the drop, identifying specific areas which have contributed disproportionately to the citywide fall in crime, or 'bucked the trend' and actually experienced an increase (e.g. Bannister, Bates & Kearns, 2017).

More generally, the focus of the 'new wave' is clear: urban areas in North America. Of course, this is an inevitable consequence of academic interest being concentrated in the United States. An unwanted by-product of this is that our understanding of the generalisability of findings is limited in scope. Urban areas in the United States were characterised by specific problems with gun crime and drug usage during many of the study periods. The convergence of these issues, whilst prevalent in many North American cities, is unique to time and space. The mechanisms by which results can be explained, and effective policy recommendations made, is likely to be dependent on the context of the geographic study area, or at least, the country in which the study area is nested. This narrow focus is encapsulated in a recent comparative study on the longitudinal concentration of crime in eight different cities, only one of which, Tel Aviv, was outside North America (see Weisburd, 2015). Despite the impressive range of cities in this comparison, the author still draws attention to the importance of generalisability, and calls for further research to carry out similar examinations in other urban areas (see also Andresen, Linning & Malleson, 2017).

2.9.2 Spatial scale

The majority of 'new wave' studies have adopted a micro-level spatial scale as their geographic unit of analysis. In the spirit of Weisburd *et al* (2004), the use of micro-level spatial scales in spatially-orientated developmental research has centred around the street segment (Groff, Weisburd & Yang, 2010; Weisburd, Morris & Groff, 2009; Groff et al., 2009; Weisburd, Groff & Yang, 2014; Curman et al., 2015; Hibdon, Telep & Groff, 2017; Andresen, Curman & Linning, 2017; Gill, Wooditch & Weisburd, 2017). As outlined earlier, this was justified on theoretical and empirical grounds. Firstly, the street segment was hypothesised to unmask variation that would otherwise be hidden using larger units such as neighbourhoods. Secondly, street segments were considered to be a valid 'behavioural setting' where social mechanisms like informal social control would manifest, making it relevant for studying the affects of social disorganisation (e.g. Favarin, 2018). The new wave also featured 'street units' which were the sum of both street segments and street intersections (Braga, Hureau & Papachristos, 2011; Braga et al., 2010) and even individual properties (Payne & Gallagher, 2016). Having said that, the spirit of neighbourhood-level research from the Chicago School, Morris (1957), Baldwin and Bottoms (1976), *Communities and Crime* (1986) and Griffiths & Chavez (2004) did continue. In the UK, small neighbourhood units were deployed for a study in Glasgow (Bannister et al., 2017). This was largely because the idea of the 'street segment' in the British urban setting would not be convincing. As discussed in the next chapter, British cities are largely devoid of grid street networks, but instead have small administrative units which can be considered approximations of 'micro' neighbourhoods. Studies in North America also continued to use neighbourhood units, justified on theoretical grounds relating to social disorganisation or related informal social control mechanisms that were considered to manifest at the community-level (Stults, 2010; Kikuchi & Desmond, 2010; Yang, 2010). Although the new wave was dominated by micro-place research, the debate between the use of street segments and neighbourhoods was certainly not over, especially when considering international replication.

2.9.3 Longitudinal stability

The most substantial contribution of the new wave was to advance understanding into the longitudinal stability of offence concentrations. Firstly, most studies found evidence to support the idea of stability in crime concentrations over time, even amidst citywide fluctuations in overall levels. This was very much in the spirit of the claims of stability made by Shaw and McKay (1942/1972), even if the focus had now shifted from offenders to offences. The new wave found that, irrespective of whether an urban area was characterised by a decade-long crime decrease, increase or cyclical combinations of increases and decreases, the outright concentrations would remain static. This finding in new wave studies would become the primary evidence-base in support of the so-called 'law of crime concentration' (Weisburd, 2015), which is continuing to gather evidence to this day (Braga, Andresen & Lawton, 2017). The law states that "for a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime" (Weisburd, 2015, p. 138). The evidence-base is largely based on descriptive statements. For instance, during a citywide decline in calls for police service in Vancouver, Curman *et al* (2015) found that 60% of all calls occurred in only 8% of street segments, and that 40% of street segments were completely free of calls during the time period. Weisburd *et al* (2009) reported that all incidents of juvenile arrests in Seattle between 1989 and 2002 occurred in just 3-5% of street segments. Comparable statements have been made about the study areas in North America outlined in Table 2.1, as well as Tel Aviv-Yafo in Israel (see Weisburd & Amram, 2014) in support of the law of crime concentration.

Table 2.1: New wave criminal career literature review summary

Author(s)	Year	Unit of analysis	Location	Timeframe	Variable	Theoretical framework	Key findings
Weisburd, Bushway, Lum & Yang	2004	Street segment	Seattle, Washington, United States	14 years (1989-2002)	Total incident reports	Social disorganisation, routine activities	High stability of criminality in micro-places over time; evidence for trajectory group clustering.
Griffiths & Chavez	2004	Neighbourhood	Chicago, Illinois, United States	16 years (1980-1995)	Incidences of homicide by weapon type (street gun and other weapon)	Social disorganisation, routine activities	Slow, long-term stability but also short-term fluctuations; evidence of trajectory group clustering; concentric zones of homicide
Groff (masters dissertation)	2005	Street segment	Seattle, Washington, United States	14 years (1989-2002)	Total incident reports involving juvenile arrest	Routine activities	Evidence of group spatial clustering; varied evidence of spatial dependence between trajectory groups.

Table 2.1: New wave criminal career literature review summary *(continued)*

Author(s)	Year	Unit of analysis	Location	Timeframe	Variable	Theoretical framework	Key findings
Weisburd, Morris & Groff	2009	Street segment	Seattle, Washington, United States	14 years (1989-2002)	Total incident reports involving juvenile arrest	Routine activities	Group trends temporally stable; some evidence of spatial clustering; some trajectories buck the city-wide trend.
Groff, Weisburd & Morris	2009	Street segment	Seattle, Washington, United States	14 years (1989-2002)	Total incident reports involving juvenile arrest	Opportunity	Findings largely consistent with stability, mixed evidence of spatial clustering.
Chavez & Griffiths	2009	N'hood	Chicago, Illinois, United States	14 years (1980-1995)	Incidences of homicide	Social disorganisation	Most neighbourhoods free of homicide, stability in low-rate areas, volatility in high-rate.

Table 2.1: New wave criminal career literature review summary *(continued)*

Author(s)	Year	Unit of analysis	Location	Timeframe	Variable	Theoretical framework	Key findings
Groff, Weisburd & Yang	2010	Street segment	Seattle, Washington, United States	16 years (1989-2004)	Total incident reports	Routine activities, crime pattern	Most street segments crime free or stable, variable strength of spatial clustering between trajectory groups.
Braga, Papachristos & Hureau	2010	Street unit	Boston, Massachusetts, United States	29 years (1980-2008)	Firearm incident reports	None	Highly violent street units are most volatile over time, and tend to cluster around main thoroughfares.
Stults	2010	N'hood	Chicago, Illinois, United States	31 years (1965-1995)	Homicide	Social disorganisation	Some evidence for widespread stability, but structural characteristics can predict trajectory group membership.

Table 2.1: New wave criminal career literature review summary *(continued)*

Author(s)	Year	Unit of analysis	Location	Timeframe	Variable	Theoretical framework	Key findings
Kikuchi & Desmond	2010	N'hood	Indianapolis, Indiana, United States	15 years (1992-2006)	Residential burglary and vehicle theft	Social disorganisation	Evidence of change over time, deviations from citywide trend; neighbourhood characteristics associated with changes.
Yang	2010	N'hood	Seattle, Washington, United States	16 years (1989-2004)	Incidents of violence, physical and social disorder	Broken windows, social control	Longitudinal correlation between disorder and violence, but the relationship is not symmetric; similar trajectories geographically cluster.

Table 2.1: New wave criminal career literature review summary *(continued)*

Author(s)	Year	Unit of analysis	Location	Timeframe	Variable	Theoretical framework	Key findings
Braga, Hureau & Papachristos	2011	Street unit	Boston, Massachusetts, United States	29 years (1980-2008)	Robbery incident reports	Opportunity	Street units are temporally stable; high activity units appear spatially clustered; small number of micro-places responsible for citywide decline.
Weisburd, Groff & Yang	2014	Street segment	Seattle, Washington, United States	16 years (1989-2004)	Total incident reports	Social disorganisation, opportunity	Street segments largely stable, but situational opportunities and risk factors can predict group membership.

Table 2.1: New wave criminal career literature review summary *(continued)*

Author(s)	Year	Unit of analysis	Location	Timeframe	Variable	Theoretical framework	Key findings
Bates (PhD dissertation)	2014	N'hood	Glasgow, United Kingdom	6 years (2004-2010)	Vandalism incidents	Social disorganisation, routine activities, collective efficacy	Some evidence of stability; small number of neighbourhoods contribute to crime drop.
Curman, Andresen & Brantingham	2015	Street segment	Vancouver, British Columbia, Canada	16 years (1991-2006)	Total property and violence calls-for-service	None	Stable criminal trajectories over time; small places responsible for drop; mixed clustering of like-for-like trajectories.
Wheeler, Worden & McLean	2016	Street units	Albany, New York, United States	14 years (2000-2013)	Total reported crimes	None	Group trajectories mimic city-wide trends; evidence for high-crime group clustering.

Table 2.1: New wave criminal career literature review summary *(continued)*

Author(s)	Year	Unit of analysis	Location	Timeframe	Variable	Theoretical framework	Key findings
Payne & Gallagher	2016	Property	Cincinnati, Ohio, United States	15 years (1998-2012)	Disorder, property and violent crime incident reports	None	Properties with varying trajectories co-exist spatially; largely stable trends.
Grossman (PhD dissertation)	2016	Street segment	Newark, New Jersey, United States	6 years (2008-2013)	Total street violence incidents (murder, aggravated, robbery)	Routine activities, opportunity	Highly violent street segments stable over time; crime opportunity measures can predict group membership.
Bannister, Bates & Kearns	2017	N'hood	Glasgow, United Kingdom	14 years (1998-2012)	Total recorded crime	Social disorganisation, opportunity	Stable trajectories, widening inequities in the drop, spatial clustering of high crime around centre.

Table 2.1: New wave criminal career literature review summary *(continued)*

Author(s)	Year	Unit of analysis	Location	Timeframe	Variable	Theoretical framework	Key findings
Hibdon, Telep & Groff	2017	Street segment	Seattle, Washington, United States	5 years (2009-2014)	Drug activity calls for service, drug-related emergency medical services calls	None	Overall stability, most streets free of calls, with a small number of streets driving citywide trends.
Andresen, Curman & Linning	2017	Street segment	Vancouver, British Columbia, Canada	16 years (1991-2006)	Calls for service by assault, burglary, theft from vehicle, theft of vehicle, theft, other	Routine activities	Total crime stability, small number of streets responsible for drops, results broadly similar across crime types, although differences exist.

Table 2.1: New wave criminal career literature review summary *(continued)*

Author(s)	Year	Unit of analysis	Location	Timeframe	Variable	Theoretical framework	Key findings
Gill, Wooditch & Weisburd	2017	Street segments	Brooklyn Park, Minnesota, United States	15 years (2000-2014)	Recorded crime incidents	Routine activities, social disorganisation	High stability, small number of places dictate the citywide crime drop, high degree of hotspot clustering.
Favarin	2018	Street segments	Milan, Italy	7 years (2007-2013)	Robbery and burglary incidents	Social disorganisation, opportunity	Some evidence of stability, but also volatility, evidence to support social disorganisation and opportunity theories.
Adpejeu, Langton & Bannister	Under review	N'hood	Birmingham, United Kingdom	15 years (2001-2016)	Recorded property crime incidents	Social disorganisation	Evidence of long-term stability in crime concentrations consistent with theoretical expectations.

At the same time, the new wave offered further demonstration of the benefit of disentangling local variance in citywide trends, continuing what the *Criminology* papers in 2004 had begun. Statements in support of the law of crime concentration were interesting, but said little about localised stability. Street segments and neighbourhoods might be experiencing volatile crime trajectories even if overall concentration was stable. Methods used to simplify longitudinal data through cluster analysis, outlined in the next chapter, served to disentangle these local trajectories, and uncover non-uniformity in local trajectories compared to the citywide trend. Findings largely supported the idea that citywide crime trends were driven by a small number of local areas, with most remaining stable over time. In cities with a fall in recorded crime during the study period, a handful of micro-places (e.g. Weisburd et al., 2004; Andresen et al., 2017) or neighbourhoods (e.g. Bannister et al., 2017) were disproportionately responsible for the decrease. Other areas remained stable or declined in unison with the citywide trend.

More contemporary studies in the new wave also offered a less academic and more policy-orientated reason to examine longitudinal stability. Evidence that there has been spatial inequalities in the recorded crime drop would cast doubt on police legitimacy and the ability of law enforcement to effectively and equitably maintain order (Adepeju et al., *under review*). The ability to identify areas which are contributing disproportionately to long-term crime trends in a city would also assist in the effective targeting of highly problematic areas, and help efficiently reduce citywide crime levels. Such an approach helps provide a bridge between the historically theoretical interest in longitudinal stability, and more contemporary challenges being faced by police forces amidst rising public expectation and funding cuts.

The evidence-base generated and contributions made from these studies had important implications. Firstly, it generated substantial support for the finding of stability, which researchers tended to suggest was supportive of social disorganisation and routine activities theory. This signalled a dramatic revival of Shaw and McKay's interest in the dynamic nature of geographic areas, acting on calls by the likes of Reiss (1986) in *Communities and Crime*, even though now, the variable of interest had shifted from offender residences to offences. Secondly, it raised questions around the more traditional explanations for the crime drop, which tended to manifest at the nation-state level (e.g. target hardening, rising well-being, falling unemployment). If such macro-level conditions were deterring or inhibiting crime, it was not doing so equally across urban areas. In other words, whilst many neighbourhoods and street segments were benefitting from the crime drop, some areas were befitting more than others. In making this demonstration, studies in the new wave were also able to make their endevours more practically useful for police forces and governments by speaking to arguments of equality and efficiency.

2.9.4 Explanatory frameworks

As noted, the contributions of the *Criminology* papers in 2004 implied that both social disorganisation, and more contemporary frameworks such as routine activities theory, could explain longitudinal trends in crime concentration at neighbourhood and street segment-level. However, the overwhelming use of the street segment as the unit of analysis limited researchers' ability to provide evidence to empirically test hypotheses derived from theory. In some cases, new wave papers offered no theoretical framework whatsoever, relying entirely on substantive, inductive attempts to disentangle local variation in citywide trends (e.g. Hibdon et al., 2017). Some only used theory to justify their unit of analysis, with no comment on its relevance to findings of longitudinal stability or explanation (Groff et al., 2009). Most garnered evidence in support of theories following exploratory univariate cluster analysis conducted on the dependent variable (e.g. crime counts), rather than using independent variables to explain variation. Thus, explanations have primarily been limited to speculative discussion on how social disorganisation, or opportunity theories like routine activities, could explain the observed stability in crime concentrations. Sometimes this discussion was limited to one or two sentences (e.g. Braga et al., 2011). In general, studies found evidence to support the notion of stability in crime concentrations, even amidst citywide fluctuations in crime. Evidence of stability was tentatively used to support social disorganisation theory, but also opportunity theories, just as Weisburd *et al* (2004) had argued.

A handful of studies managed to offer explanatory models at the street segment level (Weisburd et al., 2014; Favarin, 2018) and neighbourhood-level (Bannister et al., 2017; Stults, 2010; Kikuchi & Desmond, 2010), whilst still incorporating the longitudinal dimension. These tended to find reasonable evidence to support the explanatory power of routine activities and social disorganisation theory. This cemented the idea that social disorganisation had become a theory which straddles both offender residences and offences: originally developed to explain the former, it had been adopted as a means to explain the latter in conjunction with routine activities. Why both theories were required, and often tested simultaneously (see Weisburd et al., 2014) has never been overtly justified. The new wave continues to lack studies which model and explain the longitudinal (in)stability of offender residences, as was originally intended. Despite having its roots in the Chicago School, and their interest in delinquency areas (i.e. where offenders lived), the new wave has diverted its attention almost exclusively towards offences.

In this manner, the new wave made two somewhat contradicting contributions to explanatory frameworks. Firstly, it cemented the role of social disorganisation and opportunity theories (predominantly routine activities) in spatially orientated criminal career research. Social disorganisation had been there since the Chicago School as the key explanation for the longitudinal stability observed in offender residence concentrations. Routine activities theory had emerged much later (Cohen & Felson, 1979) and was used to explain both longitudinal fluctuations (e.g. Griffiths & Chavez, 2004) and stability (e.g. Weisburd et al., 2004) in crime. As the new wave developed, most authors began adopting the Weisburd *et al* (2004) usage of routine activities, arguing that the patterns dictating the convergence of motivated offenders, suitable targets and capable guardians were stable, and as such, findings of stability in crime concentrations were consistent with the theory. This first contribution was therefore theoretical, whereby univariate inductive analyses generated results which were used to provide evidence to support or reject expectations of stability.

Nonetheless, this process was also harmful, which brings us to our second explanatory contribution of the new wave. Focus began shifting from independent variables (as derived from theory) to the dependent variable (by now, largely police recorded offence incidents). The explanatory power was left almost entirely in the hands of exploratory analysis, which disentangled local variation in citywide crime trends, to permit a judgement on the stability of crime concentrations over time. Once results were generated, a brief comment was made on whether the findings supported the theory. The usage of the street segment as the unit of analysis can be held largely responsible for this move: explanatory data is rarely available at such fine-grained spatial scales. There are only a handful of exceptions (Weisburd et al., 2014; Faravin, 2018). Explanatory models were largely left to neighbourhood-level research, which only make up a small proportion of the new wave. The by-product of the field's focus on micro-level exploratory research was that the field became largely devoid of attempts to directly test theoretically-derived hypotheses.

2.9.5 The new wave: contributions

The overall contributions of the new wave that followed the two key publications in *Criminology* (Weisburd et al., 2004; Griffiths & Chavez, 2004) are threefold, and follow the dimensions of our primary themes. Firstly, a concerted effort was made to use increasingly fine-grained *spatial scales* as the geographic unit of analysis. These included the street segment, along with a continuation of small neighbourhood units[5]. Secondly, the *longitudinal stability* of crime concentrations over time, inspired by the Chicago School, was cemented as a major theme in spatial criminology. Thirdly, the theoretical focus shifted from the *explanatory* power of independent variables to what was being observed in the dependent variable. Evidence for theory was garnered based on findings from univariate analysis which measured the degree of stability in crime concentrations over time. This shift can largely be attributed to the usage of street segments as the unit of analysis, since associative data is rarely available at this spatial scale.

In making these contributions, though, interest in 'delinquency areas' (where offenders lived) was neglected. The momentum behind the new wave was significant, and studies mostly used some measure of police recorded crime, or related variable such as emergency calls-for-service. With the usage of increasingly fine-grained spatial scales, and findings from the journey to crime literature, the idea that the spatial patterning of offender residences and offences could be empirically synonymous was ever-more invalid. It was clear that scholarly interest had simply shifted, perhaps largely due to the availability of police recorded crime data, and collaborations with police forces, who had a key interest in tackling crime hotspots. As such, the new wave cannot claim to have truly revived interest in the longitudinal stability of delinquency areas, but rather, simply drew inspiration from Shaw and McKay's dynamic approach to studying criminality in urban areas.

[5] As we shall see in the next chapter, a handful of studies deployed statistical methods to empirically demonstrate the variation unmasked when using fine-grained spatial scales. However, these studies have only occurred since 2016. By that point, the new wave had already gathered momentum in the usage of micro-places.

2.9.6 Keeping offenders afloat

Whilst endevours to examine the spatial patterning of offender residences were being neglected in many parts of criminology, some were attempting to keep interest afloat during this period. The issue was that there was little concerted effort to carry out applied research using fine-grained spatial units of analysis, and compared to the offence strand, there was little development along the three key themes identified. Anthony Bottoms, one of the key authors of the 1976 Sheffield study, continued to promote the importance of offender residences in spatial criminology with specific reference to the theoretical and empirical distinction to offences (e.g. Bottoms, 2007; 2012; 2018). In some his most recent work, Bottoms argues that highly influential crime studies (identified in this chapter as 'new wave' studies) such as those conducted by Weisburd and his colleagues (2012), "would be enriched by considering the offender rates of the street segment itself, and of neighbouring street segments" (Bottoms, 2017, p. 10). However, in making this argument, Bottoms can only draw upon his original data in Sheffield by means of a demonstration. As we shall see in the next chapter, attempts continued to try and explain offender residence rates, but not in the same spirit as the influential new wave, with studies largely still relying on cross-sectional data.

There remain some specific dimensions of criminology which examined offender residence locations, but not in the same manner as the new wave literature which was pushing the boundaries of crime concentration research. David Kirk published a handful of studies examining residential concentrations of formerly incarcerated prisoners in the United States (see Kirk, 2015; Kirk, 2019). He found, for example, that individuals released from prison tended to be moving further away from the city centre, potentially being driven by the suburbanisation of poverty noted by Kneebone and Garr (2010). Hipp and colleagues (2010) found that sex offenders tended to move to economically deprived and residentially unstable neighbourhoods[6]. Nick Flynn (2012) has written extensively on phenomena such as the 'revolving door' whereby prisoners tend to return to the same or similar areas, characterised by deprivation, upon release. Former prisoners returning to their resident neighbourhoods after

[6] A subfield of spatial criminology not discussed in detail here is the examination of the geographic distribution of convicted sex offender residences. This research is not covered in detail because it is often set against policies relating to housing restrictions following conviction (for a recent review, see Savage & Windsor, 2018), and therefore has specific aims and context, rather than the broader aims of this thesis.

release are said to be more likely to re-offend (Kirk, 2009). Flynn's work also included interviews with the formerly incarcerated, which included discussions on the difficulties of obtaining housing upon leaving prison, and the pull of their home neighbourhoods, even when seeking out a new life. Although Flynn's work touched on the explanations provided through social disorganisation theory and the Chicago School, it did not make the kind of advancements which were complimentary to those made during the new wave of research in spatial criminology, by the likes of David Weisburd, such as those relating to spatial scale and longitudinal stability. So much so that, even in Anthony Bottoms' latest review of literature (2018), he does not mention the work of Kirk or Flynn[7]. However, the findings of these studies are still relevant, and prove significant when discussing the results from this thesis.

2.9.7 Research questions

Whilst the new wave made significant contributions to the field, especially when framed against the policy implications of police legitimacy and equality, the neglect of *offender residences* left questions unanswered. Firstly, a thorough examination into spatial scale had not yet been offered. The use of street segments demonstrated the benefits of using ever-more fine-grained units of analysis to unmask variation in crime concentrations that would otherwise be hidden. Following Shaw and McKay (1942/1972), and studies by Morris (1957), Baldwin and Bottoms (1976) and *Communities and Crime* (e.g. Reiss, 1986; Bottoms & Wiles, 1986), the neighbourhood appeared to be the most theoretically meaningful, especially when considering social disorganisation theory, and using study areas outside of North America (e.g. Bannister et al., 2017). But how would one define a 'neighbourhood'? Would it be consistent with the contemporary usage of the street segment? This brings us to our first research question:

- RQ1: What is the most appropriate spatial scale to study offender residential concentrations?

Secondly, the new wave failed to comprehensively examine the longitudinal stability of offender residences, instead focusing their efforts on offences, and as such, the field currently lacks a contemporary examination of the persistency of delinquency areas

[7]That said, Kirk's most recent work examining offender residence locations with respect to the suburbanisation of poverty was published in 2019, after Anthony Bottoms' latest review in The Oxford Handbook of Environmental Criminology (2018).

over time, despite the journey to crime literature demonstrating how important this might be in determining long-term crime trends. With this in mind, we can propose:

- RQ2: To what extent do offender residential concentrations demonstrate stability over time?

Thirdly, as an inevitable consequence of the lack of investigation into the longitudinal stability of offender residences, the field has lacked as examination into how the *persistency* of delinquency areas over time can be explained using frameworks like social disorganisation theory, and key variables relating to housing and deprivation. This informs our final research question:

- RQ3: How can we explain the longitudinal (in)stability of offender residential concentrations?

Amidst this, there also remains some degree of ambiguity about the spatial relationship between offender residences and offence locations over time, and importantly, how this relationship varies by spatial scale. An examination of this is certainly warranted. Whilst not posed formally as a research question, in order to maintain focus on the above three themes, this thesis will also offer a empirical demonstration of the distinctions between offender residences and offences over time, and the impact of spatial scale on this relationship.

2.10 Conclusion

This chapter has traced the development of research examining the spatial patterning of offender residences and offence locations, from the 19th Century to present day, along three dimensions: spatial scale, longitudinal stability and explanation. Whilst significant advance has been made along these lines, the offender residence strand of research has long since been neglected in favour of research examining offences. Whilst we now have a modest understanding about the benefits of examining offence concentrations at fine-grained *spatial scales*, such as street segments, little is known about the merits of such an approach when examining offender residences. Although important early works in the field focused on the *longitudinal stability* of offender residence concentrations, contemporary research has only made significant advance in examining the longitudinal stability of offence concentrations, in a body of literature termed here as the 'new wave'. As a consequence, contemporary research has failed to investigate *explanations* for the longitudinal (in)stability in the spatial patterning of offender residences. Despite calls for a revival of research into offender residence locations in spatial criminology, in order to compliment our understanding of crime concentrations, no concerted attempts have been made to reconcile the two fields. An exception is the journey to crime literature, which has tended to find that there is a close (but distinguishable) relationship between where offenders live and where crimes occur.

To achieve the aim of this thesis, namely, to advance understanding into the geographic distribution of offender residences, three research questions were posed. The first asks what the most suitable spatial scale is to examine offender residence concentrations. The second questions the extent to which there is longitudinal stability in offender residence concentrations. The third asks how the (in)stability observed can be explained. Amidst this, an effort will be made to examine the degree to which the spatial patterning of offender residences and offences is empirically distinct, and the extent to which this relationship is dictated by the choice of spatial scale. It is proposed that, by bringing the offender residence strand of research back up to speed along these themes, the field can begin reconciling the two strands of research, complimenting existing knowledge and advancing our understanding of the crime problem.

Chapter 3

Considerations of data and method

3.1 Introduction

So far, we have traced a historical narrative of spatial criminology from the 19th Century pioneers to the present day. Focus has been placed on the two primary strands of research in the field, which explore *where offenders reside* and *where offences occur*. It has been demonstrated that, despite the origins of the field examining the spatial patterning of both offender residences and offences, with a focus on the former, contemporary research has tended to focus solely on the latter. This has occurred despite there being strong theoretical and empirical reasons for examining both offender residences and offence locations, largely supported by the distinct theoretical frameworks for each, and findings from the journey to crime literature. In tracing this narrative, three key themes were identified.

Firstly, there is spatial scale. This refers to the geographic unit of analysis at which phenomena are examined. As we have seen, spatial scales have tended to get increasingly more fine-grained over time, from the macro-level region-wide districts of the 19th Century to the micro-scale street segments of many current studies. Recent research has made a concerted effort to demonstrate the theoretical and methodological relevance of these units using longitudinal data in a body of literature which is termed here as the 'new wave'. However, no such endeavour has been made for offender residence concentrations.

Secondly, the field has been characterised by a debate over the longitudinal stability of offender residence and offence concentrations over time. This line of inquiry has its origins in the Chicago School, who found evidence to suggest that the spatial patterning of offender residences was fairly stable over time. However, subsequent research found evidence of developmental processes and volatility, which fuelled a renewed focus on the topic in the 1980s. In doing so, however, interest shifted from offender residences to offence concentrations. As the new wave gained momentum post-2004, endeavours to examine the longitudinal concentration of offender residences have faded. As such, little is known about the longitudinal stability of offender residence concentrations, particularly at fine-grained spatial scales.

Thirdly, there has always been some attempt at explaining the phenomena being observed, largely through theoretical frameworks. The Chicago School's finding of stability in offender concentrations spurred the development of social disorganisation theory, which was said to manifest at the neighbourhood-level and explain the persistence of offender residence concentrations over time. However, subsequent (more recent) research has adopted the theory to explain longitudinal offence patterns, arguing that the causal mechanism is not only relevant for crime, but can also manifest at micro-spatial scales, such as street segments. The contemporary focus on modelling and explaining the longitudinal patterns of offences in space has inevitably led to a shortcoming in the offender residence strand of research. Even in the offence field, the use of micro places has limited the explanatory power of studies due to a lack of available data.

An additional consideration was also raised regarding the distinction between offender residence and offence distributions in space. There are strong theoretical reasons to treat the two as distinct phenomena, with studies as far back as El-Saaty (1946) recognising the unique causal mechanisms of each. And yet, there remains some ambiguity about the extent to which offender residences and crimes are empirically distinct, especially when considering the extent to which this relationship changes over time, and the extent to which it is dictated by the choice of spatial scale.

With the narrative of these key dimensions in mind, new research questions were derived in the closing stages of the previous chapter. In posing and answering these research questions, this thesis seeks to fulfill the overarching aim stated in Chapter

1, namely, to advance understanding into offender residence concentrations. The research questions were posed as follows:

- RQ1: What is the most appropriate spatial scale to study offender residential concentrations?
- RQ2: To what extent do offender residential concentrations demonstrate stability over time?
- RQ3: How can we explain the longitudinal (in)stability of offender residential concentrations?

To ensure that these research questions are answered comprehensively, and using the appropriate techniques, it was deemed necessary to review the state-of-the-art methods currently being deployed in the (more advanced) offence strand of research along these three themes, largely in the post-2004 new wave. Although much progress has been made across these dimensions in relation to offences, the methods used are varied and may have shortcomings that need rectifying for use with offender residence data in this thesis. As such, this chapter serves to provide an overview and critique of contemporary methods to gauge their suitability for use in answering our three key offender-based research questions above. Each is now addressed and discussed in turn, before the chapter concludes.

3.2 Spatial scale

3.2.1 Background

The previous chapter outlined how spatial criminology has undergone significant change when it comes spatial scale. The 19th Century was largely dominated by macro-level analysis, whereby the patterning of where offenders lived and where offences were committed was mapped out using regions or districts (e.g. Quetelet, 1831/1984). Nevertheless, it was acknowledged that such large units of analysis masked underlying variation that might occur within districts, towns (Glyde, 1856) and even streets (Mayhew, 1851/1862). This understanding followed through to the Chicago School, who used neighbourhood units nested within specific cities as their unit of analysis. Boundaries were stipulated through either administratively-defined census tracts or bespoke square-mile units. North American scholars supplemented this analysis with pinpoint maps which defined the exact location of offender residences. In doing so, attention shifted away from the macro-level towards meso (e.g. neighbourhood) and micro (e.g. street segment) spatial scales, uncovering variation that would have been masked by using larger units[1]. The use of neighbourhood units, and their evolution over time, was formally revived in *Communities and Crime* (1986). Inspired by this, two key publications began what is termed in this thesis as the 'new wave' (see Chapter 2), namely, Weisburd and colleagues (2004) and Griffiths and Chavez (2004). The new wave focused largely on offences, not offender residences, and conducted analyses using small neighbourhood units or 'micro-place' street segments.

3.2.2 Operationalising scale

To maintain focus on contemporary research, Table 3.1 provides a summary of the studies comprising the new wave, specifying the spatial scale at which analysis was conducted. This intentionally contains the same papers as the tabular summary in Chapter 2 (Table 2.1) but specifies how theoretical units of analysis like the 'neighbourhood' were operationalised, as well as the sample size. Most studies opted for a micro-scale unit, including street segments, street intersections or street units, defined in Table 3.2. Although the qualitative description of these units is clear-cut, there is little open source code or data to verify the exact procedure by which micro-place units were generated. This is worth noting, because it makes replication and critical discussions about existing research problematic when hoping to draw inspiration for equivalent operationalisation using offender residences.

Those that use neighbourhood units, usually considered to be meso-level, have tended to define the spatial scale in alignment with boundaries drawn up by administrative bodies, which are publicly available, such as those used to collect census data. As demonstrated in Figure 3.1, these units vary considerably in terms of resident

[1]The use of the terms 'macro', 'meso' and 'micro' in spatial criminology can be somewhat ambiguous. In economics, and in some sociological work, the micro-level is that of the individual, and the macro that of an aggregated unit like a society or country (Coleman, 1994). In spatial criminology, in which focus is not on individuals but places, 'macro' has also tended to refer to large aggregations such as countries or cities, 'micro' to fine-grained units like specific properties or streets, and 'meso' to somewhere inbetween, such as neighbourhoods (see Weisburd, 2015). As we will see, these terms are not definitive, as some definitions of neighbourhood are as equally fine-grained as micro-places such as street segments. However, for consistency, terms are used in alignment with Weisburd (2015).

population size, which has two major consequences that are worth considering when debating usage for offender residence research.

Firstly, it limits comparison of neighbourhood-level research between countries, and questions the extent to which different studies are testing the same mechanisms. Theories relating to social disorganisation and informal social control, in the spirit of the Chicago School and the studies published in *Communities and Crime* (1986), assume that the offence (or offender) generating mechanisms manifest at the neighbourhood-level. But the potential impact of how this is operationalised is considerable. For instance, both Griffiths and Chavez (2004) and Bannister *et al* (2017) sought to examine the stability of offence concentrations over time at the neighbourhood-level, but one used census tracts in the United States (between 1,000 and 8,000 residents) and the other used data zones in Scotland (between 500 and 1,000 residents). To Weisburd (2015) both of these studies were conducted at the meso-level, and yet it would be surprising to find that the same explanatory mechanisms were operating at such vastly different spatial scales. Other studies in England have suggested that 'smaller is better' in defining the boundaries of neighbourhoods (Oberwittler & Wikstrom, 2009). In such cases, the 'neighbourhood' is still a theoretically meaningful unit of analysis, where social control can manifest, but it is not so large that individuals lose perception of their local space. This is worth accounting for when discussing the most suitable scale to study offender residence concentrations and associated social disorganisation theory.

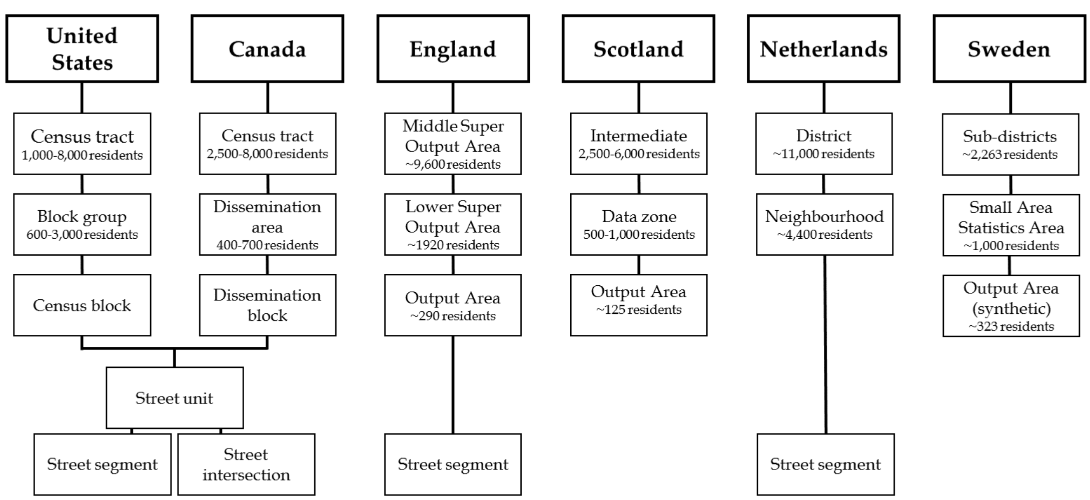

Figure 3.1: Nested spatial scales by country

Secondly, related to the varying sizes of neighbourhood units, the lines between meso and micro-scale units of analyses have become blurred. Weisburd (2015) argued that spatial criminology should turn away from meso units “such as census tracts, census block groups, and neighbourhoods”, and instead focus on micro-places “such as addresses… street segments, or small clusters of street segments” (p. 135). However, there is no attempt to discuss the relevance of this for countries outside of North America. The smallest definable scale in Weisburd’s list of meso units is the United States census block group, which contains between 600 and 3000 residents. This is far larger than the smallest administrative unit in England and Scotland (Output Area), for instance, which contain approximately 290 and 125 residents respectively. It is difficult to make estimates about population at street segment level in North America because census data is not collected at such fine-grained scales. That said, Weisburd *et al* (2004) note that street segments in Seattle tend to contain 99 street addresses, which would put the average resident population at a similar level to Output Areas in England and Scotland.

Even irrespective of resident population, the size of street segments still remains unclear. Braga and colleagues (2010) report the average street segment length in Boston as 130 metres, but with a standard deviation of 86 metres. The shortest street segment was 3 metres and the longest was 642 metres. A study examining spatial scale in The Hague, the Netherlands, reported a mean street segment length of 94 metres and a standard deviation of 108 metres (Steenbeek & Weisburd, 2016). This study is discussed in more detail later. A new wave study in Milan, Italy, reported a mean street segment length of 106 metres but did not report the standard deviation (Favarin, 2018). For the UK, Johnson (2010) used a street segment unit of analysis, but did not report descriptives about length. In the new wave studies in Table 3.1, many simply do not report statistics about the estimated length and population size of street segments (e.g. Wheeler, Worden & McLean, 2016; Curman, Andresen & Brantingham, 2015), so it is difficult to draw definitive conclusions. However, there is enough evidence to question whether street segments are a truly uniform definition of a micro-place. Given that urban areas in the UK tend not to be built around street grids of ‘blocks’ and uniform street segments, the Output Area may be a viable micro-level unit of analysis. This has been argued in a recent new wave study conducted in Birmingham (Adepeju, Langton & Bannister, *under review*).

It is beyond the scope of this chapter to offer a definitive conclusion on these discussions. However, it is worth acknowledging the complexity of the topic, and the complications that arise from defining, operationalising and comparing spatial scales. There is certainly a strong theoretical argument for selecting the smallest spatial scale available, following concerns over the ecological fallacy, and associated Modifiable Areal Unit Problem (Gerell, 2017), discussed in the previous chapter. However, recent research has made attempts to empirically demonstrate the benefits of fine-grained spatial scales by comparing nested units, albeit almost exclusively for offences. These methods include Lorenz curves, Gini coefficients, multilevel variance partitions and multivariable models. A review of these approaches is now outlined and discussed, in order to establish their suitability for answering our first research question relating to spatial scale (RQ1).

3.2.3 Lorenz curve

Lorenz curves have been used in spatial criminology to visualise the extent to which offence location and offender residences concentrate in a given study area. Typically a visual representation of income inequality in a given sample or population, a Lorenz curve plots the cumulative percentage of observations (e.g. individuals, neighbourhoods) against the cumulative percentage of a given variable (e.g. income, crime). In this field, the cumulative percentage of spatial units and offence counts (or offender residences) are plotted against one another. It is therefore a 'global' measure, providing a visual representation of the degree of concentration in the entire study region. One of the first uses of the Lorenz curve in spatial criminology, in the spirit of the narrative traced in Chapter 2, was actually on both offence and offender residence locations (see Wikstrom, 1991). Here, the Lorenz curve demonstrated the non-random distribution of the two phenomena using cross-sectional data from Stockholm, Sweden.

Since then, it has been used in a number of studies in the United Kingdom to visualise offence concentrations (Johnson, 2010; Johnson & Bowers; 2010; Bowers; 2014; Davies & Johnson, 2015). The principle benefit of the Lorenz curve is that it avoids the use of arbitrary thresholds when using quantitative descriptive statistics. Studies in the spirit of the law of crime concentration have relied almost entirely on arbitrary cumulative percentage thresholds of crime occurring at a cumulative percentage of street segments (see Weisburd, 2015). This is largely inspired by the influential work of Sherman *et al* (1989) discussed in the previous chapter, who found that 50% of crime occurred at only 3.3% of addresses. Comparable statements using similarly arbitrary thresholds (25% and 100%) form the evidence-base for the law of crime concentration. And yet, the Lorenz curve plots out every possible combination of cumulative value, permitting a degree of robustness and transparency. Some studies have reported both the arbitrary thresholds, in the interests of comparison to the law of crime concentration literature, as well as the Lorenz curve, for full transparency (see Favarin, 2018).

The use of Lorenz curves for examining differences in the degree of concentration *between spatial scales* is limited, with only three known examples, all relating to offences, rather than offenders (see Johnson, 2010; Steenbeek & Weisburd, 2016; Schnell, Braga & Piza, 2017). In such cases, Lorenz curves for each spatial scale are plotted on the same graph, permitting a comparison on the degree of concentration occurring at each level. Johnson (2010) compared burglary concentrations at street segment and Output Area level in Birmingham, England. Steenbeek and Weisburd (2016) used total crime incident data from The Hague, aggregated to three nested spatial scales: street segment, neighbourhood and district (see Figure 3.1). In a replication of this study, Schnell and his colleagues (2017) used violent crime incident reports from Chicago, aggregated to street segments (mean length 130 metres, standard deviation 71 metres), neighbourhood clusters (approximately 8,000 residents) and community areas (approximately 36,000 residents). No resident population statistics were reported for street segments. Neighbourhood clusters are a scale exclusive to Chicago, formed from census tracts by the Project on Human Development in Chicago Neighbourhoods (see Sampson, 2012), and are therefore not included in Figure 3.1.

In all three studies, there was compelling evidence to suggest that crime concentrations are *greater* at more fine-grained spatial scales. Johnson (2010) found that burglary incidents were more concentrated at street segment level than at Output Areas. Steenbeek and Weisburd (2016) reported that crime was most concentrated at street segment level, although the difference between neighbourhoods and districts was minimal. This finding was broadly replicated by Schnell *et al* (2017) for violent crime, although interestingly, incidents were actually more concentrated at community areas (macro) compared to neighbourhood clusters (meso).

The results served to confirm expectations that the degree to which offence locations concentrate varies depending on the spatial scale selected. Broadly speaking, these studies have demonstrated that so-called micro-place units of analysis, in the form of street segments, exhibit the highest degree of concentration, suggesting that larger aggregations would mask underlying detail. However, the relationship between scale and concentration is not straightforward, evidenced by Schnell and colleagues' finding that crime can concentrate more at the macro-level than at the meso-level. Although in this study, the street segment still came out 'top', in the sense that offences were concentrated most at this level, it does highlight the sensitivity of findings to how meso-level units are defined.

These findings from the offence strand of literature demonstrate the usefulness and insight gained from deploying Lorenz curves: they are a straightforward and visual way of establishing the degree to which phenomena concentrate across spatial scales. Although they have been deployed for offender residences, studies have only done so at one level of aggregation (see Wikstrom, 1991). The drawback of such visualisations is that the results are not quantified. Specific comparisons between units, between study areas and across multiple years, are problematic. The remedy to these issues is the Gini coefficient.

3.2.4 Gini coefficient

The Gini coefficient is a quantitative representation of a Lorenz curve. Ranging between 0 and 1, it measures the areal ratio between the observed Lorenz curve for the spatial unit in question, and a line representing perfect equality, which would have a Gini coefficient of zero. In the context of offence concentrations, the closer the score is to 1, the more crime is concentrated in a smaller number of places. The benefit of this over the Lorenz curve is that it offers a specific number which represents a global measure of concentration. For new wave studies, which focus on the longitudinal stability of concentrations, the Gini coefficient can be visually plotted over time, as opposed to plotting a Lorenz curve for each year of the data, which would lack clarity (e.g. Favarin, 2018). For those also interested in demonstrating the impact of spatial scale, a specific comparison can be made across both scale and time.

This is what both Steenbeek and Weisburd (2016) and Schnell *et al* (2017) have done in their studies of The Hague and Chicago, respectively. The former reported, as one would expect from the Lorenz curve findings, that crime is more concentrated at more fine-grained spatial scales. By plotting the Gini coefficients over time, the authors were also able to demonstrate that crime was becoming less concentrated over time at neighbourhood and district level, the former dropping from around 0.56 to 0.50, and the latter from 0.54 to 0.46. At street segment level it remained quite stable, lingering around 0.78 throughout the study period. Schnell *et al* (2017) found remarkable stability across all spatial scales, although the most noticeable change was at street segment level, which was characterised by an increase in crime concentration over time, from 0.79 to 0.83 in the Gini coefficient. As such, the statistic has demonstrated its usefulness as a global descriptive statistic not just when quantifying snapshots of concentration, but also when examining the stability of overall concentrations over time. This would offer unique insight when deployed on offender residence data, which to date, has not been carried out.

Nevertheless, its implementation comes with considerations. Readers' visual interpretation of the Lorenz curve, and the associated quantitative statistic of the Gini coefficient, are dependent upon the estimated line of equality. The estimation of the line must be calculated based on the ratio between the number of observations (i.e. units of analysis) and the number of events (i.e. crimes). The standard representation of the line of perfect equality (zero intercept, 45 degrees), which represents a Gini coefficient of zero, is only possible in data where the number of events is greater than the number of observations. In cases where the number of events is smaller than the number of observations, the lowest possible value of Gini is greater than zero. The more fine-grained the unit of analysis becomes, the larger the number of observations tends to be (see Table 3.1), making this a common issue in contemporary spatial criminology. This was illustrated by Johnson (2010) and later by Bernasco and Steenbeek (2017). The latter paper demonstrated a straightforward remedy for this issue, replacing the standard line of perfect equality with a line of *maximal* equality, which is the maximum equality that could be achieved given the number of observations and crimes in the data (Bernasco & Steenbeek, 2017). This was considered to be an improvement over more complex simulation-based remedies (e.g. Johnson, 2010) and options which involve dropping units with zero crimes.

In applying Lorenz curves and Gini coefficients to offender residence data, full consideration needs to be given to the suitability of the line of perfect equality. In police recorded data, at least, there are less recorded offender residences than there are recorded crimes, because of repeat offenders and detection rates, amongst other reasons[2]. As such, the risk of there being less offender residence records than the number of observations (units) is greater. In such circumstances, using the standard line of perfect equality and Gini coefficient calculation would be an imprecise method for demonstrating the difference in concentrations across spatial scales. As noted, this is an even greater risk when using fine-grained units of analysis, because this tends to increase the number of observations in the data. So, both Lorenz curves and Gini coefficients can provide useful insight in the offender residence literature, but should be used with full consideration to the sparsity of the data.

3.2.5 Multilevel variance partition

Model-based approaches permit researchers to make specific statements about how overall variance in a phenomenon (e.g. offences) is attributable to each spatial scale. In other words, one can estimate the degree of between-unit heterogeneity at different spatial scales. The handful of studies discussed so far which have empirically examined the impact of spatial scale when studying crime concentrations, have tended to augment such descriptive statistics with a multilevel variance partition (Steenbeek & Weisburd, 2016; Schnell et al., 2017). Although there was already some understanding that between-unit variance in crime concentrations would increase as units became more fine-grained (Ouimet, 2000), this had not been empirically demonstrated until the use of multilevel variance partitions.

Given the total variance observed in an outcome variable, such as crime counts, a null multilevel model (i.e. with no independent variables) will estimate the variance attributable to each level. These estimated variances can then be reported as a proportion, using the total variance as the denominator, for ease of interpretation. The method necessitates a hierarchical dataset, whereby the smallest spatial scale (i.e. level 1) is perfectly nested within the second smallest (i.e. level 2) and so on. That said, the two studies in question have tended to have the temporal scale (i.e. year) at level 1, including a random slope of time, accounting for how variance may have changed over time.

The first study to adopt this method used data from The Hague, the Netherlands,

[2]Discussed in detail in the next chapter.

with a nested data structure outlined in Figure 3.1 for crime counts over a decade (Steenbeek & Weisburd, 2016). The authors found that on average 62% of the total variance in crime counts during the period was attributable to the street segment. By contrast, the larger neighbourhood unit was responsible for an average of 32% and the largest scale (district) around 6%. Over time, the proportion of variance at the street segment increased from 58% in 2001 to 69% in 2009. In a replication of this study in Chicago, Illinois, between 2001 and 2014, Schnell and his colleagues (2017) reported a similar picture. On average, 59% of variance in crime counts was attributable to the street segment level, with this share increasing over time. An interesting discrepancy was that the community area had a greater variance in crime counts during the study period (25% average), despite being larger than neighbourhood clusters (16% average), which was in alignment with their descriptive findings. This might be down to the bespoke method by which the neighbourhood clusters were drawn up by the Project on Human Development in Chicago Neighbourhoods, as noted earlier (see Sampson, 2012). Such a finding indicates that, when the aim is to uncover variation in a phenomenon, smaller does not necessarily mean more appropriate. The method by which boundaries are defined might be more important.

Other studies with comparable aims have reported similar results to a multilevel variance partition, but have done so using an intra class correlation (Gerell, 2017). Using data on arson incidents in Malmo, Sweden, between the years 2007 and 2011, Gerell examined two geographical units unique to Sweden, and a synthetic unit said to replicate an English Output Area (see Figure 3.1). Whilst a variance partition model estimates the variance attributable to each spatial scale, reporting the intra class correlation tells us the similarity between observations nested with a particular cluster. In this case, for instance, the intra class correlation is the correlation between two observations at level 1 (i.e. two synthetic Output Areas) nested within a cluster at level 2 (i.e. one 'Small Area Statistics Area'). The degree of similarity between the pair is indicative of homogeneity within that cluster, and can be interpreted using variance, in a similar manner to the papers outlined above. Although large and medium-sized administrative units of analyses (sub-district and Small Area Statistical Area) were indistinguishable, most variance in incidents of arson was attributable to the smallest spatial scale (synthetic Output Area). As such, the substantive conclusions from the Malmo study are largely comparable to the variance partition models deployed on data in The Hague and Chicago.

The multilevel variance partition findings in crime concentration research are therefore in many ways a robustness check of the descriptive methods. That said, the usage of a variance partition has offered an alternative way of interpreting the degree of heterogeneity between units at different spatial scales, with comments about variance perhaps more easily interpretable than a Gini coefficient in isolation. Although findings are generally interpreted as supporting Weisburd's (2015) argument that micro-places are the way forward in spatial criminology, findings do indicate that greater between-unit variance (i.e. greater heterogeneity) can be found at larger aggregations. One cannot assume there is a law-like relationship between spatial scale and concentration of crime, and as such, no such assumption can be made for offender residences without thorough testing. Thus, there is plenty of scope for an examination of spatial scale using a combination of these methods, in order to establish the most suitable geographic unit of analysis to examine offender residence concentrations, and to assess the similarity to offences.

3.2.6 Multivariable analysis

So far in this section, studies have tended to focus only on the impact of spatial scale using univariate analyses. Others have taken a multivariable approach, running identical, theoretically-driven models using the same data, but aggregated to different scales. One can then observe the impact on the explanatory power of each model. Researchers have largely been inspired by Openshaw's (1984) examination of the ecological fallacy, which compared model results from individual-level and aggregated census data to demonstrate the concerns raised by Robinson (1950). As discussed in Chapter 2, spatial criminologists acknowledge the concerns over the ecological fallacy and have made significant progress with it in mind, refraining from drawing conclusions on individual behaviour from analysis on aggregated data. Here, attention shifted towards the impact spatial scale might have on substantive findings from multivariable analyses.

The first direct application of this approach in spatial criminology was in a study in Montreal, Canada (Ouimet, 2000). The author collated independent variables informed by social disorganisation and opportunity theories, aggregated to both census tract and neighbourhood level. Census tracts contained a mean of 3,531 residents (N = 495). Neighbourhoods were bespoke, natural areas, based on old municipality boundaries, containing a mean of 20,808 residents (N = 84).

Recognising that social disorganisation and opportunity theories are distinct explanations for offence and offender rates (see Chapter 2), separate models were ran to predict offender residence and offence rates respectively. Overall, the models were considered to predict each well, and the impact of aggregation bias was not considerable. That said, the amount of explained variance was greater in the models using data aggregated to the neighbourhood level (55%) compared to the much smaller census tract level (15%).

The author discusses possible explanations for this discrepancy, particularly regarding issues of reliability in measures at smaller aggregations. The finding that 'smaller is not necessarily better' is consistent with the more recent research noted above (see Schnell et al., 2017). Clearly, it is not just size that dictates the suitability of a spatial scale, but the definition of the unit. In Montreal, census tracts, whilst smaller than neighbourhoods, were not designed with consideration for sociological research, and might not capture mechanisms like social disorganisation that theoretically manifest at the level of a 'community'. The neighbourhoods in this study, on the other hand, whilst larger, were drawn up with consideration to historical boundaries, which may hold more significance to residents, and make it more suitable when modelling the manifestation of mechanisms like social disorganisation.

A follow-up to this study took place soon afterwards in Cincinnati, Ohio (Wooldredge, 2002). The author examined a sample of individual-level residential address locations for suspects re-arrested for domestic violence, which were nested in census tracts (N = 129) and larger, neighbourhood units recognised by the city authority (N = 48). Social disorganisation theory was used to inform the selection of independent variables, similar to Ouimet (2000). Although some findings differed from the Montreal study, Wooldredge also found that the substantive conclusions drawn from analysis at two different levels of aggregation were similar. This led him to conclude that "researchers may be able to aggregate up to a larger unit… without altering the relationships examined" (Wooldredge, 2002, p. 703).

The work of Ouimet (2000) and Wooldredge (2002) made the first steps in using multivariable analysis to assess the extent to which spatial scale can impact on the explanatory power of criminological theories. Interestingly, whilst most contemporary progress in the new wave has been made using offences, Ouimet used both offence and offender residence data, and Wooldredge used offender residence data in isolation. In doing so, they demonstrated that smaller spatial scales are not necessarily 'better', and can actually hold less explanatory power than larger units. Contemporary research has continued to demonstrate that the matter is far from settled for offences, with findings suggesting that multiple scales should be considered simultaneously to fully understand the sensitivity of causal mechanisms at aggregated scales (Boessen & Hipp, 2015). In some studies which have deployed explanatory models for offences and offenders, using independent variables derived from survey data, micro-place units would lack statistical reliability due to a lack of respondents in each unit, and as such, larger meso-level aggregations are more appropriate (see Bruinsma, Pauwels, Weerman, & Bernasco 2013).

3.2.7 Discussion

This section has described and discussed various different approaches taken in spatial criminology to examine the impact of spatial scale. Descriptive statistics using arbitrary concentration thresholds, Lorenz curves and Gini coefficients have demonstrated that the degree to which offences concentrate in urban areas can vary by the spatial scale being used. Findings from multilevel variance partitions have been largely consistent with this, reporting that the variance attributable to each spatial scale can vary considerably. Generally speaking, these methods have highlighted that so-called micro-places, such as street segments, unmask the highest degree of concentration and between-unit heterogeneity. However, findings suggest that the relationship between spatial scale and concentration is not straightforward, with some macro-level units actually characterised by greater concentration and a higher proportion of total variance than those meso units nested within them. These empirical examinations have been made almost exclusively for offences. However, with consideration to the nuances of the data, there is certainly scope to provide fresh insight by deploying these methods to answer our first research question relating to spatial scale.

3.3 Longitudinal stability

3.3.1 Background

In Chapter 2, the theme of longitudinal stability was introduced as a key dimension in spatial criminology. Formal questions surrounding longitudinal stability in offender residence concentrations were raised in Shaw and McKay's 1942 study in Chicago. Although their key finding was of stability (i.e. persistence of 'delinquency areas' over time), this would later be questioned through replications and extensions of their work (see Bursik & Webb, 1982; Bursik, 1986). As noted in Chapter 2, the 'new wave' that emerged in more recent years (post-2004) would revive this discussion in relation to offence concentrations. Research questions were reformulated to examine longitudinal stability set against the citywide trend in crime, with the recognition that localised areas could deviate from this macro-level trend, even amidst overall stability in concentrations. In doing so, studies have demonstrated how a small number of places are often responsible for driving citywide changes. That said, there is considerable evidence to suggest that most micro or meso-level areas remain stable, changing in unison, mimicking wider trends.

This section begins by briefly outlining the methods used to unpick the degree of longitudinal (in)stability in offence concentrations in the new wave. This includes descriptive statistics, often deployed to set the scene, and longitudinal clustering methods, to gauge micro-level deviations from macro-level trends. In doing so, consideration is given to the usefulness and relevance of these methods for deployment in the offender residence strand of research in order to design a suitable strategy for answering our second research question (RQ2).

3.3.2 Descriptive statistics

The two papers in *Criminology* that have been identified as beginning the 'new wave' (Weisburd et al., 2004; Griffiths & Chavez, 2004) both use similar descriptive statistics to describe the study region prior to engaging in more complex analyses. Both papers formalised the idea that the degree of longitudinal stability in crime concentrations could be measured by establishing whether localised trajectories differed from the citywide trend. For instance, should a city have experienced a fall in recorded crime over a ten-year period, researchers would endeavour to find out whether streets or neighbourhoods within that city had experienced this fall in unison. The plotting of the citywide trend provides a visual reference for what is about to be dissected.

For instance, Griffiths and Chavez (2004), sought to disentangle the volatile trend in the Chicago homicide rate, particularly the rapid increase from 1988 to 1992. Weisburd and his colleagues (2004), on the other hand, aimed to dissect the drop in total recorded crime that had occurred in Seattle during the 1990s. Subsequent studies in the new wave followed suit, amidst varying contexts, such as the crime drop in Scotland (Bannister et al., 2017), declines in police calls-for-service relating to drug activity (Hibdon, Telep & Groff, 2017) and volatile trends in gun homicides (Braga et al., 2010), amongst others. By visualising these 'global' trends, the baseline was set from which localised trajectories could be compared, and conclusions on homogeneity and uniformity made. Often, these visuals were combined with descriptive information about overall concentrations, such as the Gini coefficient, noted earlier.

The manner in which these studies framed their research question brought discussions back to what Albert Reiss had questioned in *Communities in Crime* (1986, p. 2). Are today's trouble-free communities tomorrow's perilous ones, just as he had claimed? Do local areas experience their own distinct 'criminal careers'? This is where longitudinal clustering makes its contribution. As we shall see, however, it is a methodology widely exploited in the offence strand of research, with offender residences largely being neglected.

3.3.3 Clustering

As outlined, one of the key ways in which the new wave defined longitudinal stability was the extent to which local areas (i.e. micro or meso units) deviated from the citywide trend. While global measures of concentration (e.g. Gini coefficients) tell a story about overall stability, the extent of uniformity in local trajectories tells us more about the persistency of specific crime hotspots (or delinquency areas) over time. As we shall see, a consensus has emerged in the new wave literature to unpick this non-uniformity using longitudinal clustering. Following Weisburd *et al* (2004) and Griffiths and Chavez (2004), group-based trajectory modelling (GBTM) has become by far the most popular method of clustering longitudinal data in spatial criminology (see Table 3.1). It has been used at multiple different spatial scales, across numerous study regions. More recently, studies have demonstrated the merits of k-means, although its application has thus far been limited. To meet the same ends, but without the specific aim of clustering, latent growth curve modelling has also been implemented to disentangle uniformity. These methods will now be discussed in turn to assess their suitability and relevance for adoption using offender residence data.

3.3.4 Group-based trajectory modelling: background

The first use of GBTM in spatial criminology (Weisburd et al., 2004; Griffiths & Chavez, 2004) was made to meet the challenges arising from the revival of key questions about longitudinal stability. As briefly touched upon in Chapter 2, the origins of their methodological contributions can be traced back to the individual-level criminal career field which had gained prominence in the 1980s and 1990s (e.g. Blumstein, 1986; Sampson & Laub, 1993). The relevance of these origins is a useful tangent to pursue briefly. The fundamental discussion within this individual-level criminal career field was the age-crime curve. Observed across numerous time periods and study regions, the age-crime curve visualises how the proportion of offenders in a population (i.e. country) tends to peak in the late-teens, and then decline during the 20s (Loeber & Farrington, 2014). With the persistence of this finding, people asked to what extent this curve was simply an artefact of aggregating data from a heterogeneous group of individuals. Moffitt (1993) posited an influential taxonomy for this, suggesting that individual-level criminal careers were not all characterised by such a shape in offending, but instead, it was a result of aggregating data from life-course persistent and adolescence-limited offenders. The former was the so-called ‘career criminal’, whose onset was followed by long-term persistence, and the latter represented most offenders, whose onset is swiftly followed by desistence. This presented researchers with the methodological challenge of disentangling theoretically-defined groups, characterised by within-group homogeneity in criminal trajectories, from large samples of individual offenders tracked over the life-course. The demand for a methodology that could meet this challenge motivated the development of GBTM, which was capable of identifying clusters of internally homogeneous trajectories from longitudinal data (Nagin & Land, 1993; Nagin, 1999; Nagin, 2005).

The similarities between the methodological challenges faced by individual-level criminal career researchers, in dissecting the age-crime curve, and spatially orientated criminal career researchers, in dissecting citywide trends, are not coincidental. Although the place-based criminal career field only bloomed during the new wave, the idea that geographic units could have criminal careers was emerging around the same time as discussions around individuals (Reiss, 1986), as discussed in Chapter 2. For instance, Schuerman and Kobrin (1986) used a longitudinal clustering algorithm to create a typology of community criminal crime careers. The critique of their algorithm, based largely on its simplicity, was first made by Griffiths and Chavez (2004) and justified their adoption of GBTM. The new method had already demonstrated its ability to group homogeneous clusters of varying complexity in individual-level criminal career research (see Piquero, 2008 for a systematic review) but also in clinical research (Nagin & Odgers, 2010). This was acknowledged by Weisburd and his colleagues (2004) around the same time, and paved the way for the new wave to begin.

3.3.5 Group-based trajectory modelling: operationalisation in the new wave

Although the debate surrounding longitudinal stability was rooted in theoretical discussions, outlined in Chapter 2, the use of GBTM itself has been deployed in an inductive manner. Researchers have not speculated or derived hypotheses *a priori* on the extent of volatility in local area trajectories compared to the citywide trend, or the manner (i.e. shape) of non-uniformity. Instead, analysis is exploratory, and a post-analysis adjudication is made on whether the evidence provides support for social disorganisation or opportunity theories. This has had a number of important implications.

Firstly, the focus on exploratory analysis has meant that researchers have relied almost exclusively on model fit statistics when selecting the number of clusters to best represent the data. GBTM does not uncover homogeneous clusters that actually 'exist', rather, the cluster solution provides a categorisation of "individual-level developmental trajectories continuously distributed across population members" (Nagin & Tremblay, 2005, p. 879). In other words, the cluster solution is an approximation of the original data, made for the purposes of data simplification[3]. There are no "literally distinct" groups and no outright correct cluster solution (Nagin, 1999, p. 140). Faced with this difficulty, studies in the new wave in Table 3.1 have tended to choose the number of groups based on the Bayesian Information Criterion (BIC). Easily interpretable as a single figure that can be compared across models with different numbers of groups, a lower value suggests 'better' model fit (for technical details see Nagin, 2005). In the interests of parsimony, the statistic balances improvement in model fit (i.e. how well the categorisations represent the underlying continuous distribution) with model complexity (i.e. number of groups). Despite its usefulness, and widespread deployment in the new wave, "the choice of the best model specification cannot be reduced to the application of a single test statistic" (Nagin & Odgers, 2010, p. 118). The impact of this becomes evident when looking at the results in Table 3.1. Studies using street segments (and consequently, larger sample sizes) that have relied solely on the BIC tend to end up with too many clusters to be useful, defeating the aims of the data simplification process. Consequently, the number of clusters is reduced manually based on a post-analysis judgement on what is deemed interesting (e.g. Weisburd et al., 2004; Groff, Weisburd & Yang, 2010). Some have taken the BIC into account, balanced along with other metrics, such as the mean posterior probabilities of observations falling into a particular group (e.g. Hibdon et al., 2017). Some papers do not even report how the cluster solution was achieved (e.g. Favarin, 2018). In all, studies in the new wave have fallen short of the standards expected in reporting the results of group-based trajectory models (see Van De Schoot, Sijbrandij, Winter, Depaoli & Vermunt, 2016). Application of these methods using offender residence data should bear such shortcomings in mind.

That said, once a cluster solution has been decided upon, by whatever means, the findings reported have shed new light on the extent to which micro and meso-places experience macro-level trends in unison. The results and theoretical implications of these studies for longitudinal stability have been discussed in Chapter 2. However, there are methodological points worth noting. Firstly, the use of a polynomial, like the cluster solution, has been guided exclusively by model fit statistics. As such,

[3]This is not a feature unique to group-based trajectory modelling, but rather, a comment on clustering methods in the field more generally. Crudely speaking, the process of clustering data in the new wave is not used to identify underlying groups which actually exist, but rather, a method of simplifying data which would otherwise be too cumbersome, to ease interpretation.

the longitudinal shape (e.g. linear, quadratic, cubic) of crime trajectories are not guided by theory, despite the context-dependent (i.e. time period, study region) and theoretically-driven reasons behind such studies. It is not clear, looking at the results, whether the choice of polynomial has an impact on the substantive findings. Secondly, and relatedly, the descriptive statistics and visualisations used for the results have rarely given readers insight into the variation within each cluster. In all but one study, a smoothed line of best fit (e.g. mean by year) is visualised for each group, which gives readers no indication of the deviance between this estimated line and the observed value. The exception was Wheeler *et al* (2016), who visualised the individual crime count trajectories of each observation, faceted by each cluster. This approach is certainly worthwhile to consider for future research, in order to justify both the appropriateness of cluster solutions (beyond model fit statistics) and also the meaning of each cluster when it comes to the post-hoc theoretical discussion.

3.3.6 K-means: operationalisation in the new wave

Although, as Table 3.1 demonstrates, GBTM has been more popular in the new wave, recent papers have implemented a longitudinal variant of k-means as a non-parametric alternative (Genolini & Falissard, 2010; Genolini, Alacoque, Sentenac & Arnaud, 2015). The method was first deployed in the new wave by Curman *et al* (2015), motivated by concerns over some of the assumptions that must be made when using GBTM, as a semi-parametric method, in spatial criminology. First, the measure (e.g. crime count) for each observation for any given year is assumed to be independent of the measure for preceding or subsequent years. Given what is known theoretically about the longitudinal stability of crime, and the expectations from social disorganisation and opportunity theories, this assumption is at risk of being violated, in terms of both crime and offender residences. Secondly, each observation is assumed to have spatial independence from its neighbours, which "may be problematic because criminal activity does not exist in a geographic silo" (Curman et al., 2015, p. 134). Crime and offender residences have consistently been demonstrated as being phenomena that geographically cluster, ever since the early visualisations of Mayhew (1851/1862), Shaw and McKay (1942/1972), through to Morris (1957), Wikstrom (1991) and the measures of positive spatial autocorrelation in the new wave (Bannister et al., 2017), to name but a few. As such, this assumption is also one that is likely to be violated for both offences and offender residences.

The benefit of k-means is that it does not rely on these assumptions, and yet it still serves to cluster observations based on the homogeneity of their trajectories to disentangle local variations from the citywide trend. Based on this reasoning, Curman and her colleagues (2015) deployed the method in their Vancouver study, and compared the results to those achieved through GBTM. The k-means cluster solution contained less groups and was chosen based on the Calinski Criterion (Calinski & Harabasz, 1974). This metric provides an indication as to the extent of within and between-group variance of any given cluster solution. Higher values indicate a 'better' solution, in the sense that within-group variance is minimised (i.e. observations within a cluster are homogeneous) and between-group variance is maximised (i.e. clusters are different from one another). The cluster solution for GBTM was established based on the stability of the BIC result upon re-runs. Although the number of groups in each cluster solution was different for each method (see Table 3.1) the substantive findings were comparable, making k-means an attractive alternative to GBTM when answering questions of stability in place-based criminal careers, especially because it is also less computationally intensive. More recent studies have done away with GBTM altogether, in favour of k-means, based on these reasons (Andresen, Curman & Linning, 2017).

That said, it is not without drawbacks. Issues around choosing the number of clusters remain, with the two studies having used k-means in spatial criminology relying solely on the Calinski Criterion (Curman et al., 2015; Andresen et al., 2017). Both studies have also failed to offer descriptive statistics or visualisations that give the reader a sense of the homogeneity of trajectories in each cluster. The method by which k-means has been deployed (discussed further in Chapter 4) has also been devoid of theory, relying instead on an unsupervised, iterative, inductive process, which allows patterns to emerge from random starting points, which are not necessarily meaningful.

In fact, there is little scope of a theoretically driven usage of k-means in its generic form, because the algorithm is not restricted by polynomial shapes. The freedom that this offers has consequences. The cluster solutions from k-means have demonstrated extreme disproportionately due to a sensitivity towards erratic outliers. That is, some groups contain a very small percentage of the overall sample. In the Curman *et al* (2015) study, a four-cluster solution was reached, but two out of four of these groups contained less than 1% of the total sample. The other two clusters contained approximately 94% and 5% respectively. Andresen and his colleagues (2017) reported similarly, with their solution for total crime containing five groups, with one group containing 92% of the sample, and three of the remaining groups together containing less than 2% of the sample in sum. It is impossible to comment on whether such (highly disproportionate) cluster solutions are meaningful, because just as in other papers of the new wave, a line of best fit summarises the trends of each group, rather than the individual trajectories (with the exception of Wheeler et al., 2016). However, given that both studies, in different study areas and time periods, demonstrate similar traits, it is a reasonable to speculate that the cluster solution might simply be an artefact of k-means being sensitive to outliers. This shortcoming has also recently been empirically demonstrated using simulated data (Adepeju et al., *under review*).

Of course, sensitivity to outliers and short-term fluctuation is not necessarily a problem if the sole aim is to identify specific areas for targeted police or policy intervention. However, such areas are often identifiable by hand, and at this stage, the primary aim of the new wave is to identify meaningful groups which permit a comment on the stability and uniformity of the localised crime trends over time, and their deviation from the citywide trend. The way in which new wave studies report findings makes it difficult to tell whether the sensitivity of k-means to outliers provides meaningful groups, but it is certainly worth bearing in mind for future investigation, particularly when seeking to deploy a suitable method to examine the longitudinal stability of offender residence concentrations.

3.3.7 Latent growth curve regression: operationalisation in the new wave

A comparable but different approach has been latent growth curve modelling, which has been deployed in two separate (but highly similar) studies in the post-2004 new wave (Braga et al., 2010; Braga , Hureau & Papachristos, 2011). It is also comparable to the hierarchical linear model used by Bursik and Grasmick (1992). Whilst GBTM and k-means use clustering to disentangle local trajectories, latent growth curve regression estimates between and within variation, to varying degrees of complexity. It allows researchers to assess the degree to which observations differ in their starting points (between) and longitudinal rate of change (within) in relation to the outcome variable (i.e. crime counts). To aid in interpretation, these two papers still created clusters post-analysis by splitting observations into quartiles from the estimated slopes. The benefit of this approach over GBTM is that it encourages a more quantitative description of longitudinal stability, whereby the estimated coefficients of 'time' (e.g. linear, quadratic, cubic) are reported with statistical significance, rather than a descriptive cluster solution chosen through model fit statistics. That said, the authors' interpretation of the results relied entirely on qualitative statements on the direction of estimated coefficients and visualisations of the mean slopes for each quartile, and as such, findings provided little more insight than those deploying GBTM or k-means. No comment was made on how explained variance increased from the basic models, with fixed intercepts and slopes, to more complex models, in which intercepts and slopes are free to vary. A notable pre-new wave study which deployed latent growth curve regression to model neighbourhood change noted how explained variance increased with random slopes, providing evidence for non-uniformity in local area trajectories (see Kubrin & Herting, 2003).

Table 3.1: New wave longitudinal data and clustering methods

Author(s)	Year	Spatial unit (sample size)	Time unit	Grouping method	Max. polynomial	Method for group N	N groups
Weisburd, Bushway, Lum & Yang	2004	Street segment (N=29,849)	Year	GBTM	2	BIC	18 (narrowed to 8)
Griffiths & Chavez	2004	Census tract (N=831)	Year	GBTM (ZIP)	3	BIC	3 (total) 2 (street gun) 3 (other weapon)
Groff (masters dissertation)	2005	Street segment (N=29,405)	Year	GBTM (assumed Poisson)	Not reported	Posterior probabilities (not reported, BIC not discussed)	11 (narrowed to 4)
Weisburd, Morris & Groff	2009	Street segment (N=29,405)	Year	GBTM (Poisson reported, ZIP used for robustness)	2	Posterior probabilities (BIC noted but not discussed or reported)	8
Groff, Weisburd & Morris	2009	Street segment (N=29,405)	Year	GBTM (assumed approach as 2009 paper)	Not reported	Not reported (reference to previous paper)	8 (narrowed to 5)

Table 3.1: New wave longitudinal data and clustering methods *(continued)*

Author(s)	Year	Spatial unit (sample size)	Time unit	Grouping method	Max. polynomial	Method for group N	N groups
Chavez & Griffiths	2009	Census tracts (N=831)	Year	GBTM (assumed ZIP as replication)	3	Not reported.	3
Groff, Weisburd & Yang	2010	Street segment (N=24,023)	Year	GBTM (Poisson reported, ZIP considered)	2	BIC	22 (narrowed to 8)
Braga, Hureau & Papachristos	2010	Street segment, intersection, street unit (N=28,530)	Year	GCRM	3	Quartiles of predicted slope	4
Stults	2010	Census tracts (N=831)	Year	GBTM	3	BIC	7
Kikuchi & Desmond	2010	Census block groups (N=466 / 454)	Year	LGCA	2	Not reported.	Not estimated

Table 3.1: New wave longitudinal data and clustering methods *(continued)*

Author(s)	Year	Spatial unit (sample size)	Time unit	Grouping method	Max. polynomial	Method for group N	N groups
Yang	2010	Census block groups (N=570)	Year	GBTM, JTA	Not reported	BIC, reliability of assignment, odds of correct classification, usefulness	4 (violence) 3 (social disorder) 4 (physical disorder)
Braga, Hureau & Papachristos	2011	Street segment, intersection, street unit (N=28,530)	Year	GCRM	1	Quartiles of predicted slope	3 (after combining 2 of 4 groups
Bates (PhD dissertation)	2014	Output area	Year	GBTM	3	BIC	4
Weisburd, Groff & Yang	2014	Street segment (N=24,023)	Year	GBTM (ZIP was best fit)	Not reported	BIC, posterior probabilities	22 (narrowed to 8)
Curman, Andresen & Brantingham	2015	Street segment (N=12,980)	Year	GBTM, k-means	1	Stability on re-runs (GBTM), Calinski Criterion (k-means)	7 (GBTM), 4 (k-means)

Table 3.1: New wave longitudinal data and clustering methods *(continued)*

Author(s)	Year	Spatial unit (sample size)	Time unit	Grouping method	Max. polynomial	Method for group N	N groups
Wheeler, Worden & McLean	2016	Street units (N=4,535)	Year	GBTM (ZIP)	3	BIC, AIC, cross-validation error	8
Payne & Gallagher	2016	Property (N=125,226)	Year	GBTM (ZIP)	Not reported	BIC, visual inspection	6
Grossman (PhD dissertation)	2016	Street segment (N=5,078)	Year	GBTM	3	BIC, posterior probabilities, odds of correct classification	3
Bannister, Bates & Kearns	2017	Data zone (N=934)	Year	GBTM	2	BIC	16
Hibdon, Telep & Groff	2017	Street segment (N=24,023)	Year	GBTM (ZIP)	2	BIC (consideration of posterior probabilities and odds of correct classification)	8 (drug activity calls to police), 6 (drug activity calls to emergency medical services)

Table 3.1: New wave longitudinal data and clustering methods *(continued)*

Author(s)	Year	Spatial unit (sample size)	Time unit	Grouping method	Max. polynomial	Method for group N	N groups
Andresen, Curman & Linning	2017	Street segments and intersections combined (N=18,455)	Year	K-means	-	Calinksi Criterion	5 (total), 5 (assault), 2 (burglary), 2 (other), 3 (robbery), 2 (theft from vehicle), 4 (theft), 3 (theft of vehicle)
Gill, Wooditch & Weisburd	2017	Street segment (N=2,937)	Year	GBTM (ZIP)	3	BIC, statistical significance, researcher judgement	18
Favarin	2018	Street segment (N=18,973)	Year	GBTM (ZIP)	Not reported.	Not reported.	7 (burglary), 4 (robbery)
Adepeju, Langton & Bannister	Under review	Output area (N=3223)	Year	K-means, ak-medoids	-	Calinksi Criterion	3 (k-means), 5 (ak-medoids)

Table 3.2: Definitions of micro spatial scales

Micro scale	Definition
Street segment	" ... the two block faces on both sides of a street between two intersections" (Weisburd et al., 2004, p. 290)
Street intersection	" ... locations where two or more streets crossed" (Braga et al., 2010, p. 39)
Street unit	Both street segments and street intersections combined (Braga et al., 2010).

3.3.8 Discussion

The new wave has demonstrated the substantive benefits of using longitudinal clustering methods in spatially orientated criminal career research. Inspired by the individual-level criminal career field's attempts to disentangle the age-crime curve, new wave researchers have demonstrated that local areas do not experience citywide crime trends in unison. Even amidst global stability in crime concentrations, street segments and neighbourhoods experience some degree of volatility, although there is evidence that a small proportion of areas drive macro-level trends, or buck them entirely. The interest in longitudinal stability has, in part, been motivated by Shaw and McKay's (1942/1972) observations regarding the persistency of delinquency areas (where offenders live) over time, and their explanation through social disorganisation theory. However, new wave studies have made their advancements largely using data on crimes. As such, the methodological advancements and theoretical contributions of the new wave are yet to be exploited for the (neglected) offender residence strand of research. Given the theoretical and empirical link between where offenders live, and where offences occur, as per discussions in Chapter 2, this represents an oversight by the field. However, the issues raised in this section demand that the deployment of longitudinal clustering methods on offender residence data is scrutinised, and tailored accordingly, before being deployed.

Firstly, the field has not reached a consensus over whether cluster-specific methods (GBTM and k-means) are more or less useful than latent growth curve modelling to answer questions about longitudinal stability. However, the field has indirectly made their preferences clear by the overwhelming use of either GBTM or k-means.

This may come under criticism for being too descriptive, relying too heavily on visualisations to convey the message of how stable localised offence trajectories are over time. However, the descriptive, visual dimension is accessible and intuitive for readers and police forces to interpret. Personnel at West Midlands Police expressed interest in the descriptive, visual element of clustering. The new wave has demonstrated that such methods are perfectly capable of answering the questions posed regarding stability, although there is clearly room for improvement.

The question then becomes whether GBTM or k-means is preferable, which brings us to our second issue. Selecting k-means over GBTM comes at a cost. The latter has an established array of model-based fit statistics which can be collated for a comprehensive adjudication on the most appropriate cluster solution. Although spatial criminology has often failed to make use of these statistics, or at least failed to report them, the offender life-course field from which the method was borrowed has demonstrated their merits (e.g. Nagin, 2005; Francis, Elliot & Weldon, 2016; Girard, Tremblay, Nagin & Cote, 2019). The reporting of model-fit criterion, such as the average posterior probabilities of group membership (e.g. Girard et al., 2019), both for the chosen cluster solution, but also the reasonable alternative solutions, allows for transparency and permits the reader to assess the appropriateness of the final decision. K-means offers benefits in terms of its more relaxed statistical assumptions and computational efficiency. It is also commonly accompanied by the Calinski Criterion (introduced earlier) as a metric for assessing the appropriate number of clusters. And yet, it has shortcomings that might need rectifying for deployment with offender residence data. The question of long-term stability in offender residence concentrations is a theoretical one, and yet so far, the deployment of k-means in the new wave has been entirely exploratory, relying heavily on the random component of the method. It remains unclear to what extent results are being dictated by this approach, although the apparent sensitivity to outliers, and highly unbalanced groupings, suggest that there could be room for improvement.

Thirdly, the way in which cluster solutions are reported is insufficient. As it stands, the visualisations used in the new wave do not give readers any indication as to the suitability of the groups obtained, and using smoothed mean lines of best fit to summarise groups in isolation could potentially be misleading. In deploying clustering methods to examine the longitudinal stability of offender residences, one might consider more transparent methods for reporting, such as more detailed visualisations (e.g. Wheeler et al., 2016) and basic descriptive statistics about the clusters obtained.

3.4 Explanatory frameworks

3.4.1 Background

The discussions so far relating to spatial scale and longitudinal stability have drawn heavily on the work carried out during the new wave, which has dealt almost exclusively with the spatial patterning of offences, rather than offender residences. As noted, many of the methods addressed so far would be appropriate (and provide considerable insight) for use with offender data, albeit with some adjustments and additional considerations. However, as outlined in Chapter 2, the theoretical explanations for offences and offender residence concentrations are not synonymous, contrary to many contemporary interpretations (or oversights) of the literature. As such, multivariable models used to explain the longitudinal (in)stability in offender concentrations must be designed with consideration to the relevant theories, rather than simply mimicking existing work from offence studies. As outlined in Chapter 2, broadly speaking, social disorganisation theory was a framework originally specific to offenders, whereas opportunity theories have been developed for offences (Bottoms, 2018).

As such, whilst the methods deployed in the offence strand might be appropriate, the operationalisation of variables must be considered in isolation. As we'll see, the dependent variable has very specific characteristics, and independent variables must be constructed with offender-specific theory in mind. This section will offer an overview of existing research in order to best understand how an explanatory framework for the (in)stability of offender residence concentrations can be operationalised. Specific attention will be paid to how the dependent variable (i.e. measures of offenders) and independent variables (i.e. explanatory measures) are derived and constructed. Inevitably, due to the lack of research into offender residences in the new wave, discussions must shift away from longitudinal studies on stability to include cross-sectional studies too, in order to gain a full understanding of how previous research has constructed their respective measures.

3.4.2 Operationalising theoretical constructs: dependent variable

This section will discuss how a measure for 'offenders' has been operationalised in previous spatial criminology research. Here, the focus will be on police recorded data. There are known issues relating to the accuracy and bias in police recorded data on crime and offenders, particularly over time, which are discussed here and in Chapter 4. There are alternative data sources for identifying offenders in a population, namely, self-report studies. However, the number of responses required to create accurate measures when using fine-grained spatial scales is often unfeasible. As such, police recorded data (or data obtained from courts) on offenders has been the principal source of data for spatial criminologists examining offender residence concentrations. The focus on such data when reviewing existing material is therefore considered justified, especially when combined with an open discussion on its shortcomings.

This section begins with an overview of how previous research has defined 'offender' using the data available. An overview is then provided on how measures of offender concentrations at the aggregate-level have been constructed. In doing so, the purpose is not to provide a systematic review of every single study that has used some definition of 'offender', but rather, to focus on publications that have formed a key part of the narrative traced thus far in spatial criminology (see Chapter 2).

Defining offender

The 19th Century pioneers defined offenders to varying degrees of specificity, including individuals committed to prison (Glyde, 1856), brought to the attention of the police (Mayhew, 1851/1862) and combinations of imprisoned individuals and those sentenced to fines or alternative punishments to prison (Rawson, 1839). Even then, there was a recognition that the definition of an offender was one subject to a complex discussion, and heavily influenced by data availability. Joseph Fletcher, for instance, recognised that Home Office returns about prisoners were likely a significant underestimate of the offending population, as minor transgressions were likely dealt with through alternative means that do not involve formal imprisonment (1850). This was also recognised by the Chicago School, who proposed a variety of definitions specifically for young, male offenders. These included "alleged" offenders who had been brought before court, individuals committed (imprisoned) by the court, and individuals who were alleged to have committed an offence, but were "dealt with by police probation officers with or without court appearance" (Shaw & McKay, 1942/1972, p. 46).

In England, Morris (1957) focused much of his analysis on offenders who were defined as having been charged for an offence that was committed within the study area of Croydon. Baldwin and Bottoms (1976) made more specific distinctions between offenders who resided within the study area, Sheffield, but offended outside its borders, and those who resided outside of Sheffield but offended within the city. Until then, the distinction was not made, or it was assumed that offenders in the data both resided and offended within the study area (e.g. Morris, 1957). Often, the data simply is not available to make such distinctions, and as such, Baldwin only used offenders who both resided and committed their offences within Sheffield. An offender was defined as anyone who had been convicted or cautioned during the time period (Baldwin & Bottoms, 1976). A similar definition was used for the related study published in *Communities and Crime* some years later (Bottoms & Wiles, 1986), whereby 'offenders' were those convicted or cautioned for 'notifiable offences' (crimes for which police have to submit statistical returns to the Home Office). Soon after, Wikstrom (1991) drew upon a register of known offenders which included all "reasonable suspicions", thus including those who are not necessarily convicted for a crime, but also individuals who receive a summary penalty (p. 263). More recent research has defined offenders as "suspects", where individuals have been "sent to the public prosecutor's office" but have not yet been sentenced (Bruinsma et al., 2013, p. 949). Others have made the distinction between existing and newly active offenders (Livingston et al., 2014).

In considering these definitions, researchers have tended to use some form of police recorded data, obtained following the reporting and recording of a crime. Specific attention is paid to the issues associated with this in the next chapter, primarily relating to bias in reporting and recording practices. To avoid these issues, a small number of studies have used self-report data, whereby individuals report their offending activity and home location through interviews or surveys. Such data has been used in concert with police recorded offender data (e.g. Sampson & Groves, 1989), even at small spatial scales such as English Output Areas (Wikstrom, Oberwittler, Treiber & Hardie, 2012). However, such studies are rare for a reason, since self-reported offender data which is reliable at fine-grained spatial scales is logistically difficult, time-consuming and expensive, even more so when there is a need for longitudinal analysis. As such, the vast majority of studies examining delinquency areas have used police recorded data. It is clear from just this brief overview that defining an offender in spatial criminology has not been straightforward. Researchers do not always have a choice in how such definitions are made, and instead are often restricted by the limitations of the data.

Aggregate measures

Once the concept of an 'offender' has been identified, researchers then face the task of creating aggregate measures by whichever spatial scale is chosen. This is a much more challenging task compared to offence-based literature. Crime is a discrete event that can be recorded and plotted on a map, geocoded and time-stamped. These points are then aggregated up to the chosen spatial scale (e.g. census tract) by count and possibly normalised into a rate, adjusted for resident population, for instance. Offenders are similarly discrete (i.e. there is only one of each), but police records, which tend to link crimes to offenders, will duplicate offender records for each offence committed, so as to ensure that each offence has its own associated offender, if known. There is good reason for doing so: offenders may have moved to a new house during the time period, and other characteristics which the police record, such as age, may have changed. But how, then, should these records be aggregated to a spatial scale? Spatial criminologists drawing upon social disorganisation theory have tended to aim for measures of *unique* offenders. That is, even repeat offenders who appear multiple times in the data are only counted once within the same geographic observation (e.g. neighbourhood). The result has been termed 'participation rates', as a measure of the resident population that have engaged in criminal activity (Wikstrom, 1991). Participation rates were the focal point for Shaw and McKay (1942/1972), who were interested in neighbourhoods that had a high proportion of offenders in the resident population. Subsequent research has noted this, and usually followed suit (e.g. Baldwin & Bottoms, 1976; Bottoms & Wiles, 1986). In cases where data limitations mean that duplicates are likely, but could not be dealt with appropriately, researchers have admitted that this was far from ideal, and attempted to argue that measures are likely to approximate participation rates when using short time periods (Wikstrom, 1991). Some contemporary research has not overtly described how measures were generated from raw records (e.g. Bruinsma et al., 2013), despite these theoretical and methodological concerns. These discussions are certainly worth considering when constructing measures of offender concentrations in future research, and are dealt with in detail in Chapter 4.

3.4.3 Operationalising theoretical constructs: independent variable

As outlined in Chapter 2, it was the Chicago School's theoretical contributions which have had the most impact on the explanatory frameworks developed to explain offender residence concentrations, and more specifically, their longitudinal stability. Drawing on earlier work in Chicago, Shaw and McKay (1942/1972) suggested that delinquency areas, characterised by high offender resident populations, persisted over time due to a process of social disorganisation, which rendered residents unable to make a concerted effort to deter and resist delinquent behaviour in its residents (Bursik, 1986). These conditions were determined by the structural characteristics of neighbourhoods, namely, economic deprivation, high residential mobility (i.e. population turnover) and high ethnic diversity. As outlined in the previous chapter, clarified by Kornhauser (1978) and later Bursik (1986), a direct relationship between deprivation and delinquency rates was not proposed, but rather, poor areas typically gave way to ethnically diverse populations and high population turnover.

A number of advancements and additions to the 'classic' social disorganisation theory have been made over the years, however these have largely been framed around explaining offence concentrations rather than offenders. Sampson (1987) expanded on social disorganisation by suggesting that differences in family structure, such as 'disrupted' lone parent households, can be a key determinant of violent crime in the United States. Drawing upon advancements in social capital theory (e.g. Coleman, 1994; Putnam, 1995), Sampson would go on to emphasise the importance of other variables, such as the proportion of residents participating in organisations and friendship groups in determining crime concentrations, but would also continue to test social disorganisation theory's ability to explain offender rates (Sampson & Groves, 1989). These theories were developed further, culminating in the idea of collective efficacy, thought of as "social cohesion among neighbors combined with their willingness to intervene on behalf of the common good" (Sampson, Raudenbush & Earls, 1997, p. 918). Although clearly an extension of social disorganisation, the theory has been overtly defined in relation to the "control of crime" (Sampson, 2010,

p. 802), even though subsequent research has used it to explain both offence and offender residence concentrations (Bruinsma et al., 2013)[4].

Here, focus is maintained on the three structural variables (deprivation, ethnic diversity, residential mobility) said to induce socially disorganised neighbourhoods, and in turn, delinquency areas, as per Shaw and McKay's conceptionalisation. Some attention is paid to extensions when explaining offender residences, which as we will see, does include some overlap with Sampson's contribution of disrupted families, for instance. With this in mind, Table 3.3 provides a tabular summary of key studies which have sought to deploy theoretically-driven explanatory models to explain variations in offender residence concentrations in specific urban areas[5]. The purpose of this table is to provide an overview of how concepts are often constructed, and identify patterns in how variables are treated as proxies for a theoretical concept, in some key publications, rather than to provide an exhaustive review of every study which has used associative data to examine offender residence concentrations. For that reason, Table 3.3 has a specific but useful purpose when considering how to explain delinquency areas using the social disorganisation framework, but within the constraints of data availability.

[4] The Bruinsma *et al* (2013) study tested numerous different 'versions' of social disorganisation, from the classic model of Shaw and McKay to Sampson's extension of collective efficacy. The authors did this using both offence and offender residence rates as the dependent variable (in separate models). This study assumed that "the causal mechanisms are similar for the rates of crime and offenders in neighbourhoods" (p. 948). The findings strongly suggested that this assumption was misguided, by the authors' own admission, with different findings from each model, and no statistically significant correlation between the two.

[5] Attention is paid to studies which use geographic units of analysis in isolation. For this reason, multilevel studies which focus on individuals nested within areas (e.g. McVie & Norris, 2006; Wikstrom & Loeber, 2000) are not included. The significance of these studies in unquestionable, but their inclusion here would involve delving into new literature and discussions about individual-level risks characteristics. This focus ensures that the findings and discussions which emerge from this thesis speak to the existing body of research in (offence-based) spatial criminology, from which the three key research questions were derived.

Table 3.3: Summary of independent variables for offender studies

Author(s)	Year	Deprivation	Ethnic diversity	Residential mobility	Housing tenure	Land use	Family disruption	High-risk population
Shaw & McKay	1942/1972	Families on relief rates; median rental cost; % unemp.; % families having radios	% Foreign born and black/foreign born heads of families	% Family owning homes	-	Manufacturing railroads, parks, commercial, residential, building demolishment	-	-
Morris	1957	Overcrowding as % households >2 people per room; population density; social class, property condition; land value	-	-	-	Residential, industrial, commercial	-	-

Table 3.3: Summary of independent variables for offender studies *(continued)*

Author(s)	Year	Deprivation	Ethnic diversity	Residential mobility	Housing tenure	Land use	Family disruption	High-risk population
Schmid	1960	Social rank, socio-economic independence (Tryon typology)	Assimilation (Tryon typology), segregation (Shevky typology)	-	-	Shopping, manufacturing industrial, railroad, vacant properties	Family life (Tryon typology)	-
Baldwin & Bottoms	1976	Pop. density; social class classification; shared accommodation rates	Rates of minority immigrants, Irish immigrants	-	% Households privately rented, rented from council or owned occupied	Industrial, student or middle or working class housing, slums	Unmarried households rates	Young adults, young males rates

Table 3.3: Summary of independent variables for offender studies *(continued)*

Author(s)	Year	Deprivation	Ethnic diversity	Residential mobility	Housing tenure	Land use	Family disruption	High-risk population
Herbert	1982	% Unemp. males, % overcrowded households (>1.5 persons per room), % households no bath, social class categorisation	% Foreign born	% Movers within local area, % movers into local area	% Private tenants; % owner occupied households	-	% Lone parent households	Sex ratio male to female; % residents under 20 years old
Bursik & Webb	1982	Overcrowding as % households >1 person per room	% Non-white, % foreign born	-	-	-	-	-
Bursik	1986	Overcrowding (average persons per room); % unemployed	% Non-white, % foreign born	% Owner occupied households	-	-	-	-

Table 3.3: Summary of independent variables for offender studies *(continued)*

Author(s)	Year	Deprivation	Ethnic diversity	Residential mobility	Housing tenure	Land use	Family disruption	High-risk population
Bottoms & Wiles	1986	Social class classification, housing condition classification	Country of origin	Length of stay in current dwelling (years)	% Owner occupied, public, privately rented, housing association	-	-	Sex
Schuerman & Kobrin	1986	% Skilled / unskilled occupation; % unemp.; % advanced educational attainment; % overcrowded households	Ethnic composition	Residential mobility	% Owned housing, rental housing, apartments,	% Commercial units, industrial units,	Household rates widowed and divorced	Median age

Table 3.3: Summary of independent variables for offender studies *(continued)*

Author(s)	Year	Deprivation	Ethnic diversity	Residential mobility	Housing tenure	Land use	Family disruption	High-risk population
Sampson & Groves	1989	Socio-economic status construct (education, occupation, income)	Blau ethnic diversity index	% Residents brought up nearby	-	-	% Divorced adults; % single parent households	-
Wikstrom	1991	% On public welfare; % blue collar workers	% Non-native	% Residents moving or out	% Rented, owner occupied, non-profit, mixed	-	% Single parents	-

Table 3.3: Summary of independent variables for offender studies *(continued)*

Author(s)	Year	Deprivation	Ethnic diversity	Residential mobility	Housing tenure	Land use	Family disruption	High-risk population
Bursik & Grasmick	1993	% Prof. occupations, median education level and family income, % families in poverty, unemp. rate, public welfare rate	-	% Residents not lived same address >4 years, % net migration	% Owner occupancy	-	% Children with married parents	-
Eisner & Wikstrom	1999	% Unemployed, % social security	% Immigrants	% Residents not moving in a year	% Owner occupied	-	-	-

Table 3.3: Summary of independent variables for offender studies *(continued)*

Author(s)	Year	Deprivation	Ethnic diversity	Residential mobility	Housing tenure	Land use	Family disruption	High-risk population
Ouimet	2000	% Single parent families	% Immigrants, % black	% Residents moved in the last 5 years	-	-	-	-
Wooldredge	2002	Social class (% high school/college graduates; % employed; % skilled occupation; % no public assistance)	% African American	% Same residence >5 years	-	-	-	% Males; mean age

Table 3.3: Summary of independent variables for offender studies *(continued)*

Author(s)	Year	Deprivation	Ethnic diversity	Residential mobility	Housing tenure	Land use	Family disruption	High-risk population
Law & Quick	2013	% Low family income; % government transfer payments; % unemployed; % high occupational status; % high education	Blau ethnic diversity index; % immigrants; % aboriginal	Number of house movers last year; number moved in last 5 years	% Rented households	-	% Lone parent family	-
Bruinsma et al.	2013	Average property value; unemployment rate; % households low income; % on welfare	Blau diversity index from country of origin	% Same neighbourh residents >5 years; resident outflows	-	-	% Single parent families	-

Table 3.3: Summary of independent variables for offender studies *(continued)*

Author(s)	Year	Deprivation	Ethnic diversity	Residential mobility	Housing tenure	Land use	Family disruption	High-risk population
Law, Quick & Chan	2016	% Government transfer payments	Blau ethnic diversity index	% Residents moved in the last year	-	Road density, commercial, residential, open space, education, shopping	-	-
Liu, Feng, Ren & Xiao	2018	% Advanced education; % low cost rent	% Migrants		% Rented households	-	-	% Young adults (aged 19-30)

There are some key themes which emerge from the operationalisation of concepts in Table 3.3, but at the same time, some points of inconsistency. For instance, every study used a variable to represent deprivation, but it was constructed in a variety of different ways. Many studies use variables which measure the rate (per resident population) or proportion (of resident population) of households on some form of government income or benefit (Shaw & McKay, 1942/1972; Wikstrom, 1991; Bruinsma et al., 2013; Law & Quick, 2013). Others use measures such as household overcrowding (Bursik & Webb, 1982; Bursik, 1986; Morris, 1957; Herbert, 1982), educational attainment (Schuerman & Kobrin, 1986; Liu, Feng, Ren & Xiao, 2018; Wooldredge, 2002) income (Law & Quick, 2013; Bruinsma et al., 2013) or rental cost (Shaw & McKay, 1942/1972; Liu et al., 2018). Some have created composite variables which represent socio-economic status (Sampson & Groves, 1989) or used country-specific measures of social class (Schmid, 1960; Bottoms & Wiles, 1986). One study used the proportion of single parent families, because it was deemed a viable proxy for poverty (Ouimet, 2000), although this variable has also been used as a measure for family disruption. The Chicago School were initially interested in aspects of health, such as tuberculosis rates, but interest rapidly faded out, perhaps for the same reason that it correlated highly with deprivation measures.

Measures for ethnic diversity offer a little more consistency in contemporary research. Whilst many early studies simply used the proportion of foreign-born (Herbert, 1982) or black heads of household (Shaw & McKay. 1942), or the proportion of non-white residents (Bursik & Webb, 1982; Bursik, 1986), following Sampson and Groves (1986), studies have tended to use an index of ethnic heterogeneity. These more recent studies (Law & Quick, 2012; Bruinsma et al., 2013; Law et al., 2016) have used Blau's (1977) index, which represents a measure of the degree to which the ethnic populations (or country of origin, for instance) of each geographic observation (e.g. neighbourhood) are homogeneous. This measure is much more interpretable and transparent, and offers a more direct approximation of ethnic diversity, compared to more dated measures such as the Tryon typology (Schmid, 1960) or variables which are essentially measures of the immigrant or ethnic minority populations. Interestingly, some studies have moved away from examining ethnic diversity directly in favour of variables said to measure the 'regulatory capacity' of residents, such as residential mobility (Bursik & Grasmick, 1993). In their study, Bursik and Grasmick did use measures relating to the ethnic composition of neighbourhoods, but did so as a proxy for the level of deprivation, by using the proportion of black residents. This is an uncommon approach which has tended not to have been repeated since.

The residential mobility of residents in each local area has been measured fairly consistently. Shaw and McKay appeared to approximate it using the proportion of families who owned their house, which was later used by Bursik (1986). Bursik and Grasmick (1992) also used the proportion of owner occupied houses as an indirect measure for the regulatory capacity of neighbourhoods. This inevitably results in some overlap with those specifically interested in household tenure, which has tended to be a measure of house ownership, or the proportion of households which are rented by type (e.g. Baldwin & Bottoms, 1976). Neighbourhoods with a high proportion of owned-occupied houses are assumed to have less residentially-mobile residents, whereas a high proportion of rented accommodation suggests a more mobile population. More recently, residential mobility has tended to be estimated more directly using census data on whether the resident has moved house in the last year (e.g. Law et al., 2016) or last five years (e.g. Wooldredge, 2002; Ouimet, 2000). In England, David Herbert was able to gather data on the percentage of house movers within and into the local area (1982). Others have used measures ranging from unspecified variables (Schuerman & Kobrin, 1986) or more detailed calculations which actually provide a measure of flow using data on residents moving in and out of the neighbourhood in a year (Bruinsma et al., 2013). This flow calculation has been used elsewhere in Dutch studies (see Bernasco & Nieuwbeerta, 2005) because the data is available annually from city resident registration information.

Recent reviews (Bruinsma et al., 2013) have identified Sampson (1987) as introducing a family disruption variable to Shaw and McKay's classic model, but this was considered less formally at least as far back as Schmid (1960) who used the family life dimension of the Tryon typology[6]. In Sheffield, Baldwin and Bottoms (1976) would use a measure of unmarried household rates, and Schuerman and Kobrin (1986) used a variable for the percentage of widowed or divorced households. Sampson and Groves (1989) would then go on to use the proportion of divorced adults and single parent households as their measure for family disruption. This would somewhat dictate subsequent research, which has primarily used a measure for lone parent households to gauge the degree of family disruption (e.g. Bruinsma et al., 2013;

[6]This was derived from cluster analysis and included variables such as the number of single-family homes, 'housewives' and young males (Tryon, 1955).

Law & Quick, 2013). On the topic of family, some studies use a measure of young people, sometimes specifically young men. The inclusion of this variable is not always elaborated upon in detail, but it appears to be because young men are disproportionately represented amongst known offenders, and is therefore identified as a control variable rather than a theoretically-driven variable which measures a concept related to social disorganisation[7].

Shaw and McKay's interest in land use, stemming from their observation that delinquency areas tended to be in close proximity to areas of heavy industry, would feature heavily in early studies. Subsequent research would continue their interest in industrial, manufacturing or commercial land uses (Morris, 1957; Schmid, 1960; Baldwin & Bottoms, 1976; Schuerman & Kobrin, 1986), with contemporary research having made specific efforts to examine the impact of different forms, including variables such as the density of roads (Law et al., 2016). Shaw and McKay's specific interest in the degeneration of urban areas, characterised by changes such as building demolitions, appear to have only been revived in the crime concentration literature (Wheeler et al., 2018; Frazier et al., 2013).

3.4.4 Operationalising explanatory models

The development of methods to examine the relationship between these independent variables and offender residence rates has been fairly consistent with research in spatial criminology more generally. Beginning with descriptive and correlation statistics, studies have been increasingly deploying spatially-sensitive methods, incorporating Bayesian modelling (Law et al., 2016; Law & Quick, 2013) and spatial lags (Liu et al., 2018; Bruinsma et al., 2013) in multivariable regression models[8]. The principal purpose for incorporating the spatial dimension of meso and micro-level offender residence data is to address issues that arise from statistical assumptions. One of the key assumptions made when running regression models

[7]As noted earlier, studies which examine individuals nested within neighbourhoods are not covered here, however, it is likely that this would highlight whether young men are particularly susceptible to socially disorganised neighbourhoods through a cross-level interaction.

[8]Common regression models include Ordinary Least Squares (e.g. Ouimet, 2000), for which the dependent variable is often transformed to account for a non-normal distribution, and Poisson or (zero-inflated) negative binomial (e.g. Feng, Liu, Long & Liao, 2019), which is appropriate for count data or data for which there are excessive zeros. Logistic regression (or related methods, such as multinomial logistic regression) has been used for when the dependent variable is an outcome generated from longitudinal cluster analysis, but this appears to have only been deployed in crime concentration literature (see Weisburd et al., 2014; Bates, 2014).

is the independence of observations. When modelling offender residences using meso or micro-level units of analysis, this assumption is likely violated due to the presence of spatial autocorrelation. Neighbourhoods (or street segments) which are geographically proximal to one another are more likely to have similar values, due to wider causal mechanisms or spillover effects. The extent of this spatial clustering can be visualised using maps or quantified using a local or global indicator of spatial autocorrelation (Anselin, 1995; Ord & Getis, 1995). In cases where there is such spatial autocorrelation, which is most likely positive (e.g. Bruinsma et al., 2013), a spatial lag variable, which represents some measure of neighbouring offender residence rates, can be included. This has also become common in crime concentration studies (e.g. Favarin, 2018; Weisburd et al., 2014). Bayesian models are also capable of addressing issues arising from spatial autocorrelation (Law & Haining, 2004; Law et al., 2016).

3.4.5 Discussion

It is clear from this brief overview that numerous questions arise when seeking to explain offender residence concentrations. The construction of the dependent variable in itself is not straightforward. Police recorded data on known 'offenders' can be defined in multiple ways, from those suspected of committing offences to those prosecuted. Self-reported data is a rarity but it is certainly worth considering its availability, especially given the constraints in using police recorded data covered in the next chapter. Even once a definition for 'offender' has been generated, there are many decisions to be made on how counts are aggregated to the spatial scale chosen, in order to create a theoretically meaningful measure. These are issues which do not arise with police recorded offence data, and therefore deserve special consideration when designing studies to examine offender residences. Independent variables operationalised to measure concepts derived from social disorganisation theory have been fairly inconsistent in previous research, but there are clear trends towards established measures, such as using a diversity index to measure ethnic heterogeneity. There has also been an acceptance that the multivariable regression models used to test hypotheses should be spatially-sensitive. That is, they should account for the dependency between observations which is likely evident when using offender residence data at meso or micro-level spatial scales.

The merits and shortcomings of existing attempts to explain offender residence concentrations should be discussed with the *longitudinal* component of RQ3 in mind. When seeking to explain the (in)stability of offender residence concentrations over time, the independent and dependent variables might have to be constructed differently to previous studies, which are primarily cross-sectional. Issues over causality are perhaps even more salient, since the independent variables said to explain longitudinal changes in offender residences must be measured at a point that is theoretically justifiable. This temporal lag is fundamental to any arguments of causality (Blossfeld, Rohwer & Schneider, 2019). Moreover, the construction of the dependent variable must somehow account for the longitudinal nature of the offender residence data. So far, offender residence concentrations have largely been explained using a dependent variable which is a continuous measure of counts or rates for any given year, rather than over multiple years. In the crime concentration literature, longitudinal data has first been clustered using the techniques discussed in the previous section, with the cluster solution then being used as the dependent variable in subsequent regression models (see Weisburd et al., 2014). This approach has not been utilised in the offender-strand of literature, and could offer novel insight into how (in)stability could be explained.

3.5 Conclusions

This chapter has outlined and discussed considerations of data and methods in relation to the three key research questions derived in the previous chapter, namely, those relating to the most suitable spatial scale at which to study offender residence concentrations, the extent of longitudinal stability of these concentrations, and how this (in)stability can be explained.

The first section outlined the descriptive, visual and multilevel methods deployed in the offence concentration literature to examine the impact of using different nested spatial scales. The merits and issues which would arise from deploying these methods on offender residence data were outlined. Attention was also given to a small number of studies which have used multivariable regression models on both offence and offender residence data to highlight differences in explanatory power across aggregations. It is clear from these studies that there are major advantages in using micro-scale geographic units of analysis, but that there is certainly no rule of thumb over their use, and that a thorough examination using comparable methods would be required to justify the choice of spatial scale when examining offender residences. The second section detailed the longitudinal methods used in 'new wave' crime concentration literature, due to its advance in examining stability of concentrations over time, and its applicability to offender residence studies. The advantages and disadvantages of various clustering methods, as well as growth curve models, were outlined, with particular consideration given to shortcomings which could be rectified when deploying such methods on offender residence data. These primarily relate to the sensitivity of existing methods to outliers and short-term volatility, questions over the theoretical meaningfulness of cluster solutions, and the manner in which clusters are reported. The third and final section addressed the ways in which studies have sought to explain offender residence concentrations. Discussions around the construction of the dependent variable, as a measure for offender residences, were outlined, along with the additional considerations required when working with longitudinal data. A summary of how concepts derived from social disorganisation theory have been operationalised in existing research was provided, giving insight into how the construction of theoretical concepts has developed over time. There is some evidence of inconsistency in how models are deployed, but also some clear trends towards established measures. A note was made on the increasing use of spatially-sensitive multivariable regression techniques.

The discussions raised in this chapter, and subsequent conclusions, have provided important insight into how existing methods, and approaches to constructing theoretically meaningful dependent and independent measurements, can be adopted or amended to answer the three research questions posed relating to spatial scale, longitudinal stability and explanation. With these points in mind, the following chapter will outline the data used and methods deployed in this thesis.

Chapter 4

Data, methods and analytical strategy

4.1 Introduction

This chapter outlines the data used and the methods deployed to answer the three primary research questions derived and discussed in preceding chapters. Namely:

- RQ1: What is the most appropriate spatial scale to study offender residential concentrations?
- RQ2: To what extent do offender residential concentrations demonstrate stability over time?
- RQ3: How can we explain the longitudinal (in)stability of offender residential concentrations?

As discussed in Chapter 3, existing research has made a number of methodological contributions to the field under the three themes of spatial scale, longitudinal stability and explanation. This review of the literature found that a number of these advancements have yet to be exploited for use in offender concentration research, despite the theoretical and empirical insight that this could offer, covered in Chapter 2. That said, the review highlighted that the methods deployed in the offence strand of research are not necessarily directly transferable. In particular, there remain some limitations with the methods used to explore longitudinal stability, which demand rectification through a refinement of existing methods. More generally, the deployment of both existing and novel methods relies upon the availability of specific data, which may have all sorts of advantages and shortcomings, which also demand detailed consideration.

With this in mind, this chapter will be structured as follows. First, an outline will be given of the police recorded offender data available for this project, as provided by West Midlands Police Force, noting the ethical considerations, data characteristics, integrity and suitability given the research questions posed above. Secondly, an outline of the study region, Birmingham, will be provided followed by a discussion in relation to the spatial scales available as potential units of analyses. Thirdly, the construction of theoretically-driven independent variables from the census will be described. This brings us to the methods section, which will be outlined in relation to the three dimensions of spatial scale, longitudinal stability and explanation. As identified in the previous chapter, many methods currently being deployed in the offence strand of research are transferable to examine the spatial scale and explanations for offender residence concentrations. However, shortcomings in previous applications of longitudinal clustering detailed in Chapter 3 leave plenty of room for improvement. As such, particular attention is paid to how a novel implementation of k-means clustering, termed anchored ak-medoids, which was developed alongside this thesis, rectifies shortcomings in previous methods. After outlining the analytical strategy proposed for examining these three research questions, the chapter then concludes.

4.2 Data

4.2.1 Offender data requirements

The primary source of data for obtaining a measure of offender residence concentrations will be police recorded data. This is because the research questions derived in preceding chapters demand data on offender residences that have both spatial and temporal dimensions, which tends to be only accessible through police records (Chainey & Ratcliffe, 2013). To examine the spatial dimension of offender residences, especially across multiple spatial scales (RQ1), the geocoded location of offender residences is necessary in order to have flexibility across aggregations. This fits the ideal of having data "at the most detailed level possible" in order to aggregate across "different areal units for comparison" (Brantingham, Brantingham, Vajihollahi & Wuschke, 2009, p. 90). To examine the temporal dimension, in terms of the longitudinal stability of concentrations (RQ2), offender residence data also requires a time stamp, which can be aggregated to the desired temporal unit (e.g. month, year). The strict nature of these requirements means that previous research, as outlined in Chapters 2 and 3, has tended to be limited to police recorded data. This study is no exception, using data provided by West Midlands Police Force.

4.2.2 West Midlands Police Force

Ethical considerations

The police recorded data on offender residential locations was initially provided through a formal Information Sharing Agreement between West Midlands Police Force and the Manchester Metropolitan Crime and Well-Being Big Data Centre. Access to data was only granted following the successful completion of Non-Police Personnel Vetting (Level 3) carried out by Greater Manchester Police, which was subject to annual review. West Midlands Police accepted this vetting process as sufficient to be granted access to their data. The initial agreement was valid from 29 January 2016 to 28 January 2018. A new Information Sharing Agreement was updated and signed by both parties on 6 February 2019 and active from 7 January 2018, subject to an annual review process. Internal ethical approval for this project was retrospectively approved following a review of these agreements on 31 March 2019.

4.2.3 Data content

Offender records

The recorded data provided by West Midlands Police Force on offender residential locations covers the period 1 April 2006 to 31 March 2016. Each file ran from 1 April to the following 31 March. The raw data is contained in 'people reports' which include information on a number of different individuals known to police in relation to a recorded crime (e.g. offenders, victims). The data contains a number of categories which might potentially fall within the definition of an offender, namely: (1) defendant/offender, (2) person thought responsible for the offence and (3) suspect.

Defendants and/or offenders can only be categorised as such with a clear up code which is allocated following a formal charge or caution. Persons thought responsible for an offence are individuals suspected as being the culprit but police are unable to continue with prosecution. Suspects can be entered as such with confirmation from a ranking sergeant, but do not have to have been cautioned or charged. As discussed in the previous chapter, the limited studies that have used police recorded offender data have defined the variable in a number of different ways, ranging from those who had been convicted or cautioned (Bottoms & Wiles, 1986) to those who were simply under suspicion (Wikstrom, 1991). For the purposes of this study, only the 'defendant/offender' category was used as it was deemed most similar to the general concept of an 'offender'. The suitability of this category for the project was confirmed by personnel familiar with data within West Midlands Police Force. Henceforth, this category of individuals is simply referred to as either offenders or defendants.

Each offender in the data is assigned a 'nominal reference' which is used as an anonymous identifier. As such, no personal names were included in the raw data. Nominal references are created when an individual is entered onto the system for the first time. On any subsequent occasion, officers are expected to select the existing nominal reference identifier from a search/dropdown menu, so as to avoid individuals appearing in police records numerous times under different nominal reference identifiers. That said, nominal references can appear multiple times in records for the legitimate reason that an individual has been identified as an offender/defendant for a different recorded crime. This is the fundamental feature that distinguishes how offender and offence data can be treated, and measures of each constructed. In police records, offences are a discrete event, and barring administrative errors, recorded crimes and their associated crime number only appear once. As has been the case throughout studies examining offences in the new wave, a measurement of crime concentration is then constructed, either using outright counts per spatial scale (of total crime or by crime type) or by some other standardised measure (e.g. crime count divided by resident population). The potential (legitimate) duplication of offender nominal references, however, demands more nuanced consideration.

Counting all individual records, including duplicates, might grossly inflate the offender count or rate of a specific area because of repeat offenders who get caught multiple times. As outlined in the previous chapter, this situation is to be avoided, and instead, a measure of 'participation rates' is constructed, whereby duplicates are removed, and the variable measures the resident population that have been identified as an offender (count or resident population adjusted rate). This was the main variable of interest for the Chicago School (e.g. Shaw & McKay, 1942/1972), which is a main source of inspiration for this project. That said, data limitations in previous studies have meant that this has not always possible (e.g. Wikstrom, 1991).

For this study, duplicate records were only counted more than once if the offender was known to have moved to a new area (defined as Output Area, discussed later) within the same year. For instance, an offender identified for a crime in April, and recorded as such, would be counted again if they were identified for a separate offence in December, but were living at a different property located in a different Output Area. This was done so as not to underestimate the prevalence rate of other areas. Should an individual be identified in the same manner, but recorded as still living in the same Output Area, the individual would only be counted once in any given year. This was to avoid over-inflating the prevalence rate. It is recognised that these decisions are subject to debate, and other researchers may have constructed the measurement differently. However, it is considered to be a balanced approximation of resident population offending, and an improvement over previous studies that were unable to account for duplicates (e.g. Wikstrom, 1991) or did not report what method was used (e.g. Bruinsma, Pauwels, Weerman & Bernasco, 2013).

Offender location

For each offender record there is a matching grid reference easting and northing coordinates using the British National Grid. These coordinates can provide precision accurate to 1 metre. The raw data did not contain house numbers, street names or postcodes, but could instead could be plotted over spatial units of analysis and aggregated accordingly, as discussed later in this chapter. The location recorded for each offender is where the offender was living when identified by police. The completeness of these locations for the whole of the West Midlands was quite high, with an average of around 83% of offenders on record having a complete pair of easting and northing coordinates, and no obvious fluctuations over time (see Table 4.1).

Offender crime

For each offender record there is a matching crime number. Information pertaining to the offence itself, such as the offence type and location coordinates, could be obtained by using the crime number as a common identifier to link the offender and crime data together. This was only done to provide preliminary descriptives to demonstrate the offender/offence journey to crime relationship, and to ascertain specifics regarding data integrity (see later in this chapter). As this is one of the first studies to examine the longitudinal concentration of offender residences, a decision was made to include all individuals identified as being an offender during the study period, rather than subset the data by offence type. In doing so, a baseline is provided for further research to build upon by examining specific crime types. It has only been recent research in the new wave of offence literature which has begun to systematically examine longitudinal crime concentrations by crime type (e.g. Andresen, Linning & Malleson, 2017), with the bulk of previous research having used generic measures such as total recorded crime incidents. As such, it was considered prudent to begin with this broad approach when forging a new path into offender residence research. Discussion topics around this decision are returned to in Chapter 6.

Other variables

The key variables from West Midlands Police used in this project were the nominal reference, crime number and the easting-northings of the offender residence and offence location. The raw offender data also included the age, date of birth, ethnicity, sex and occupation of each individual. Whilst these variables will be of immense value for further research projects, as returned to in the discussion, a decision was made not to subset the data into specific categories based on these variables. As outlined above, this was done to provide a baseline for further research. It aligns with the progressive trend of the new wave literature, which began broadly and has only more recently begun to narrow its focus, as outlined in Chapter 2. Again, discussions on this are returned to in Chapter 6.

4.2.4 Data integrity

Issues surrounding the use of police recorded data have been known for some time (see Myers, 1980). Citizens do not always report crimes, and people's willingness to report incidents to the police varies by crime type. This is true for serious offences such as sexual assault (Roth, Wayland & Woolsey, 2010) and domestic violence

(Corvo & Carpenter, 2000) along with more trivial offences such as bike theft (Walker, 2011). The willingness of residents to call the police can also vary from place to place. Reporting behaviour can vary according to deprivation, trust in the police or resident attitudes towards particular crime types that have become normalised (Hope, 2014). As a consequence, police recorded crime is not a true reflection of reality. This inherently impacts on police offender records, as crimes that are never reported cannot be investigated and offenders will not be subsequently identified. The issue of underreporting has been demonstrated most saliently through the use of crime surveys. The Crime Survey for England and Wales (CSEW) has highlighted that around two thirds of crimes are not reported to the police (ONS, 2015). Despite the benefits of such victimisation surveys, the data is not suitable for examining offender residential concentrations, but rather in this case, simply to demonstrate that police recorded crime data is subject to a bias. That said, in recent years, long-term declines in recorded crime have tended to more or less mirror the CSEW during periods of time when police recording practices were unchanged, even if the absolute level was much lower than the survey suggested (for more details see ONS, 2016).

Irrespective of the underreporting bias in police recorded crime data, offender data has an additional obstacle: the detection rate. Once crimes have been reported, and a crime reference number generated, officers conduct an assessment to decide whether the report should be investigated further. Of these, 48% are closed without a suspect being identified, although this varies considerably by crime type (Home Office, 2018). Even once suspects are identified, Home Office figures show that around 11% of offences result in charges or summons being brought against them. This figure was around 15% in 2015, declining since the introduction of the new outcomes framework in 2014. Offender data on police record is therefore subject to the initial bias of police recorded crime data, and then the subsequent detection rate. This topic, and issues relating to the over-policing of certain areas and people (McAra, 2017; McAra & McVie, 2005) will be returned to when discussing analyses and the implications of the results from this project.

West Midlands Police Force data integrity

West Midlands Police Force, who provided the data for this project, is no exception to these difficulties. A recent crime data inspection by Her Majesties Inspectorate of Constabulary and Fire & Rescue Services (HMICFRS) found that only 84%

of crimes reported to the Force were actually recorded (HMICFRS, 2017). The reviewers largely blamed this deficiency on a lack of understanding from officers on the requirements of crime recording, and a lack of appropriate supervision. This means that the recorded crime data available for this project is imperfect, and in all probability underrepresents the true level of crime that citizens have reported to the police, which then reflects upon the offender data. That said, the detection rate of crime that was recorded was found to be quite high, with between 13% and 24% of recorded crimes having a matching offender record during the study period, as per the definition above (i.e. individuals given a clear up code given following a formal charge or caution). These figures are summarised in Table 4.1.

Table 4.1: Descriptives of West Midlands Police recorded data

Year (April-March)	Offenders with residence coordinates complete (West Midlands)	Recorded crime with matching offender (Birmingham)
2006/07	84%	22%
2007/08	83%	22%
2008/09	83%	24%
2009/10	84%	21%
2010/11	83%	16%
2011/12	81%	19%
2012/13	86%	22%
2013/14	86%	20%
2014/15	85%	16%
2015/16	83%	13%

That said, a high detection rate does not necessarily imply that the offender sample is representative of offenders in general. Of course, that is more or less impossible to verify for many characteristics, since nothing is known about offenders that do not get apprehended. However, we do know about crimes for which offenders were never apprehended, since crimes are recorded by the police irrespective of whether an offender is identified (subject to the shortcomings above). One way of testing whether the offender sample is at least spatially representative in terms of crimes is to compare the distribution of known crimes by unknown offenders to the distribution of known crimes committed by known offenders. In the West Midlands, the correlation between these two phenomena when counts were aggregated to Lower Super Output Area census units (discussed later) was consistently high (around 0.9, $p < 0.05$). As such, we can at least be reasonably confident that crimes committed by offenders on police record are spatially representative of recorded crimes committed in the West Midlands in general.

4.2.5 Study region

Choosing a city

Although the police recorded offender data was available for the West Midlands as a whole (see Figure 4.1), a decision was made early on to focus on one particular district, namely, Birmingham. This decision was made for a number of reasons, some of which relate specifically to the data. Firstly, the handling of spatial data can be computationally intensive. The West Midlands is nearly a thousand square kilometres and therefore contains hundreds of thousands of data points and thousands of spatial units, outlined in the next section. Initial phases of data exploration and data integrity, as reported above, were conducted using the entire dataset, but this could be immensely time consuming when using standard computer hardware. As such, the data was narrowed down for a more efficient workflow. Secondly, using data from a particular district was considered to minimise the impact of data disparities occurring simply due to differences in recording practices or policing tactics across the West Midlands. Birmingham contains two Neighbourhood Policing Units (Birmingham East and West) out of the eight representing the region as a whole in 2016.

Irrespective of these discussions surrounding data, there are other reasons to choose a specific city. Previous research has always focused on a specific urban conurbation rather than regions which include multiple cities (see Chapter 2). With studies rarely justifying their choice of study region, one can only assume that the decision was made due to comparable data concerns stated above, or because data availability meant there was no choice. But here, we have a selection of urban districts, and three major urban conurbations: Wolverhampton, Coventry and Birmingham. Of course, these cities share fundamental cultural similarities, some positive, such as the strong industrial heritage, and some negative, such as the extensive bombing endured during the Second World War.

That said, there is strong theoretical justification for focusing on a specific city. Firstly, previous studies which are highly influential to this project, such as Baldwin and Bottoms (1976), discussed in Chapter 2, have demonstrated the benefit of discussing findings within the historically-specific context of the study area, Sheffield, such as its idiosyncratic growth as a city and housing market. Attempting to address such nuances in an entire region, each with their own councils and local policy initiatives, for instance, would be unfeasible. Secondly, one of the key reasons for examining offender residence concentrations, theoretically and empirically, is the relationship between where offenders reside and where they commit crime. The journey to crime literature has conceptualised the behavioural spaces and routine activities of offenders, hypothesising that their targets tend to be located around, and on the way to and from, important nodes, such as home, work or leisure activities (Brantingham & Brantingham, 1984). Where people reside, move to and from, and experience their daily world, are heavily dictated by place-based identities which manifest at local city level rather than geographically vast regions (Proshansky, 1978). If these important nodes can be expected to fall within local boundaries, the implications of ignoring surrounding areas is limited, and worth accepting, given the other benefits noted above.

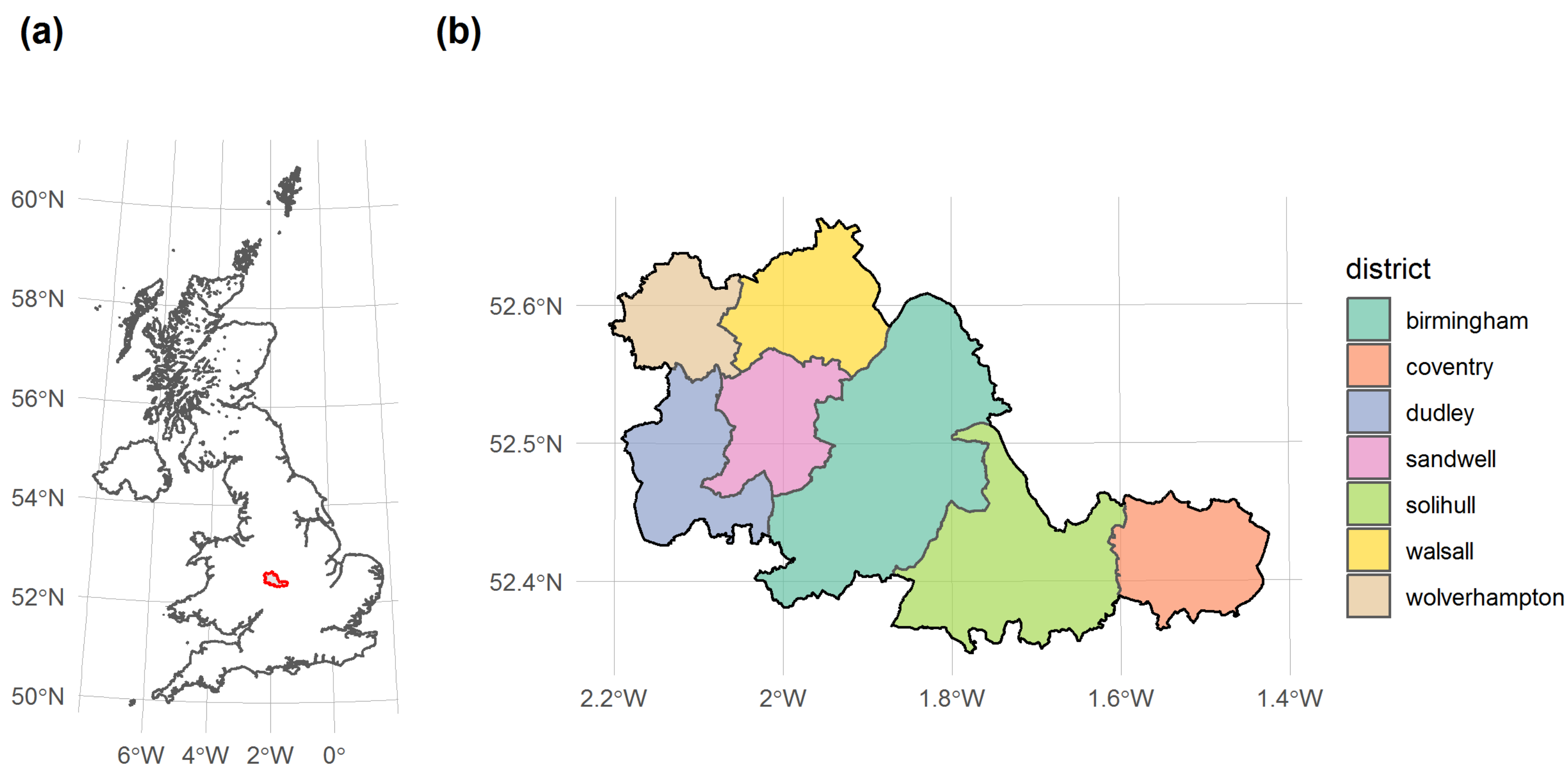

Figure 4.1: Maps showing (a) boundaries of West Midlands in the United Kingdom (in red), and (b) districts comprising the West Midlands region

Given these reasons for choosing a specific city in the West Midlands, a decision was made to select Birmingham. Not only is this the largest urban area, but it is also geographically central in the region, bordering four other districts (Walsall, Sandwell, Dudley, Solihull). This would allow further research to examine the extent to which offender residence concentrations, and associated phenomena, such as their behavioural spaces, are indeed subject to district boundaries. Choosing Coventry, for instance, would limit such examinations with the same data in the future, as it sits somewhat isolated in the West Midlands, with most of its boundaries being shared with areas outside of the data span (see Figure 4.1).

Birmingham

Birmingham is largest city in the metropolitan county of the West Midlands. It is spread over 268km squared and contains 1.1 million residents, served by West Midlands Police Force. Birmingham has a disproportionately high number of deprived areas compared to the rest of England. Figure 4.2a visualises the Index of Multiple Deprivation (IMD) for 2011 at Lower Super Output Area level (outlined later), using deciles for England, demonstrating the disproportionate number of high deprivation deciles in the city. It is one of the most ethnically diverse cities in the country, with around 53% of the resident population identifying as White British (Wessendorf, 2019). Although Birmingham is densely populated, it contains a number of parks and satellite towns in the north (e.g. Sutton Coldfield), a main university to the south with a number of green spaces, and an international airport which sits in Solihull, just outside official city limits (see Figure 4.2b).

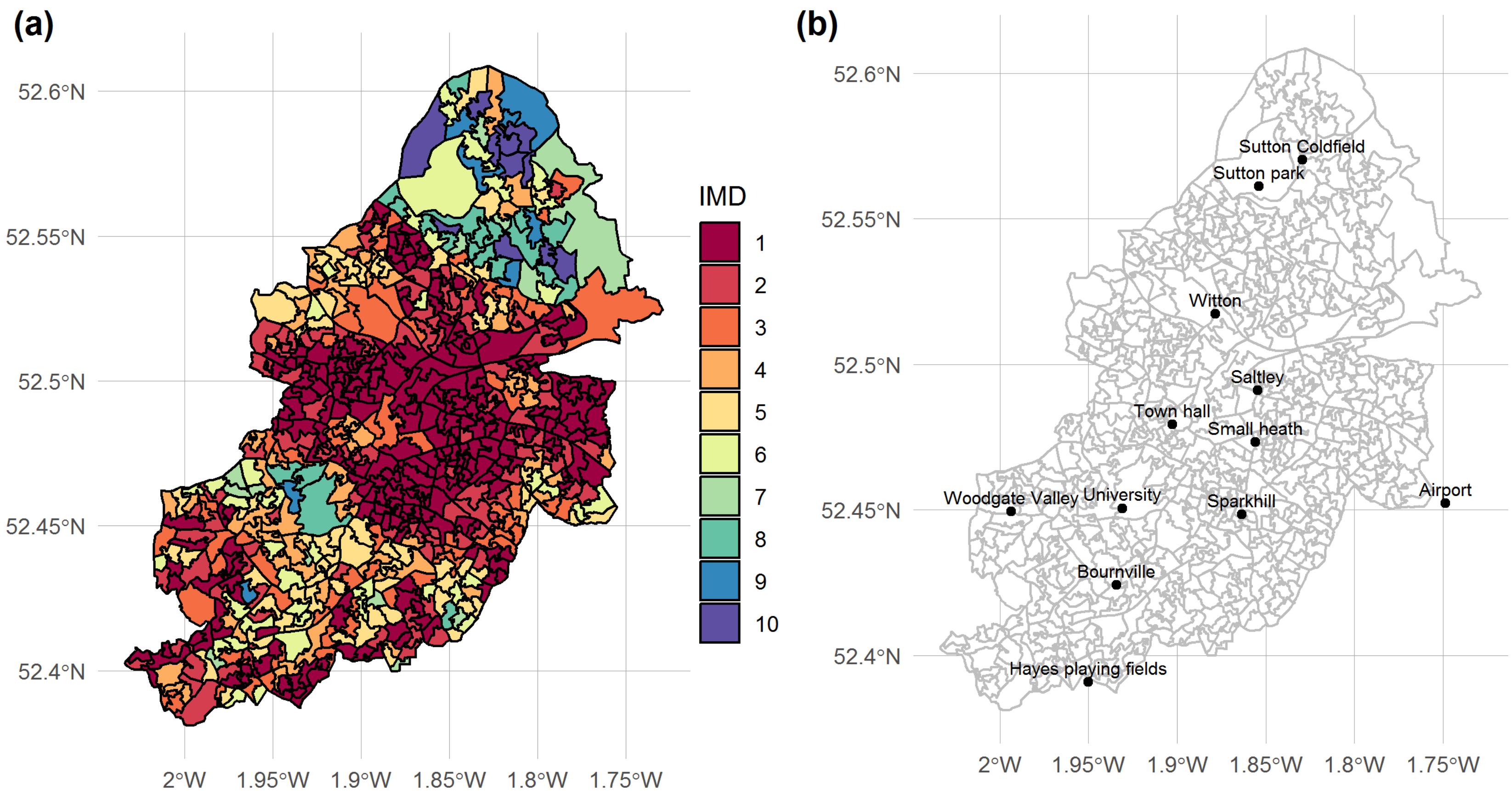

Figure 4.2: Maps showing (a) Index of Multiple Deprivation deciles for England at Lower Super Output Area level in Birmingham (1-most deprived, 10-least deprived), and (b) key points of interest in and around Birmingham with Lower Super Output Area boundaries

4.3 Spatial scales

A fundamental theme introduced in Chapter 2 related to the geographic units of analysis used in spatial criminology. It was outlined how the spatial scale at which offender residence and offence concentration research is conducted has become increasingly fine-grained over time, starting with the large nationwide regions and counties of the 19th Century pioneers, to the neighbourhood-level Chicago School, through to the contemporary focus on micro-places such as street segments. Chapter 3 discussed how recent attempts have been made to empirically demonstrate the suitability of using micro-places to study crime, showing that the use of such units can unmask variation that would otherwise be hidden by larger units. With no such evidence for offender residence concentrations, the first research question was posed ('What is the most appropriate unit of analysis to study offender residential concentrations?'). But, to even debate the theoretical or empirical merits of different units of analysis, one needs a selection to choose from, for which a number of considerations have to be made.

4.3.1 Considerations of spatial scale

Firstly, the units of analysis considered must be theoretically relevant. Social disorganisation theory, as the key framework for studying offender residence (and subsequently offence) concentrations, was originally considered to manifest at neighbourhood-level in Chicago, defined as bespoke square-mile units or merged census tracts (Shaw, 1929; Shaw & McKay, 1942/1972). Since then, studies examining social disorganisation have tended to conduct analysis at the 'neighbourhood' level, although as was made clear in Chapter 3, this can be operationalised in countless different ways, largely dictated by the administrative units of the study region's country. Despite this, recent studies promoting micro-places have argued that street segments are a theoretically relevant spatial scale at which social disorganisation can operate. The physical proximity of residents on each street segment and shared 'daily rhythms' make them meaningful behaviour spaces in which residents can make a joint effort to deter delinquent behaviour (Weisburd, Groff & Yang, 2012; Taylor, 1997; Weisburd, 2015). That said, street segments are defined as "the two block faces on both sides of a street between two intersections" (Weisburd, Bushway, Lum & Yang; 2004, p. 290) rendering them a

North American-centric unit of analysis. As noted previously, in non-grid-based countries like Britain there is immense variation in the length of street segments. This variation would weaken any argument that the spatial scale was theoretically relevant, since it would rely on the assumption that social disorganisation manifests uniformly across spatial scales which vary not just in geographic size (i.e. length), but also vary considerably in their resident populations.

With this in mind, secondly, the choice of spatial scales must still be sufficiently small to acknowledge recent research which emphasises the use of micro-places such as street segments. Street segments might not be theoretically relevant in the British context, but there are empirical reasons to use such small units, since they uncover variation which would be hidden by using larger aggregations. Although the key study that demonstrated this for offence concentrations used street segments at the lowest level of aggregation (see Steenbeek & Weisburd, 2016) it has also been replicated using synthetic area-based micro-scale geographies in Sweden, where street segments are also considered inappropriate due to the irregular street network (Gerell, 2017). That said, synthetic units designed with no consideration to population characteristics, such as regular grids (see Rosser, Davies, Bowers, Johnson & Cheng, 2017), can lack theoretical meaning when conducting explanatory analysis, as it is implausible that social disorganisation would manifest at geographies which bear no relevance to physical features on the ground or the social characteristics of resident populations.

Thirdly, units need associative data which can be used to construct theoretically relevant independent variables. The research questions for this project have been designed to flow linearly, so that once an appropriate unit is selected (RQ1), and stability modelled (RQ2) the degree to which we can explain what has been observed can be investigated (RQ3). As such, associative data must be available at all levels of aggregation considered in RQ1. This data would also need some degree of temporal lag, whereby the independent variables have been measured before the dependent variable (see Blossfeld, Rohwer & Schneider, 2019; Blossfeld & Rohwer, 1997). This temporal lag is discussed later in the chapter. The need for associative data is another reason why the use of synthetic units such as grids is inappropriate, since theoretically relevant data, such as resident population characteristics, tend to only be collected at specific administratively-defined geographies, and not at the point level.

Census blocks

Given these criteria and associated discussions, a decision was made to use a selection of three spatial scales which represent statistical building blocks for England defined by the Office for National Statistics (ONS). In order of decreasing size, these are: Middle Super Output Areas (MSOA), Lower Super Output Areas (LSOA) and Output Areas (OA). There are three principle reasons for this decision which relate to the discussion above. Firstly, these units can be considered to be a theoretically meaningful unit of analysis for examining and explaining offender residence concentrations. They are purposefully designed to contain socially homogeneous populations and have boundaries with are consistent with significant physical attributes on the ground, such as major roads (Cockings, Harfoot, Martin & Hornby, 2011). As such, they are considered to be a reasonable approximation of micro-neighbourhoods at which social disorganisation can manifest as an explanation for the spatial patterning of offender residences. Secondly, the lowest spatial scale in this selection, Output Areas, contain resident population sizes which are comparable to existing micro-scale research using street segments. Street segments contain around 99 street addresses each (Weisburd et al., 2004) and Output Areas contain approximately 125 households each (ONS, 2019). Thirdly, census data is collected and published by the ONS at all three levels. This means that irrespective of which unit is selected following analysis to answer RQ1, theoretically-relevant independent variables can be constructed and used in models for RQ3. An added benefit of using MSOA, LSOA and Output Areas is that they are geographically nested, which means a systematic comparison can be carried out in alignment with existing research relating to offences, as outlined in the methods section of this chapter.

The boundaries for Output Areas, LSOA and MSOA are defined at each census year. The most recent census years were 2011 and 2001. The smallest scale, Output Area, is the lowest building block from which LSOA and MSOA are created. They were first introduced for the 2001 census. As noted, boundaries were drawn up to reflect socially homogeneous populations and reflect major physical features on the ground. As outlined above, this design is key to the theoretical dimension of offender residence concentration research. To maintain these important characteristics for the 2011 census, some changes were made to the boundaries. For the 2001 census, Birmingham city had 3127 Output Areas but for 2011 this was increased to 3223 following a number of splits, merges and fragmentations between existing boundaries.

A total of 3032 Output Areas remained unchanged between 2001 and 2011, so when changes are made, it is usually only when necessary, with most remaining unaltered. That said, a decision has to be made as to which boundaries to use when aggregating the offender residence data. With the 2011 census falling in the middle of the police recorded data between 2006/07 and 2015/16, these latest boundaries were deemed the most appropriate, as they were designed to reflect the populations and physical environment during the 10 years in which the offender data was recorded. Each of these spatial scales are visualised in Figure 4.3a-c to demonstrate the difference in geographic scales, and nested structure. We return to the 2001 and 2011 boundary changes when discussing the census data in subsequent sections.

Visualisation

When generating spatial visualisations for examining offender residence concentrations, questions can be raised over the suitability of using raw geographic boundaries as defined by the ONS. Firstly, as demonstrated in Figure 4.3a-c, the large variation in size and shape of original boundaries can render some areas almost invisible, with larger areas dominating the map, especially for LSOA and Output Areas. Smaller areas are barely legible. This is a recognised problem when visualising area-based data using choropleth maps (see Harris, Charlton, Brunsdon & Manley, 2017). Secondly, the use of fine-grained spatial scales can introduce issues around the anonymisation of data. Open crime location data for recent years in England is available publicly (through www.police.uk) and is accurate down to LSOA level (see Tompson, Johnson, Ashby, Perkins & Edwards, 2015). However, offender residence data is more sensitive, and is not available publicly, even at larger spatial scales. Publication of any data provided by West Midlands Police is subject to their review, and thorough precautions were taken throughout the project to ensure that work aligned with the Information Sharing Agreement. Presentation of ongoing work necessitated some additional consideration on how potentially sensitive data could be visualised geographically.

Given these concerns, methods were examined which would allow geographically accurate visualisations of offender residence concentrations to be mapped out, remedying issues arising from the large variation in sizes and shapes, and at the same time providing a degree of anonymisation. A decision was made to deploy a 'hexogram', which uses an iterative binning algorithm to assign the centroids from a balanced cartogram to tessellated hexagons (see Harris, Charlton & Brunsdon, 2018). This method has been shown to transform irregularly sized and shaped polygons into regular shapes which minimise misrepresentation in area-based spatial data visualisations (Langton & Solymosi, 2019). Key characteristics of the data, such as spatial clustering, can be conveyed to readers more effectively using hexograms than with original raw boundaries. That said, the amount of distortion that the method introduces was considered to provide a level of anonymisation to the data compared to mapping the original boundaries. To this end, the specifics of how the hexograms were created (e.g. the number of bins used) is not reported, although open code for more generic use is publicly available (Harris, 2017). Any maps visualising offender residence concentrations, or related demographic data, in this thesis will do so using these hexograms. The associated hexograms for each spatial scale are visualised in Figure 4.3d-f.

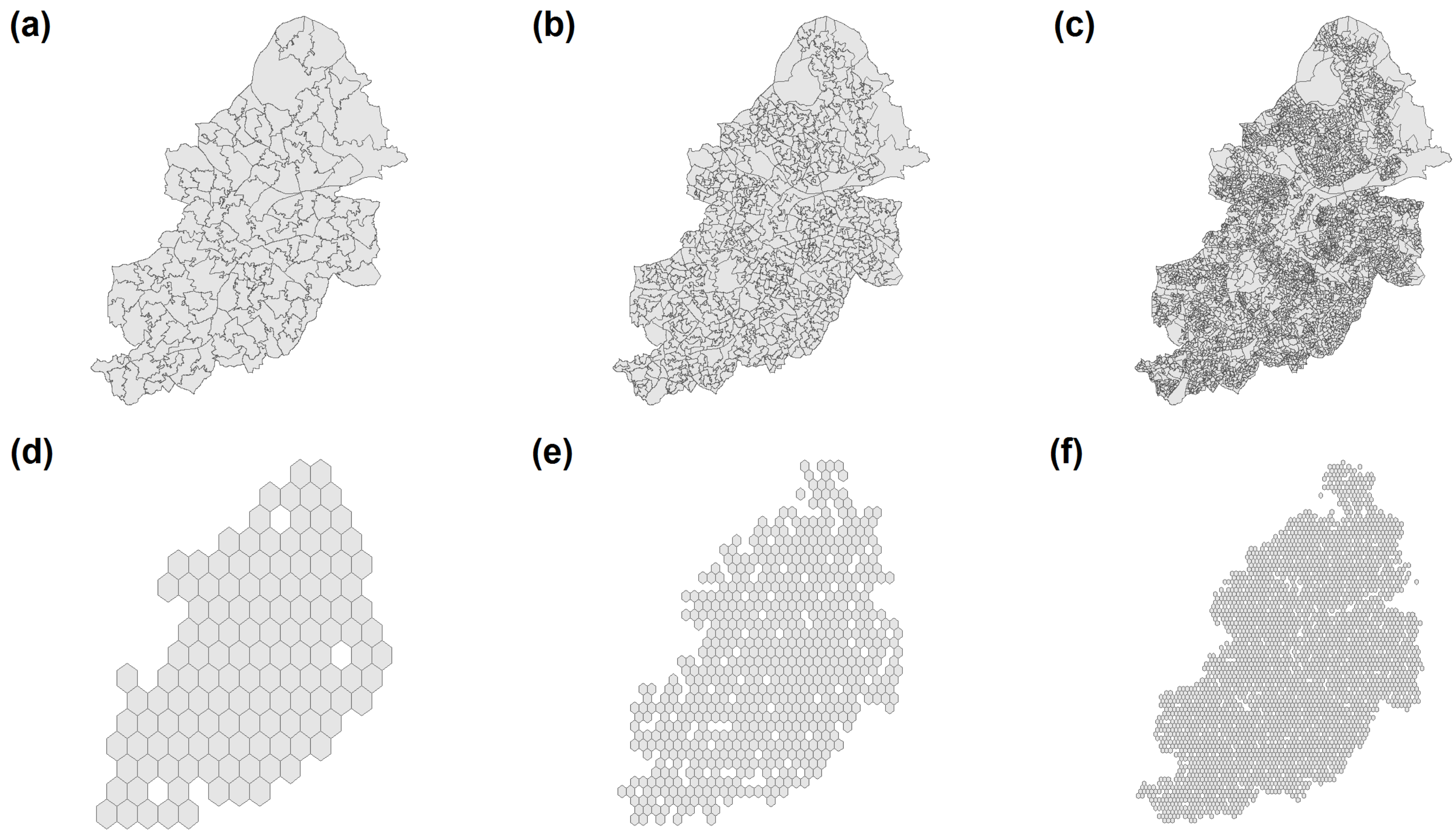

Figure 4.3: (a) MSOA original, (b) LSOA original, (c) OA original, (d) MSOA hexogram, (e) LSOA hexogram, (f) OA hexogram

4.4 Socioeconomic data

The primary variable of interest for the questions of spatial scale (RQ1) and longitudinal stability (RQ2) is constructed using the offender data from West Midlands Police, as outlined above. The question of explanation (RQ3) necessitates theoretically relevant associative information that can be linked to the offender data, once aggregated to a suitable spatial scale, for the purposes of constructing independent variables and running explanatory models. As outlined in Chapters 2 and 3, the primary theoretical framework for this study is social disorganisation theory. Ideally, existing studies would make use of bespoke surveys to measure the causal mechanisms of social disorganisation (e.g. Steenbeek & Hipp, 2011), where questions are specifically designed for the purposes of the research project, and constructs generated with statistical reliability and validity (Wikstrom, Oberwittler, Treiber & Hardie, 2012). The expense of such surveys prohibits their usage, and in alignment with most previous research (see Chapter 3), this project makes use of pre-existing census data which contains direct measures, or proxies for, theoretically relevant variables.

4.4.1 Census data for England and Wales

Census data was considered appropriate for three main reasons. Firstly, the census for England and Wales contains variables that were deemed to be theoretically relevant as per the review of previous studies examining offender residence concentrations in Chapter 3. Further detail on these variables is provided later. Secondly, the ONS publish census data at spatial scales which are theoretically appropriate for examining the manifestation of social disorganisation, as outlined above. Thirdly, census data is freely available for download via the ONS website and is subject only to the Open Government Licence, which does not restrict its uses for such projects.

4.4.2 2001 or 2011: a note on causation

The census for England and Wales is currently conducted every decade, with the latest years being 2001 and 2011. This has important implications for how the explanatory model is designed and appropriate independent variables constructed. Any case made for a causal association between socially disorganised communities and high offender residence rates, like any argument for a causal relationship, demands a temporal lag. In other words, the supposed cause must precede the effect in time (Blossfeld & Rohwer, 1997). In Chapter 2, issues surrounding the use of aggregated data were discussed, for instance in terms of the limitations this brings when drawing inferences about individual behaviour. Such issues are an inevitable consequence of using aggregated data, and can be avoided through careful interpretation of results. The temporal lag is one we can actually attempt to address with data.

The police recorded data on offender residences runs from 2006/07 to 2015/16. As discussed in more detail in the following section, this data will be simplified into a single categorical variable using longitudinal clustering, which will then become the dependent variable in a regression analysis. Thus, using the 2011 census data to predict a dependent variable which represents information pre-2011 (as it would, from 2006/07 to 2015/16) would be problematic. The alternative would be to calculate a composite variable of 2001 and 2011 census data, which represents some degree of change between the census years. Whilst there are specific differences in both census questions and boundaries between 2001 and 2011, there are methods of making the two years comparable, discussed later in this chapter. However, a meaningful measure of change (e.g. percentage change) in variables between census years is problematic in circumstances where there are zeros in either years, which is common for many census data variables. It can also produce misleading measures (e.g. the number of overcrowded households increasing from one to two would be measured as a 100% increase).

For that reason, data was chosen from the 2001 census. Consequently, the independent variables obtained from the census have a temporal lag of four years before the first year of the offender residence measurement. This was considered to be theoretically plausible, given the slow pace with which the causal process of social disorganisation is said to manifest (Griffiths & Chavez, 2004). It is worth acknowledging that there has been no theoretical argument for a specific time lag which is theoretically justified. Four years is a longer temporal lag than other studies which sought to predict offender residence rates with demographic data, for instance one year (Bruinsma et al., 2013) and two years (Ouimet, 2000). The 2001 census and the variables used from it are now outlined in turn.

4.4.3 2001 census data

Every household receives a census questionnaire through the post, and completion is mandatory, with non-compliance considered a criminal offence and subject to a fine. As such, the completion rate is high, with 94% of households estimated to have returned a completed survey in 2001. Questions contain a combination of household and individual-specific questions. Data is available through download on the NOMIS website which provides official labour market statistics from the ONS. Individual and household data is not publicly available for reasons of confidentiality, so statistics are published aggregated to a number of spatial scales (including MSOA, LSOA and Output Area) either as counts or proportions of the total number of individuals or households in each spatial unit.

The explanatory variables collated from the census were selected *a priori* with consideration to the hypotheses derived from theory and previous research in Chapter 3. Existing research covered thus far has tended to conduct their analyses similarly, with model selection being theoretically-driven and deductive. This approach lends itself to parsimony, often considered preferable in the interests of avoiding unnecessary complexity and making results better suited for wider communication (Kass et al., 2016). Indeed, this is an approach used in important studies in spatial criminology, in which "[they] refrained from using too many variables from the social disorganisation model in order to avoid statistical modeling complexity and to respect principles of conceptual clarity and parsimony" (Ouimet, 2000, p. 138-139). With this in mind, the variables chosen from the 2001 census to answer research question 3 (explanation) are now outlined in turn. Broadly, the main independent variables are those which measure the concepts introduced within the social disorganisation theory framework, relating to ethnic diversity, residential turnover and deprivation. Each of these variables can be generated using data aggregated to MSOA, LSOA or Output Area level.

4.4.4 Explanatory variables

Ethnic diversity

To measure the degree to which offender concentrations might be explained by ethnic diversity, as per existing research testing social disorganisation theory, information was needed on the ethnicity of individuals by each spatial scale. In the 2001 census individuals were asked 'What is your ethnic group?' followed by a selection of multiple-choice answers (e.g. White British, Mixed White and Black Caribbean). A measure for ethnic diversity was calculated using the Simpson's Index, commonly used to measure the degree of biodiversity in ecology research (see Hunter & Gaston, 1988). The related Blau-Herfindahl index has been used to explain (cross-sectional) offender residence concentrations within the social disorganisation framework previously (e.g. Bruinsma et al., 2013). As there is some discussion over the suitability of different diversity measures (see Oksanen, 2019) another measure was generated, namely Pielou's evenness (Pielou, 1966), which is a measure of evenness in the numbers of each ethnic group. There was a high correlation (~0.9, $p < 0.05$) between these measures, therefore for some degree of consistency with existing research (see Chapter 3), the Simpson's index was chosen for analysis.

Residential mobility

Capturing the extent of residential mobility proved more problematic. Direct measures of residential mobility tend to be constructed from survey data (e.g. Tunstall, Shortt, Pearce & Mitchell, 2015) or at larger census aggregations than the lowest in this study. Although in 2001 the question 'What was your usual address one year ago?' is asked, raising prospect of an estimation of how long residents have lived in that particular area, the question appears to be used only to help estimate the usual resident population. As such, a proxy measure was used in the form of household tenure data. This relies on the assumption that areas with a high proportion of rented accommodation were characterised by higher residential mobility, compared to say those with a high proportion of owner-occupied households. Heads of household were asked 'Does your household own or rent the accommodation?' which then sends respondents to more specific questions based on their initial answer. NOMIS release the numbers and proportions of households per spatial scale based on their tenure (e.g. owned outright, owned with a mortgage, privately rented). The proportion of households which rent their property through any means (including private and social housing) could be calculated from the raw data. The variable constructed was the proportion of households that rented accommodation in any form. This variable was also considered to reflect the interest in household tenure highlighted in Chapter 3.

Deprivation

As demonstrated in Chapter 3, variables measuring deprivation have varied considerably in previous research. A number of measures have been designed specifically at census block level to gauge poverty in England. One of the most widely used is the Index of Multiple Deprivation, which captures numerous dimensions of poverty rather than relying on one single variable from the census. Unfortunately, the measure is not available at Output Area level, which would be problematic should investigations into spatial scale (RQ1) suggest it as the most suitable. A composite variable, the Townsend Index, can be calculated using data available at Output Area level, but one (of the four) measures used in the Townsend Index uses household tenure data, which conflicts with the residential turnover variable outlined above. One variable in the index, overcrowding, holds some consistency with existing research highlighted in Chapter 3, and thus a decision was made to use this variable in isolation. A variable was constructed to reflect the proportion of households which were overcrowded, defined as there being more occupants than there are rooms (Yousaf & Bonsall, 2017).

4.4.5 Control variables

Risky population

As per Chapter 3, a control variable for risky population was created based on the age composition of each unit. For the 2001 census, individuals who reported being aged between 15 and 24 were deemed to be the most high-risk age group. As such, a proportional measure representing the percentage of residents aged 15 to 24 by spatial scale could be generated.

Spatial lag

A key assumption of parametric models used in this study, outlined in the next section, is that observations are independent of one another. In geographic terms, especially when using fine-grained units of analysis, this assumption is highly likely to be violated, as spatial units within close geographic proximity tend to have similar levels of criminal activity i.e. positive spatial autocorrelation (Curman, Andresen & Brantingham, 2015; Steenbeek & Weisburd, 2016; Bannister et al., 2017). This tends to be controlled for using a spatial lag variable which represents some measure of crime (or in this case, offender residences) for spatial units either neighbouring each observation, or within a certain pre-defined distance. For instance, Weisburd and colleagues (2014) deployed multinomial logistic regression to predict a categorical outcome variable (representing longitudinal crime trajectories), and used the average crime count of street segments within a quarter of a mile of each observation as the spatial lag. More recent research has reported using a spatial lag but have not specified how it was constructed (e.g. Favarin, 2018).

Using area-based spatial data, such as the census blocks in England (Output Area, LSOA and MSOA) the neighbours of each spatial unit can be identified, and a spatial lag calculated from the values (e.g. mean offender rate or relative proportion) of these neighbouring observations. Neighbours can be attributed to each unit based on certain criteria, the most common being 'queen', whereby polygons are considered neighbours when either a corner or side is touching. This is opposed to the 'rook' definition, whereby only shared sides (not corners) count as being a neighbour. Here, the spatial lag is created with an adjacent weight matrix using queens (as per Bruinsma et al., 2013), with each observation being attributed with the average 2006/07 relative proportion of total offenders (a measure outlined later) of its neighbours. Part of the preliminary results will be to assess the degree to which the data is actually spatially autocorrelated at each spatial scale, to demonstrate the positive spatial autocorrelation in the data. The spatial lag would only be appropriate if there was some reasonable degree of spatial autocorrelation.

4.4.6 Additional explanatory variables

A number of additional variables were collated for additional descriptive analysis relating to population flows, in the spirit of Kirk (2019), discussed later. These include the full Townsend Index and the Output Area Classification.

Townsend Index

As noted above, the Townsend Index is a composite variable available at Output Area level, but also larger aggregations including LSOA. It is comprised of four variables from the census, namely: the percentage of people who are economically active but unemployed, percentage of overcrowded households (as above), percentage of households that do not own a car or van, and the percentage of households that are not owner-occupied. These variables are standardised and then summed together, producing an equally-weighted composite measure of deprivation (Yousaf & Bonsall, 2017). For use in this thesis, the score is categorised into English deciles, in a similar manner to the Index of Multiple Deprivation. The index is used in isolation from the explanatory models, to avoid the overlap with household tenure, and instead deployed for a descriptive demonstration of the spatial relationship between deprivation and offender residence population flows between 2006/07 and 2015/16, as outlined in the analytical strategy. For that reason, the Townsend Index constructed from 2011 census data is used.

Output Area Classification

The Output Area Classification (OAC) is a much broader socio-economic classification generated through the clustering of areas based on the similarity of a number of census data attributes. The outcome is a variety of groupings ranging from the most simple 'supergroups' (eight categories), within which are nested the more detailed 'groups' and 'subgroups'. In the interests of simplicity, only supergroups are used for descriptive analyses, which consist of: rural residents, hard-pressed living, cosmopolitans, ethnicity central, multicultural metropolitans, urbanites, constrained city dwellers and suburbanites. It is beyond the scope of this review to outline the full details of how these supergroups were constructed, but full details are publicly available (see Gale, Singleton, Bates & Longley, 2016). It is worth acknowledging that these classifications were not used to test a theoretically-driven hypotheses, but more to demonstrate the residence population flows, inspired by Kirk (2019), using the offender data from 2006/07 to 2015/16. As such, just as with the Townsend Index, the OAC from the 2011 census is used. This is covered in more detail within the analytical strategy.

4.4.7 Boundary changes

As stated in previous sections, the offender residence data provided by West Midlands Police covered April-March for the years 2006/07 to 2015/16 (10 years). Thus, the offender residence point data was aggregated to spatial scale boundaries designed for the 2011 census. With 2001 census data largely being chosen for explanatory variables, for reasons of a theoretically plausible temporal lag (with the exception of the Townsend Index and OAC for descriptives), the boundary changes between 2001 and 2011 now present a major problem. Before attempts were made to resolve this issue, analysis was carried out to answer the question of spatial scale (RQ1). It would not be worthwhile resolving the boundary discrepancies for all three spatial scales when only one would be used for answering RQ3 (explanation), remembering that RQ2 (stability) only requires 2011 boundaries in isolation. Full results of the spatial scale selection analyses are reported in the following chapter, but for now, it is important to note that this analysis indicated that Output Areas would be the most suitable scale. As such, the boundary differences between 2001 and 2011 were resolved at this level of aggregation.

The crude way of dealing with this would simply be to use a sample consisting of only the Output Areas which were completely unchanged between 2001 and 2011. However, an attempt was made to maintain as many Output Areas as possible by transforming the 2001 census data in a manner which rendered it usable with 2011 boundaries. There were three fundamental changes that occurred within the Output Areas which do not match: merges, split and fragmentations. Merges occur when two Output Areas from 2001 are combined to form one Output Area in 2011. Splits are the opposite: an Output Area from 2001 is split up into two or more Output Areas for 2011. Fragmentations are more complex, whereby parts of an Output Area might have been merged and split (see Singleton, 2013).

Merges (of which N = 52) were resolved by simply summing the raw 2001 data (i.e. counts by individuals, households) for the merged Output Areas before calculating the measures outlined above (e.g. ethnic diversity). Split Output Areas (of which N = 173) were made comparable through an area-based transformation, whereby the raw data was apportioned to the new 2011 boundaries based on the proportion of areal overlap. For instance, if a 2001 Output Area was split into two new 2011 Output areas, one of which comprised 80% of the geographic area of the original, and the other 20%, the raw data would be apportioned accordingly. New measures would be approximations and rely on the assumption that households were equally distributed across the original Output Area. However, it was considered to be preferable to dropping these observations altogether. The only two fragmented units, and one split unit, were dropped from the explanatory analysis, due to their complexity in making the transformation. However, overall this meant that 3220 (out of a potential 3223) Output Areas were retained.

4.5 Methods

4.5.1 Background

Given the data available, the focus then turns to what methods will be deployed to answer the three main research questions of this project relating to spatial scale, longitudinal stability and explanation. The research questions have been designed to flow linearly, so that the answer to one informs the next. First, the most appropriate scale will be selected following a replication of methods deployed in the offence strand of literature. These methods include basic descriptive statistics and visualisations, as well as more complex model-based analysis which have been deployed in crime research. Secondly, the degree of longitudinal stability in offender residence concentrations will be examined using longitudinal clustering. Following the discussions in Chapter 3, which identified a number of flaws in existing methods for crime, two methods will be deployed here, one existing implementation of k-means, and a novel technique termed anchored k-medoids, which was developed as part of this project. In doing so, a methodological contribution is made in the process of answering the question of longitudinal stability by contrasting the results of the two methods. Thirdly, and finally, potential explanations for what has been observed are explored. This begins with descriptive visualisations of offender residence population flows, followed by explanatory models using the theoretically-driven independent variables, and a dependent variable generated through the k-means and ak-medoids analysis. Running the explanatory models on outcomes generated by both clustering methods also offers some methodological contribution through a contrast of the explanatory power of results.

These three components comprise the overall analytical strategy of this project, and this section will consider each in turn. Particular attention is paid to anchored k-medoids, as this is an entirely new method, whereas the other methods have been used elsewhere, some of which in the crime strand of literature. That said, we will begin with a descriptive demonstration of how offender residence and crime concentrations are empirically distinguishable in Birmingham using the data provided by West Midlands Police Force. As outlined in Chapter 2, there is strong theoretical reason to consider offender residences and crime concentrations as distinct (but related) phenomena. Although there has been some demonstration of this through the journey to crime literature, it was deemed useful to provide a case study showcase for the data being used specifically for this project. With this in mind, analytical strategies are now detailed in turn in relation to the empirical distinction between offender residences and crimes, spatial scale (RQ1), longitudinal stability (RQ2) and explanation (RQ3).

4.5.2 Offenders and crimes: the empirical distinction

Before a thorough examination of our three key themes begins, a number of descriptive statistics and visualisations are presented which demonstrate the empirical distinction between the spatial patterning of offender residences and crime in Birmingham during the study period. The descriptives and visuals reported are carried out on all potential spatial scales (MSOA, LSOA, Output Area). This is to highlight one of the concerns raised in Chapter 2, namely, that findings (or assumptions) suggesting that crimes and offenders are empirically synonymous may well be sensitive to the spatial scale used. Here, the implications of aggregating across crime types might be salient, and this is returned to in the discussion chapter. The analytical strategy is as follows.

Analytical strategy

1. Tabular summary of Spearman's rank correlations between offender residence and crime rates (resident population adjusted) for each year from 2006/07 to 2015/16 and each spatial scale (MSOA, LSOA, Output Area).

2. Local Moran's I is deployed and visualised to compare the spatial clustering of offender residence and crime rates for an example year (2010/11) at each spatial scale. This method is a Local Indicator of Spatial Association (LISA) (see Anselin, 1995) widely used in spatial fields, including spatial criminology (e.g. Bannister et al, 2017), to gauge "the extent of significant spatial clustering of similar values around an observation" (Brunsdon & Comber, 2015, p. 255). It can also highlight where dissimilar observations cluster. Using the 'queen' continuity to define neighbourhoods, as noted earlier, we can categorise each observation as a core of High-High (high value surrounded by other high values), Low-Low (low value surrounded by other low values), High-Low (high value surrounded by low values) or Low-High (low value surrounded by high values). It includes a test for statistical significance of the null hypothesis that there is no spatial association between the observed value and the values observed in

surrounding areas (see Anselin, 1995; 2019). Pairs of maps comparing offender residence and crime spatial cluster patternings are visualised for each spatial scale using hexograms (see above), although the Local Moran's I analysis itself was deployed on the original spatial boundaries.

3. As an aggregate-level descriptive of the journey to crime, tabular descriptive statistics are reported on the proportion of crimes committed in an offenders' home neighbourhood, defined as either MSOA, LSOA or Output Area. One might speculate as to whether this proportion goes up with the size of spatial scale.

4. Disaggregated tabular descriptives on the journey to crime are reported, including the minimum, maximum, interquartile range, mean and standard deviation of the distance traveled in metres from offender residence to crime location, for each year of the study period from 2006/07 to 2015/16.

5. As a visual descriptive of the disaggregated journey to crime, a density distribution is plotted for each year.

4.5.3 Research question 1

As noted earlier, the choice of spatial scale will be made from England census statistical building blocks, namely, Middle Super Output Area (MSOA), Lower Super Output Area (LSOA) and Output Area (OA), outlined in previous sections. As discussed in Chapter 3, a number of different methods have been deployed in the crime concentration strand of research to examine the impact of spatial scale, and in doing so, have generated a substantial evidence-base to support the usage of fine-grained aggregations. To date, no attempt has been made to deploy these methods in unison for offender residence concentrations, despite their transferability. With this in mind, the analytical strategy has been designed to purposefully replicate contemporary approaches to examining spatial scale in the crime strand.

Analytical strategy

1. Report descriptive statistics which demonstrate the degree to which offender residences are concentrated at each spatial scale. As outlined previously, the evidence-base supporting the law of crime concentration primarily consists of descriptive statements about the proportion of units accountable for 25% and

50% of citywide crime (see Weisburd, 2015). When reported for multiple nested spatial scales (e.g. Schnell et al., 2017), as we have for MSOA, LSOA and Output Area here, these figures can give an indication to what extent offender residences concentrate at each scale respectively. The scale at which offender residences concentrate *most* will be considered a more suitable candidate for the unit of analysis in subsequent research questions, to ensure that the maximum level of detail is being unmasked in spatial patterns, as per existing research (see Chapter 3).

2. Visualise example Lorenz curves for offender residence concentrations at each spatial scale. This visualisation provides a more flexible interpretation of concentrations compared to the arbitrary thresholds (e.g. 25% and 50%). Gini coefficients can then plotted for each to provide a quantitative representation of the Lorenz curve. As such, the degree to which offender residences are concentrated at each spatial scale can be compared between units, but also across years. Concerns over the line of maximal equality (see Chapter 3) were considered, but were not deemed an issue, so standard Lorenz/Gini calculations are used[1]. Again, the scale at which concentration is highest will be considered the most suitable.

3. Report results from a multilevel variance partition analysis, whereby the proportion of variance in offender residence concentrations attributable to Output Area, LSOA and MSOA is estimated and visualised for each year. Analysis will be ran using a bootstrapped, stratified sampling technique similar to the original paper which adopted this approach for crime (see Steenbeek & Weisburd, 2016) to address issues surrounding statistical assumptions, namely, that observations are independent of one another and that the sample is randomly selected. For computational ease, separate cross-sectional models will be run for each year, using 500 random samples, each consisting of 50% of Output Areas per LSOA. From across these 500 samples, the mean and median variance estimates will be calculated, and reported as proportions of total variance for each spatial scale for each year.

[1]This is because, in the Birmingham offender data, the number of observations (i.e. units of analyses) is small enough not to exceed the number of offenders. Even at Output Area level, there are always more offenders than there are observations, and thus the line of perfect equality is not problematic.

4.5.4 Research question 2

Background

As outlined in Chapter 3, longitudinal clustering methods have been widely deployed to examine the degree of stability in crime concentrations over time. The most common method has been group-based trajectory modelling (GBTM), with k-means recently emerging as a viable alternative, benefitting from more relaxed statistical assumptions. In response to shortcomings, highlighted in Chapter 3, relating to k-means' sensitivity to outliers and short-term fluctuation, a novel extension of the technique, termed anchored k-medoids (ak-medoids), is introduced here. The method has been designed as part of this project for comparable deployment in the crime concentration new wave literature, as a clustering technique which is robust to outliers and short-term fluctuation, instead prioritising the identification of clusters characterised by long-term directional homogeneity (see Adepeju, Langton & Bannister, *under review*). Used in concert, it is argued that k-means and ak-medoids can offer a comprehensive picture of the longitudinal stability of offender residence concentrations.

Ak-medoids updates two important components of k-means: the initialisation procedure and the expectation-maximisation stage. The default implementation of k-means, which has been used thus far in spatial criminology (Curman et al., 2015; Andresen et al., 2017), uses a generic random initialisation to define centroids, the number of which is defined by the researcher. The use of random starting points in crime concentration research means that researchers are letting the patterns emerge from the data in an entirely exploratory way. Computing bespoke, data-driven initialisation points has been shown to optimise the final cluster solution and provide greater computational efficiency compared to random initialisations using synthetic data (Bradley and Fayyad, 1998; Su & Dy, 2004). However, no such approach has been used for examining offender residence trajectories. Normally, during the expectation-maximisation stage, the centroid of each cluster is calculated during iteration based on the mean, which is sensitive to outliers, and uses a distance-based algorithm of the trajectory, unlimited by polynomial terms, making it sensitive to short-term volatility. In order to derive clusters characterised by directional homogeneity, which are robust to outliers and short-term fluctuations, ak-medoids takes a new approach using a bespoke initialisation procedure (informed by a trajectory approximation) and expectation-maximisation stage.

Trajectory approximation

Linear Ordinary Least Squares (OLS) regression lines are first fitted to the trajectory of each observation, having dropped the initial intercept. This enables subsequent focus on the varying directional change of a trajectory over time, ignoring intermittent short-term fluctuation, relative to a reference direction. These estimates provide the basis from which the non-random initialisation points can be calculated.

Non-random initialisations

The estimated regression lines are then ordered according to the direction and steepness of their slopes. Once done, the estimates are partitioned equally across an intended cluster solution, determined by the researcher. The median trend lines, which are medoids, of the cluster solutions are used as the 'anchors' enabling the initialisation algorithm to begin. This is termed a 'linear partition medoid' (LPM) initialisation. The purpose behind this step is to provide the algorithm with clearly delineated starting points (as oppose to the random starting points used by k-means) guided by the interest in generating clusters characterised by varying degrees of directional change (see Andresen et al., 2017), and with the purpose of ensuring that heterogeneous longer-term trends occupy different clusters.

Expectation-Maximisation procedure

Once the initial anchors have been set, Euclidean pairwise distances are computed to establish the extent of dissimilarity between each observation and the medoids. This is similar to the standard deployment of classic longitudinal k-means which uses centroids (Genolini et al., 2015), but instead of recomputing centroids as the mean distances between trend lines (which are the raw data, unlimited by approximations of the trajectory), the median trend line is selected as the next medoid. This then becomes the new anchor for the next iteration of the expectation-maximisation procedure and continues until the cluster solution becomes stable. The result is the partition of trajectories into clusters characterised by within-group directional homogeneity, but between-group heterogeneity, relative to a reference direction (the horizontal axis). The expectation is that this approach will generate more theoretically meaningful cluster solutions according to the longer-term directional change over time (e.g. Andresen et al., 2017), which have tended to be defined simply as increasing, decreasing and stable[2].

Analytical strategy

The analytical approach to RQ2 is designed to serve two purposes. The first is to examine the (in)stability of offender residence concentrations over time, in order to tackle to the research question. The second is to demonstrate the distinctions between ak-medoids and k-means, generating some discussion on their relative merits and shortcomings. Bearing in mind that the Output Area will be the chosen spatial scale, the strategy is as follows:

1. The citywide trend in known offenders will be visualised for the study period, from 2006/07 to 2015/16, to set the scene for subsequent analysis. The citywide trend becomes the reference point which will then be disentangled and unpicked through the use of k-means and ak-medoids, to establish the degree to which localised areas have experienced the citywide (macro-level) trend in unison. In doing so, both absolute (i.e. counts, rates) measures and a relative measure will be deployed. As will be demonstrated, the benefit of using a relative measure is that it permits easy interpretation of the degree to which localised areas deviate from the citywide trend, because the proportion allocated to each observation represents the percentage of offenders attributable to that unit for any given year[3].

2. A Spearman's rank correlation matrices is visualised using the offender rate for each year of the study period, comparing each year-to-year pairwise comparison. This provides a broad, quantifiable indication as to the extent of shifting instability amongst Output Areas. Crudely, should the correlation be 1 ($p < 0.05$) for each pairwise comparison, it would suggest that there

[2]The differences between k-means and ak-medoids, specifically in terms of the formers' sensitivity to outliers and short-term fluctuation, have been empirically demonstrated using simulated data in the accompanying crime concentration paper (Adepeju et al., *under review*).

[3]By way of example, a realistic scenario might be that there has been a citywide decline in the number of known offenders. Output Areas characterised by perfectly stable (flat) relative trajectories are experiencing the absolute citywide decline in unison. In other words, they are benefiting from the citywide decline equitably. Output Areas which have declining relative trajectories will have absolute trends which are *steeper* than the citywide trend, and are benefitting disproportionately from the citywide drop. Output Areas with increasing relative trajectories, are either experiencing an absolute decline which is *less steep* than the citywide fall, or conversely, are in fact experiencing an *increase* in absolute offender residence rates. Findings are reported and interpreted in Chapter 5 with consideration to both measures.

has been complete stability amongst Output Areas throughout the study period, with their rank order persisting from 2006/07 to 2015/16, even amidst fluctuations. In such a situation, there would be little point in conducting further longitudinal analysis, so although simplistic, this is important to establish before continuing.

3. Ak-medoids will then be deployed on the relative offender measure for the years 2006/07 to 2015/16. The optimal number of clusters will be determined using the Calinksi Criterion (Calinski & Harabatz, 1974) to remain consistent with research using k-means in the crime strand of research (Curman et al., 2015; Andresen et al., 2017). Ak-medoids is deployed using the *akmedoids* package in R which was developed alongside this project (Adepeju, Langton & Bannister, 2019).

4. K-means is also deployed on the same relative offender measure using the existing *kml* package in R (Genolini & Falissard, 2010; Genolini et al., 2015). This is the package reported to have been used in existing crime studies (Curman et al., 2015; Andresen et al., 2017). The Calinski Criterion will be used to establish the optimal solution, but consideration will also be given to the number of clusters found using ak-medoids, to ensure that a meaningful comparison can be made between the two methods.

5. The results for both ak-medoids and k-means will then be visualised using both relative and absolute measures of concentration. These will be produced using individual Output Area-level trajectories and median trend lines, to ensure that the characteristics of cluster solutions are reported transparently, to rectify shortcomings in previous research, outlined in Chapter 3. Moreover, descriptive statistics for each cluster, and for each method, are reported in tabular format. This will include a classification of whether the cluster is 'decreasing', 'increasing' or 'stable' for each method[4].

6. The spatial distribution of each cluster solution will then be visualised using hexograms to determine whether longitudinal relative trajectories of offender

[4]The quartile classification calculation used is comparable to that deployed in crime concentration research. Stable clusters are deemed as such "if the group slope deviated less than ±25% from the maximum slope of the citywide trend line, permitting some variability around the reference point" (Adepeju et al., *under review*, p. 12-13). Those clusters below (negative) or above (positive) this threshold are defined as declining and increasing respectively.

residences have a meaningful spatial pattern, and to determine whether these patterns vary between clustering methods.

4.5.5 Research question 3

To offer potential explanations for the longitudinal (in)stability of the offender residence concentrations observed, a number of descriptive and explanatory statistics will be reported. Firstly, in the spirit of individual-level mobility studies carried out in the United States by Kirk (2019), visualisations are reported which plot the movement patterns of known offenders throughout the study period in relation to key Output Area demographic characteristics. Part of the motivation for examining this is to understand to what extent Output Area-level fluctuations in offender residence concentrations are a result of onset/desistance of individuals, or a result of known offenders moving to and from particular areas.

Secondly, a number of theoretically-driven models will be deployed using the cluster solutions generated in answering RQ2 (longitudinal stability) as the dependent variable. This approach was inspired by previous attempts to explain the longitudinal trajectories of crime concentration at street segment level in the United States (Weisburd et al., 2014) and Output Area level in Scotland (see Bates, 2014) using (multinomial) logistic regression. This kind of approach was considered more appropriate than recent studies which have conducted longitudinal clustering analysis on police recorded crime data, only to then use a dependent variable which represents the average number of crimes occurring in each unit throughout the study period (e.g. Favarin, 2018). Such an approach might fail to capture the insight gained from examining longitudinal fluctuations and limits the post-analysis discussion of results when the key interest is explaining change over time. Instead, here, the theoretically-driven independent variables derived from the 2001 census will be used to predict a categorical outcome variable consisting of the offender residence data from 2006/07 to 2015/16. The number of categories in this outcome variable, and the characteristics of the observations assigned to each category, will be largely dictated by the results generated through ak-medoids and k-means. However, in the interests of simplicity and ease of interpretation, the aim will be to identify one category from both ak-medoids and k-means that is of most theoretical interest, so that the cluster solution can be recoded to a binary response variable for use in a logistic regression model.

With this in mind, the analytical strategy is as follows:

1. Offender residence population flows during the study period are visualised for the offenders' origin (residence in time point *t*) and destination (residence in time point *t+1*) Output Area. The variables used are the Townsend Index, as a measure of deprivation, and the Output Area Classification (OAC) as a general measure of demographic characteristics, outlined earlier in this chapter. These visuals will be accompanied by descriptive statistics on the proportion of known offenders who have moved house (or not) during the study period, to provide insight into the extent to which longitudinal aggregate-level trends are a result of house moves, or onset/desistance.

2. An assessment is made on the cluster solutions derived from ak-medoids and k-means to create a meaningful dependent variable. The clusters identified for each method will be recoded into a binary variable, indicating whether or not Output Areas were classified as having 'increasing' relative trajectories. This was considered the most theoretically meaningful categorisation. In this manner, the logistic regression model is predicting the odds of Output Areas experiencing an increasing relative offender trajectory between 2006/07 and 2015/16. Two models are run, one for each cluster solution, using independent variables with associated hypotheses (relating to the deprivation, residential turnover and ethnic diversity dimensions of social disorganisation) and control variables (risky population and spatial lag).

Given the data being utilised from the 2001 census, and the analytical strategy above, the following hypotheses are derived and tested in the two models for ak-medoids and k-means:

- H1: The higher the proportion of overcrowded households, the more likely Output Areas are to fall into the increasing relative offender residence classification.

- H2: The higher the ethnic diversity index, the more likely Output Areas are to fall into the increasing offender relative residence classification.

- H3: The higher the proportion of rented households, the more likely Output Areas are to fall into the increasing relative offender residence classification.

4.6 Additional sources

The thesis is set against the backdrop of major strands in spatial criminology, which tend to use quantitative data and methods to examine the spatial patternings of crime and offenders. However, this should by no means imply that quantitative methods are completely sufficient to design and answer the research questions posed. As has been demonstrated so far, personnel from West Midlands Police Force played a key role in guiding the focus of this project and, through a series of presentations, have played an important role in interpreting and discussing the findings from analyses. As such, comments and discussion points from personnel from West Midlands Police Force are augmented with quantitative results generated form the above analyses, to offer a more nuanced insight into results. As will become clear, detailed discussion on some of the findings will also draw upon historical accounts of how Birmingham has developed, especially in relation to housing, during the study period.

4.7 Software

The data handling, visualisations and analyses conducted in this thesis, as per the data and methods outlined above, were carried out using the open source software environment R (R Core Team, 2018). This ensured that the findings presented here are transparent and reproducible. Key packages used within R include the *tidyverse* (Wickham, 2017) for data handling and visualisation, *sp* (Pedesma & Bivand, 2005) and *sf* (Pebesma, 2018) for spatial data handling and visualisation, *viridis* for some colour palettes (Garnier, 2018), open source code (Harris, 2017) and *cartogram* (Jeworutzki, 2018) for the hexograms, and *kml* (Genolini et al., 2015) and *akmedoids* (Adepeju et al., 2019) for longitudinal clustering. The document format and compiling of the thesis itself was conducted using *bookdown* (Xie, 2016). The use of R for this thesis, and the presentation of findings to West Midlands Police Force, resulted in an invite to conduct a workshop on the software for analysts in the Force on 26 September 2019. There are plans to continue this training and encourage the widespread use of the software amongst personnel in the Force.

4.8 Conclusion

This chapter has sought to outline the data and methods deployed in this thesis to answer the three primary research questions relating to spatial scale, longitudinal stability and explanation. Consideration was also given to a preliminary demonstration of the empirical distinction between offender residence and crime concentrations. A description of the police recorded geocoded offender data provided by West Midlands Police Force was outlined, with particular consideration given to the construction of an area-based measure of offender residences, along with data integrity and biases in police data. An outline was given of the study region, Birmingham. The merits and shortcomings of different spatial scales were discussed, with a decision being made to use nested census block units (Middle Super Output Area, Lower Super Output Area and Output Area). An argument was made for the use of hexograms to visualise the spatial patternings observed, in order to maintain spatial accuracy and to ensure anonymity. Analytical strategies were proposed for the four main dimensions of analysis: the distinction between offender residences and crimes, spatial scale suitability, longitudinal stability and explanation. The next chapter will report the findings from this analyses. It will begin with the initial demonstration which highlights the distinct (but related) relationship between where offenders live and where crimes occur, to augment the theoretical arguments made in Chapter 2. Findings will then be reported in the order of our three main themes and accompanying research questions relating to spatial scale, longitudinal stability and explanation, respectively.

Chapter 5

Results: scale, instability and explanation

5.1 Introduction

Previous chapters have identified three major shortcomings in existing criminological literature relating to spatial scale, stability and explanation of longitudinal offender residence concentrations. To remedy these gaps, three research questions were posed, namely (1) What is the most appropriate spatial scale to study offender residential concentrations?; (2) To what extent do offender residential concentrations demonstrate stability over time?; (3) How can we explain the longitudinal (in)stability of offender residential concentrations? In deriving these research questions, the argument has been made for treating the spatial patterning of offenders and crimes as related but theoretically distinguishable phenomena. Using data from Birmingham provided by West Midlands Police on known offender residences and recorded crimes between 2006 and 2016, this chapter outlines findings from analyses which seek to answer these three key research questions. It also reports on findings which demonstrate, in alignment with existing journey to crime literature, that crimes and offender residences are also *empirically* distinguishable in Birmingham.

With this in mind, the chapter is split into four sections. First, descriptive statistics are reported which demonstrate that offender residences and crime locations in Birmingham are not synonymous, and in fact have unique (but related) geographic patterns. Secondly, findings are reported which answer the question of which spatial scale is most suitable for examining offender residence concentrations (RQ1). To do this, a series of replications are offered from key studies in the crime strand of literature (see Chapters 3 and 4) using three nested census units as the possible candidates. Findings from two longitudinal clustering methods (anchored k-medoids and k-means) are then reported, along with accompanying descriptive statistics, to answer the question of longitudinal stability (RQ2). As well as offering a substantive answer to the question of stability in offender residences over time, a systematic comparison is offered between existing implementations of k-means, and ak-medoids, which was developed as part of this project. Finally, descriptive statistics on individual-level population flows are reported, followed by regression models which seek to answer the question of explanation (RQ3). The chapter then concludes with a summary of the results, which leads us to the discussion in the following chapter.

5.2 Distinguishing between crimes and offenders

5.2.1 Statistical association

A standard method for comparing the similarity of crime and offender concentrations in existing research has been a correlation coefficient. It was this basic descriptive statistic which was used to justify the usage of offender residence locations as a proxy for crime in influential studies in the *Communities and Crime* special volume discussed in Chapter 2 (see Schuerman & Kobrin, 1986). With this in mind, Table 5.1 reports the Spearman's rank correlation between known offender residences and police recorded crimes, adjusted for annual resident populations, in Birmingham for each year of the study period. The correlation is reported for each census spatial unit of Output Area (OA), Lower Super Output Area (LSOA) and Middle Super Output Area (MSOA). Although the issue of spatial scale is discussed in the following section, descriptives are reported for all three potential units of analysis for completeness, and to address concerns raised in previous chapters about how the relationship between offender residences and crime may be sensitive to spatial scale.

The most salient finding is that there is indeed a statistically significant positive association between known offender residences and crime locations at each spatial scale, across all years in Birmingham data ($p < 0.05$). However, the strength of this association is modest at best and differs by level of aggregation. At the smallest level of aggregation, Output Area (OA), the correlation is consistently around 0.4 to 0.5 across years, but at the largest scale, Middle Super Output Area (MSOA), it is around 0.6 to 0.7. A preliminary remark is that this finding suggests that the degree to which crimes and offenders are distinguishable may simply be an artefact of whichever spatial scale is being used. This is noteworthy when reading previous studies which have reported a strong relationship (Schuerman & Kobrin, 1986) or no statistically significant relationship (Bruinsma et al., 2013) between the two. The findings from Birmingham suggest that the association is indeed sensitive to spatial scale, with larger units increasing the degree of similarity between crimes and offenders. With key existing studies not comparing across spatial scales for the same study area (e.g. Morris, 1957) or using large scales such enumeration districts which are no longer used (e.g. Baldwin et al., 1974) it is difficult to gauge exactly to what extent spatial scale explains this discrepancy. That said, given the findings reported here, one can read previous research differently: the assumption of similarity between crimes and offenders is clearly questionable, but might be valid with larger units of analysis.

In Birmingham, irrespective of which unit is used, the aggregate relationship between crimes and offenders is clear, but it is a relatively weak one. Given the rules of thumb commonly used in statistics (see Hinkle, Wiersma & Jurs, 1988; Mukaka, 2012) the correlation is moderate at LSOA and MSOA level, and low at OA level. It is certainly below the level at which one could reasonably argue that the two are empirically synonymous. The finding that similarity increases as spatial scale increases is perhaps unsurprising, given what we know about offenders' journey to crime (see Chapter 2). It certainly supports the notion that offenders are unwilling to commit crime in the immediate vicinity of their own home, otherwise the correlation would be much stronger. This relationship is explored further with individual-level data later in this section.

Table 5.1: Spearman's rank correlation between offender and crime rates by spatial scale ($p < 0.05$).

Unit	06/07	07/08	08/09	09/10	10/11	11/12	12/13	13/14	14/15	15/16
OA	0.44	0.43	0.43	0.48	0.47	0.44	0.47	0.49	0.49	0.46
LSOA	0.52	0.51	0.49	0.54	0.57	0.50	0.56	0.57	0.61	0.59
MSOA	0.62	0.61	0.58	0.65	0.68	0.54	0.63	0.66	0.67	0.68

5.2.2 Spatial relationship

To add a spatial component to the examination of whether offenders and crimes are empirically distinguishable, a useful endeavour is to examine the extent to which each demonstrate local positive and negative spatial autocorrelation. Evidence that crimes and offenders tend to cluster in similar areas would make claims that the two are empirically distinguishable problematic. To demonstrate the degree to which this is true, Local Moran's I results on offence and offender residence rates (counts adjusted for resident population) are reported in Figures 5.1-5.3 for each spatial scale respectively. Only the data from 2010/11 was used as an example, to avoid excessive visualisations. By way of a reminder, the visualisations used in these figures are hexograms (see Harris et al., 2018a; 2018b) which improve the representation of spatial data whilst maintaining spatial accuracy and introducing some degree of anonymity (see Langton & Solymosi, 2019). A black outline represents the city centre to aid comparisons between visualisations. The city centre was defined as the two MSOA with the highest areal density (counts normalised by metre squared) of Points of Interest for 2017 (Ordnance Survey, 2019). City centre LSOA and Output Areas were selected as those units nested within these two MSOA [1].

Even at MSOA level (see Figure 5.1), the largest spatial scale, at which there was a moderate positive correlation, there is some distinction between the clustering of offender residences and crime locations. Whilst high crime rate areas tend to

[1] In selecting the LSOA and Output Areas nested within these two city centre MSOA, a small number became 'islands' due to the hexogram transformation. This would have inhibited a contiguous ring being drawn around the city centre, and as such, these units were dropped. This had a minimal effect on the interpretation of results, and it is worth emphasising that this city centre definition is simply to ease interpretation of visualisations, rather than to draw definitive conclusions.

cluster next to one another (positive autocorrelation) in the city centre, high offender residence rates, what Shaw and McKay (1942/1972) would have referred to as 'delinquency areas', almost exclusively cluster on the outskirts of the centre, to the north and east, in the inner suburbs. MSOA with low offender residence rates appear to congregate to the south of the city centre, around the University of Birmingham and student housing areas. There is clearly some overlap in high-high and low-high areas, but the visualisations generated from the Local Moran's I analysis at MSOA level are far from synonymous.

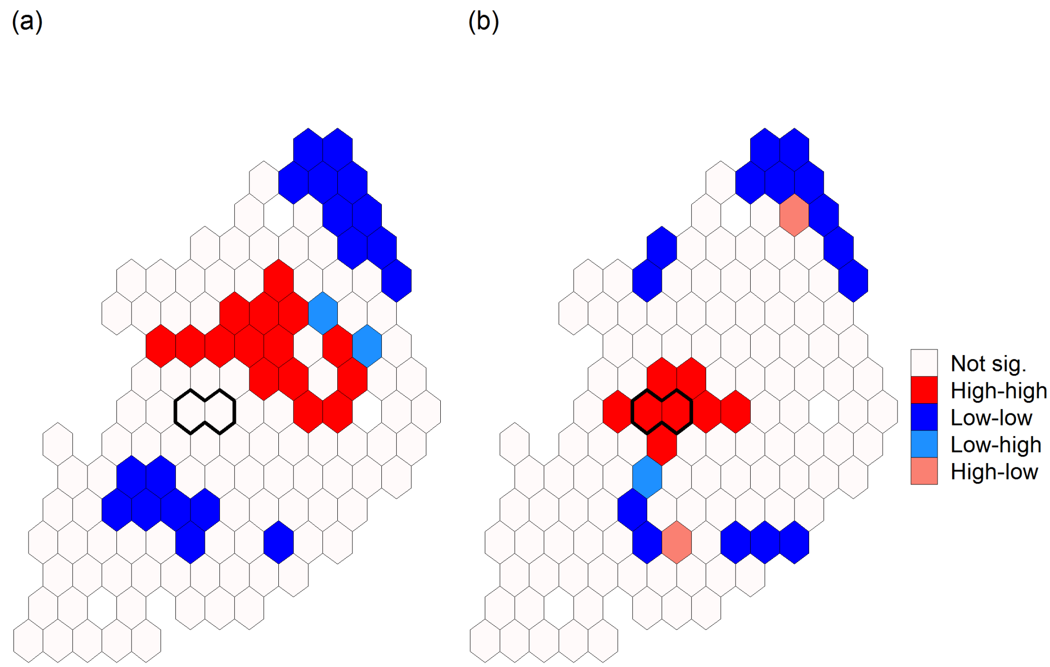

Figure 5.1: Local Moran's I for (a) offender rates (b) offence rates at MSOA level in 2010/11, with city centre boundary shown in black.

A similar pattern is evident at LSOA level (see Figure 5.2), although this more fine-grained scale also uncovers further distinctions between the spatial patterns of offender residences and crimes, along with some additional similarities. High-high crime rates continue to be clustered in the city centre, but a number of smaller clusters emerge to the west and north, along with a handful of outliers elsewhere. High offender residence rates still congregate in the inner suburbs, but negative spatial autocorrelation areas emerge dotted amongst them, where low rate LSOA tend to neighbour those with high rates (low-high). The low-low offender rate clusters remain to the south of the city centre. In the suburbs, on the northern and north-western edges of the city boundaries, low crime and offender residence rates demonstrate fairly comparable spatial clustering.

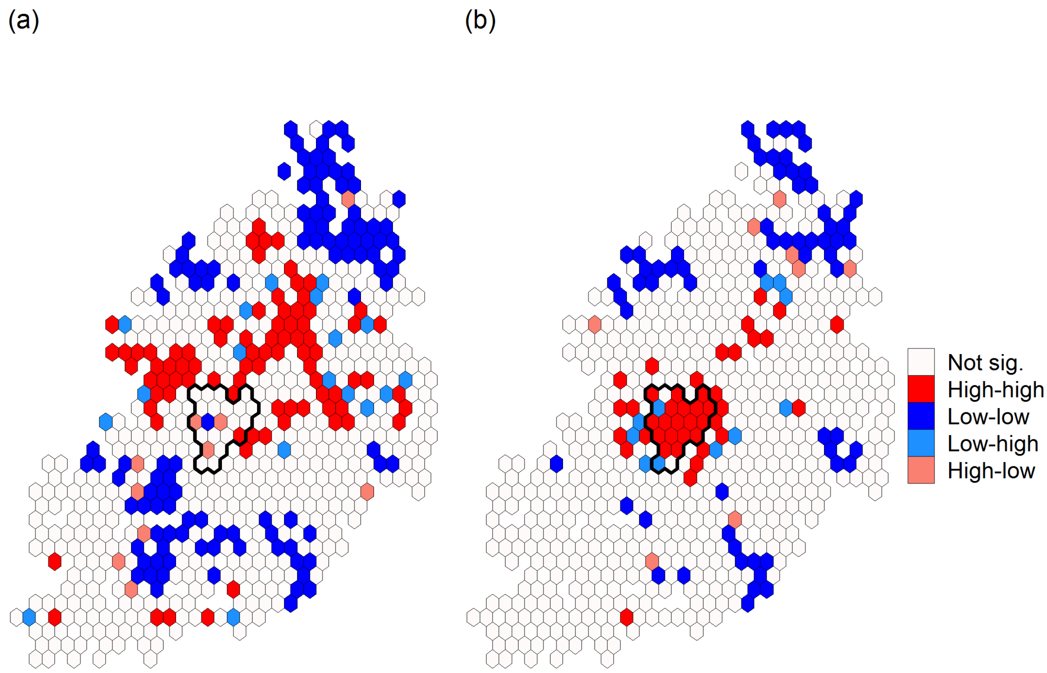

Figure 5.2: Local Moran's I for (a) offender rates (b) offence rates at LSOA level in 2010/11, with city centre boundary shown in black.

At Output Area level (see Figure 5.3) many of these patterns remain. High crime clusters continue to cluster in the city centre, with the equivalent high offender residence areas surrounding the city centre. That said, a number of smaller clusters emerge in the suburbs, but rarely are these identical for crimes and offenders. The greatest similarities continue to be in the northern outskirts of the city, which are characterised by low-low crime and offender residence rates, intermingled with some low rate Output Areas neighbouring high rate areas (low-high). In the south, there are some key high-high offender clusters which are not statistically significant for offence rates ($p > 0.05$). It is evident that, irrespective of which spatial scale is used, the spatial distribution of crimes and offenders is fairly distinct, despite there being some similarities.

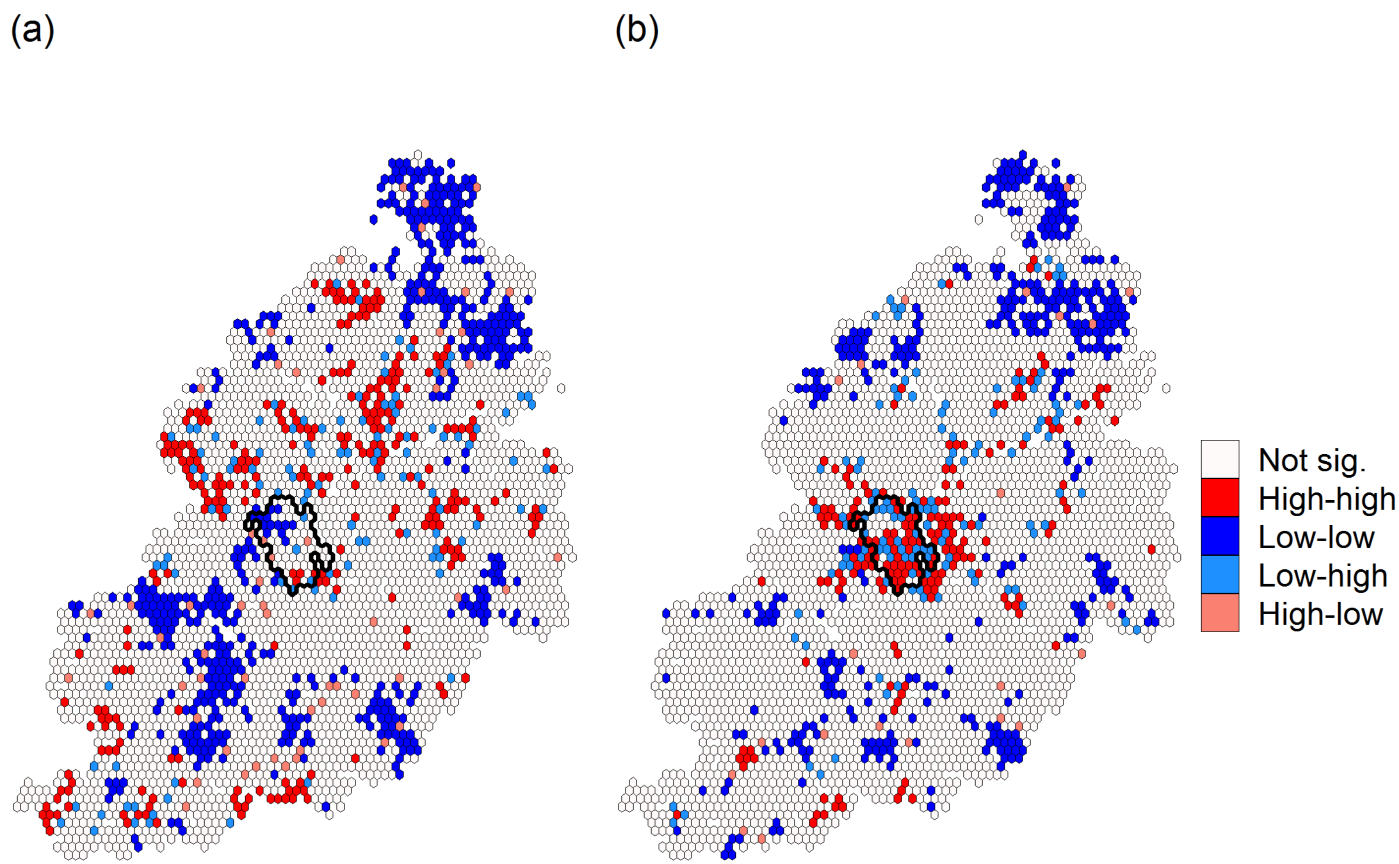

Figure 5.3: Local Moran's I for (a) offender rates (b) offence rates at Output Area level in 2010/11, with city centre boundary shown in black.

Overall, the findings highlight two important points. Firstly, whilst there are some similarities in the spatial patterns of crime and offender residence location rates, these patterns are distinct. This is consistent with the idea that crimes and offenders merit distinct explanatory frameworks, as suggested in previous research *theoretically* as far back as Morris (1957) and El-Saaty (1946), and more recently *empirically* (Bruinsma, Pauwels, Weerman, & Bernasco 2013). This suggests that the widespread adoption of social disorganisation theory, originally conceptualised to explain *delinquency areas* (i.e. where offenders live), but subsequently for crime research at the expense of offenders, has perhaps been misguided by the assumption of empirical similarity. Secondly, and relatedly, the degree of similarity between crimes and offenders is clearly sensitive to the unit of analysis being used, with fine-grained spatial scales highlighting differences that may not be evident when using larger units. Although it is difficult to draw definitive conclusions, this finding might explain inconsistent findings in previous research. Moreover, this is a finding that personnel at West Midlands Police Force were especially interested in, as their geospatial analysis tends to be conducted at much larger spatial scales which roughly equate to MSOA level. With some staff expressing their surprise at the low correlation between crimes and offenders, there is a clear need to highlight the impact of spatial scale in this area of analysis.

5.2.3 Journey to crime

So far, we have only considered the relationship between crime and known offender residence locations using aggregated data. As has been demonstrated, this can provide an interesting insight, especially given that spatial criminology inherently tends to use geographic units of analysis. That said, relying solely on aggregated data when examining the empirical similarities of crimes and offenders may mask more complex underlying patterns. The weak to moderate correlation between the two phenomena reported in Table 5.1, and the similarities in spatial clustering evident in Figures 5.1-5.3, for instance, are the product of individual-level journey to crime patterns. Even a near-perfect aggregate correlation between offender residences and crime does not mean that the two are empirically indistinguishable, and certainly would not mean that offenders only commit crime within their own residential area.

By way of example, Table 5.2 reports the proportion of crimes committed by offenders within their respective home MSOA, LSOA or Output Area throughout the study period. It suggests that the majority of offenders tend to travel outside of their own neighbourhood to commit offences, irrespective of how 'neighbourhood' is defined, which strongly supports the argument that offender residences and crime locations are empirically distinct. In 2006/07, for instance, 20% of offences were committed in same Output Area in which the perpetrator was residing. Again, this finding is consistent with the idea that crimes and offenders have distinct theoretical explanations. One factor is driving them to live in particular areas, only to then to be attracted to offend in a different location. The proportion of individuals offending in their home neighbourhood increases as the spatial scale increases, with the 2006/07 proportion standing at 25% and 34% for home LSOA and MSOA respectively. Whilst offenders seem perfectly willing to commit crime outside of their home Output Area, they are less likely to do so beyond the bounds of their home LSOA or MSOA. This is consistent with existing findings which suggest that whilst offenders tend not to commit crime in the immediate vicinity of their home, there is a drop-off at larger distances (Johnson, 2014). There is no obvious longitudinal trend for these figures in the Birmingham data, with proportions remaining fairly stable over time.

Table 5.2: Proportion of offences committed in the offender's home area by spatial scale and by year.

Unit	06/07	07/08	08/09	09/10	10/11	11/12	12/13	13/14	14/15	15/16
OA	0.20	0.20	0.22	0.25	0.23	0.21	0.22	0.22	0.22	0.22
LSOA	0.25	0.25	0.27	0.30	0.27	0.26	0.26	0.25	0.26	0.25
MSOA	0.34	0.35	0.35	0.38	0.35	0.35	0.33	0.32	0.33	0.32

Table 5.3: Journey to crime descriptives in metres for all crime types by year.

Year	Min. (m)	Max. (m)	25th perc. (m)	Median (m)	75th perc. (m)	Mean (m)	SD (m)
06/07	0	23975	253	1421	3771	2500	2940
07/08	0	23975	241	1386	3770	2471	2929
08/09	0	24375	194	1377	3775	2491	2984
09/10	0	22268	111	1261	3732	2434	3004
10/11	0	23439	164	1427	3918	2540	3033
11/12	0	22872	217	1380	3893	2583	3147
12/13	0	23370	199	1588	4109	2701	3141
13/14	0	21585	235	1696	4231	2770	3155
14/15	0	23323	228	1763	4363	2808	3151
15/16	0	22604	251	1799	4494	2889	3240

With access to point-level data on offender residence and crime locations in Birmingham during the study period, we can do away with spatial scales altogether and report descriptive statistics on the distances traveled from origin (residence) to destination (crime) in Table 5.3. The first finding of note is the range, which stretches from 0 metres (i.e. crimes committed in the perpetrators own home) to up to nearly 24 kilometres away, which is around the entire span of Birmingham from one end to the other north-south. The standard deviation is quite high, consistently higher than the mean, largely due to outliers which are evident in the density distributions visualised in Figure 5.4. Looking at the median values by year, which are less sensitive to outliers, one can see that offenders tend to commit crimes approximately 1-mile from their home address. This distance has been increasing over time, from around 1400 metres in 2006/07 to nearly 1800 metres in 2015/16, suggesting that offenders are becoming more mobile over time. This might suggest that, historically, crime and offender residence locations were analogous, with low mobility brought about by undeveloped travel infrastructure and minimal access to private modes of transport. But, with improved infrastructure and access to private transport (e.g. motor vehicles) higher than ever before, this mobility has increased. This finding might appear to be another plausible explanation for non-contemporary studies that found that offences and offender residences had a strong association, so much so that they were used as direct substitutes for one another (Schuerman & Kobrin, 1986), with more recent studies finding no relationship (Bruinsma et al., 2013). As discussed in Chapter 2, contemporary journey to crime literature has found the figure averages around 1-2 miles (Ackerman & Rossmo, 2015). Although previous research gives little indication as to how this figure has changed over time, the journey to crime distances for Birmingham are fairly consistent with existing literature.

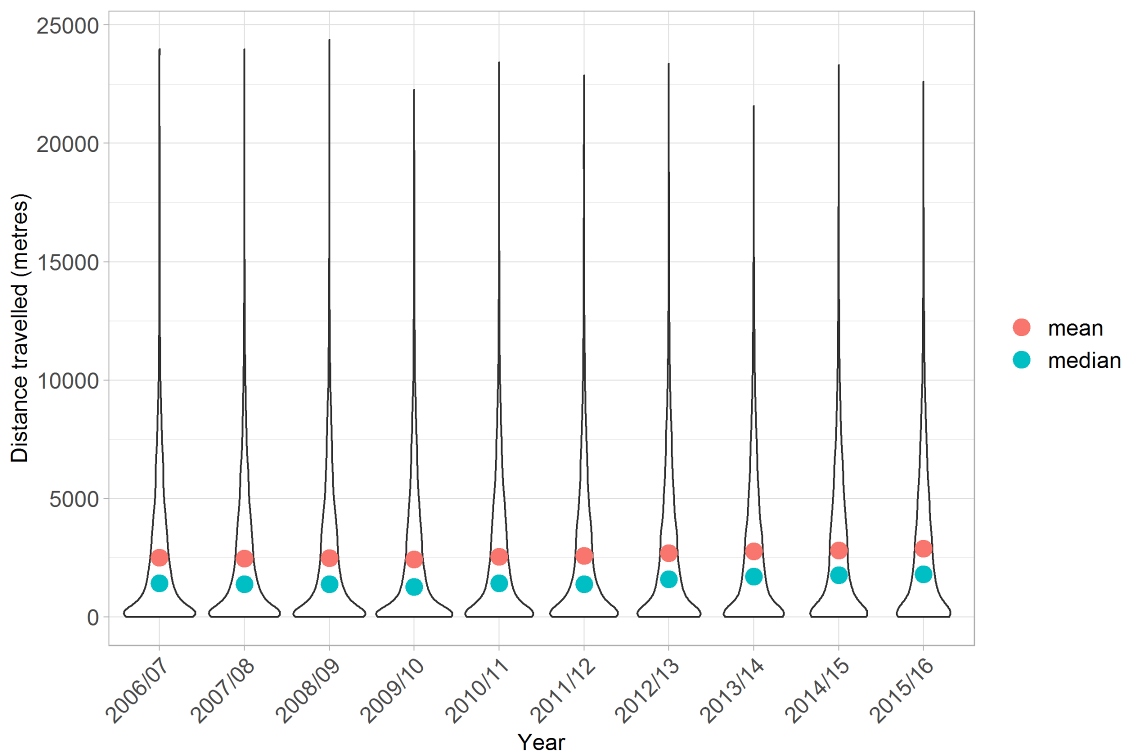

Figure 5.4: Density distributions of journey to crime including outliers by year.

5.2.4 Overview

Overall, the results reported in this section support the argument that crime and offender residence locations, whilst related, cannot be considered empirically synonymous. When data is aggregated (to MSOA, LSOA or Output Area) there is a weak to modest, positive association between the two phenomena. There is evidence to suggest that, despite some similarities, each have unique spatial clustering patterns. That said, these aggregate-level patterns can mask more complex, underlying relationships between crime and offender residence locations. Most offenders commit offences outside of their local area. Whilst the distance from home to target varies considerably, it is typically beyond the immediate vicinity of the offender's residence. Findings are consistent with the idea that the spatial patterning of crimes and offender residences merits bespoke examination and explanatory frameworks. The causal mechanisms driving offenders to reside in one area are clearly distinct from those attracting them to commit offences in certain locations.

5.3 Research question 1: spatial scale

The first research question derived from Chapters 2 and 3 relates to the most appropriate unit of analysis at which to study offender residences. Generally speaking, spatial criminologists have been using increasingly small spatial scales since the field's inception in the 19th Century, with contemporary research empirically demonstrating the benefit of doing so when studying crime. Little endeavour has been made for offender residences, and as such, the methods deployed to answer this initial question are replications of methods utilised in crime research, outlined in Chapter 4 (e.g. Schnell, Braga & Piza, 2017; Steenbeek & Weisburd, 2016), and deemed appropriate for use with offender data. The motivation behind using these techniques is to select the most appropriate unit of analysis from MSOA, LSOA and Output Area, as defined by the Office for National Statistics (ONS), to use going forward for research question 2 and 3.

5.3.1 Concentration thresholds

As outlined in the previous chapter, a common method for exploring the suitability of different spatial aggregations is the use of arbitrary concentration thresholds. These thresholds were first used by Weisburd and his colleagues (2004) to demonstrate the longitudinal stability in overall crime concentrations, and subsequently became the primary source of evidence for the so-called law of crime concentration (Weisburd, 2015). However, since then they have been deployed when comparing nested units of analysis (e.g. Steenbeek & Weisburd, 2016) to assess the degree to which crime (or in this case, offenders) concentrate at different aggregations. In order to ensure that analysis is conducted at a suitably detailed resolution, it is assumed that the spatial scale at which offender residences concentrate *most* is the most appropriate, so as not to mask underlying detail in the data.

In alignment with existing crime studies, Tables 5.4 and 5.5 report the percentage of MSOA, LSOA or Output Areas which are accountable for 25% and 50% of offender residence counts, respectively. At both thresholds, it is evident that offender residences are most concentrated when using more fine-grained spatial scales. Table

5.4 indicates that in the first study year (2006/07), 25% of all known offender residences in Birmingham were located within just 8.7% of Output Areas, but at 11.4% and 12.9% of LSOA and MSOA respectively. Using the larger threshold we are able to state that 50% of all known offender residences in Birmingham were located in 22.3% of Output Areas, 28% of LSOA and 30% of MSOA in 2006/07. In other words, residences are most concentrated at Output Area level, and least concentrated at MSOA level.

Although the next section will deal specifically with longitudinal stability, it is noteworthy that these trends of greater concentration at fine-grained spatial scales continue throughout the study period. In fact, the descriptives in Tables 5.4 and 5.5 suggest that offender residences are becoming *increasingly concentrated* over time, and that this change is most apparent at Output Area level. Although 25% of offender residences were located within 8.7% of Output Areas in the first year, by the final study year in 2015/16 this figure had dropped to 7% (1.7% less). At LSOA level the proportion fell from 11.4% to 10.6% (0.8% less), and at MSOA level it fell from 12.9% to 12.1% (0.8% less). The findings were comparable using the 50% threshold in Table 5.6. This confirms that offender residences concentrate most at Output Area level, and provides preliminary evidence to suggest that changes in these concentrations over time are most salient when using Output Areas.

Table 5.4: Concentration threshold of 25% for each spatial scale by years.

Unit	06/07	07/08	08/09	09/10	10/11	11/12	12/13	13/14	14/15	15/16
OA	8.69	8.63	8.66	9.18	8.78	8.47	8.16	7.76	7.45	6.98
LSOA	11.42	11.58	11.74	11.89	12.05	11.89	11.89	11.11	10.95	10.64
MSOA	12.88	12.88	12.88	12.12	12.88	12.88	12.12	12.12	12.12	12.12

Table 5.5: Concentration threshold of 50% for each spatial scale by years.

Unit	06/07	07/08	08/09	09/10	10/11	11/12	12/13	13/14	14/15	15/16
OA	22.31	22.03	22.22	23.12	22.22	21.69	21.50	20.88	20.57	19.42
LSOA	28.01	27.86	28.33	28.64	28.79	28.48	28.33	27.54	27.54	26.76
MSOA	30.30	30.30	30.30	30.30	31.06	30.30	30.30	30.30	30.30	29.55

There are three major findings which emerge when comparing with previous research. Firstly, the higher degree of concentration in offender residences at fine-grained spatial scales is one reflected in crime concentration studies using the same thresholds (e.g. Steenbeek & Weisburd, 2016; Schnell et al., 2017). In other words, both crime and offender residences appear to demonstrate similar behaviour, with greater concentration at smaller aggregations. Secondly, there is some evidence to suggest that offender residences are less concentrated than crimes. In Chicago, for instance, the percentage of neighbourhoods (containing around 8,000 residents) accounting for 50% of violent crime stands at 23% (in Schnell et al., 2017), which is comparable to the percentage of Output Areas (containing around 290 residents) accounting for 50% of known offenders in Birmingham, standing at around 21%. This proportion is also fairly similar when using all crimes types and a neighbourhood unit consisting of around 4,500 residents in The Hague (in Steenbeek & Weisburd, 2016). Direct comparisons are problematic due to the different spatial scales used. Thirdly, as a by-product of this examination of spatial scale, there is evidence that offender residences are become *more* concentrated over time i.e. less equitably distributed across space. This finding is consistent with results from United States when examining the residential locations of formerly incarcerated offenders in Chicago (Kirk, 2019). This could be a product of wider changes in housing policy, discussed in Chapter 6.

5.3.2 Lorenz curves

As outlined in the previous chapter, the descriptive concentration thresholds, whilst influential in crime concentration research, are subject to the arbitrary decision of 25% and 50% respectively. To gain a more nuanced picture, and to establish the sensitivity of findings to these thresholds, one can visualise Lorenz curves by spatial scale. Here, Lorenz curves plot the cumulative proportion of offender residences against the cumulative proportion of spatial units (see Figure 5.5). The same conclusions can be drawn as those in Tables 5.4 and 5.5 simply by tracing the 25% and 50% cumulative proportion along the Y-axis to the curve of each spatial scale respectively, and seeing where it meets the X-axis.

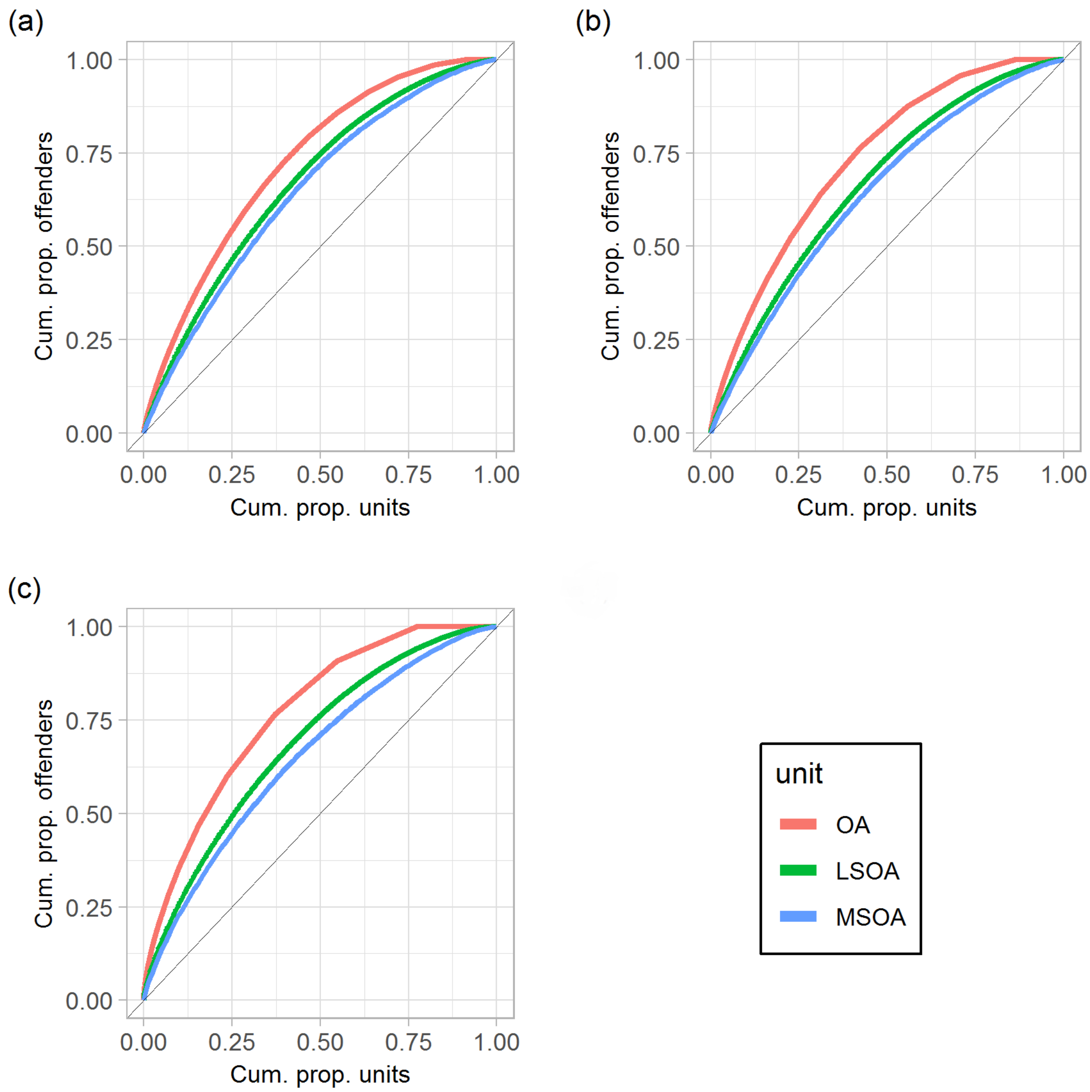

Figure 5.5: Lorenz curves for offender residence concentrations at each spatial scale for (a) 2006/07, (b) 2010/11, (c) 2015/16

Now, however, this can be done for any combination of proportional values, making it a more flexible and visually appealing method. The line of 'perfect equality' (in grey) represents a situation where offender residences are equally distributed across space e.g. whereby 25% of residences are attributable to 25% of Output Areas. The alternate years plotted in Figure 5.5 confirm that offender residences are not only concentrated unequally across all spatial scales, but that this concentration is consistently greater at lower aggregations. The increasingly wide curve at Output Area level, and a widening gap, confirm that offender residences appear to become increasingly concentrated over time at Output Area level. As such, the Lorenz curves provide a visual confirmation of the arbitrary thresholds. That said, with visual appeal comes a lack of accuracy, and difficulty in comparing to existing research, which Gini coefficients can resolve.

5.3.3 Gini coefficient

The quantitative representation of the Lorenz curve is the Gini coefficient, which as outlined in Chapter 4, represents the area between the line of perfect equality and the Lorenz curve itself. The larger this area, the larger the Gini coefficient (which ranges from 0 to 1), and the greater the phenomenon (in this case, offender residences) is concentrated. Collapsing the Lorenz curve visualisation into a single figure serves to ease interpretation and makes change over time much more apparent.

Figure 5.6 plots the Gini coefficients from 2006/07 to 2015/16 for each each spatial scale. The results confirm that offender residences are consistently more concentrated at smaller aggregations. At MSOA level, the Gini coefficient is around 0.3 throughout the study period, despite a small decline in the first five years, indicative of a fall in the degree of concentration. At the LSOA level, there is similar albeit shorter decline, with the Gini coefficient itself increasing from 0.34 to 0.38 from the first to last study year. At the most fine-grained scale, Output Area, the Gini coefficient is much larger, beginning at 0.45 and increasing to 0.54 by 2015/16. In alignment with the arbitrary thresholds reported in Tables 5.5 and 5.6, and the Lorenz curves in Figure 5.5, it is clear that not only are offender residences most concentrated at Output Area level, but that fluctuations (increases) in the extent of this concentration are most evident when using the unit. Using data aggregated to MSOA or LSOA level would mask change occurring at higher resolutions.

The general finding that Gini coefficients are higher (indicating greater concentration) at more fine-grained scales is one reflected in crime research. Street segments consistently have far higher Gini coefficients for crime than we are finding at Output Area level for offenders, with figures tending to range from around 0.75 to as a high as 0.95 (e.g. Schnell et al., 2017; Favarin, 2018), although it is not clear whether this is a result of the spatial scale or the difference in crimes and offenders. The figures reported here for offenders in Birmingham at Output Area level (around 0.5) is comparable to crimes at neighbourhood and district level (Steenbeek & Weisburd, 2016) and neighbourhood and community area level (Schnell et al., 2017), all of which contain many more residents than Output Areas. This suggests that offender residences are less concentrated than crimes, but a direct comparison using Output Area-level crime data would be required to draw definitive conclusions. The Gini coefficient findings therefore align with our two main conclusions thus far: that offender residences concentrate *more* at fine-grained spatial scales, that offender residences are becoming *increasing concentrated* over time, and that offender residences *appear* to be less concentrated than crimes.

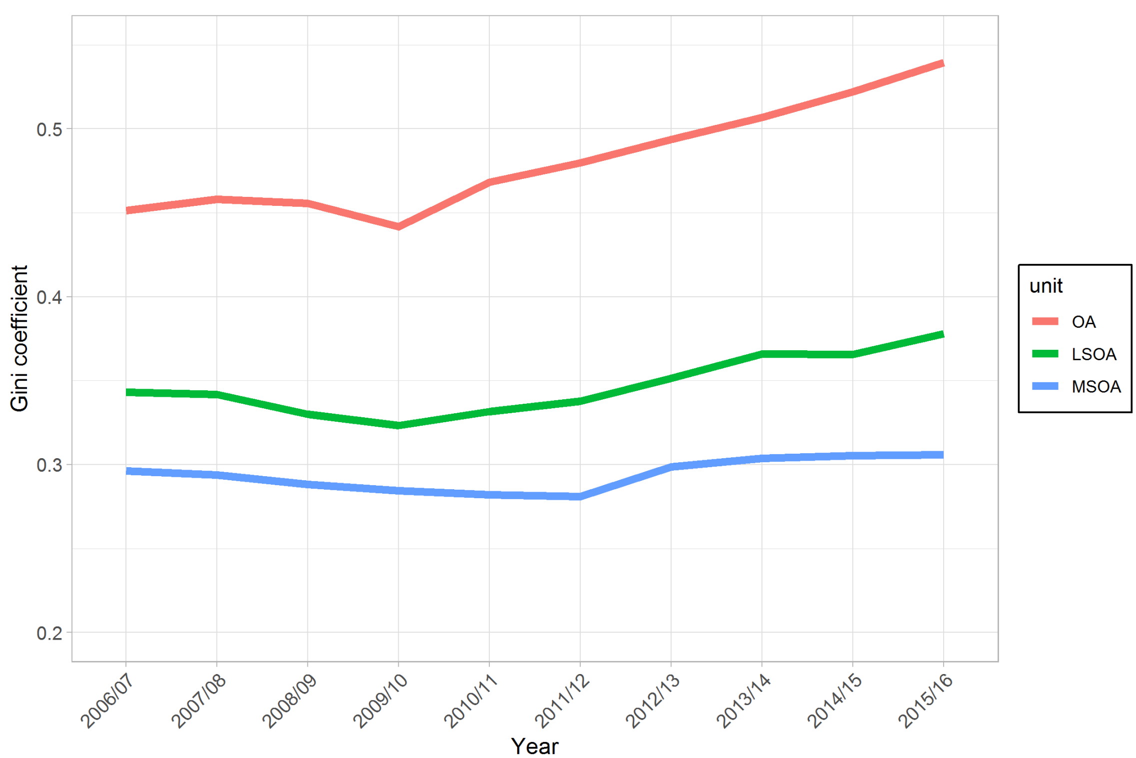

Figure 5.6: Gini coefficients for offender rates for each spatial scale by year.

Only one study has been identified as using a Gini coefficient to gauge the degree of concentration in offender residences. Using cross-sectional data from Stockholm at Ward level, Wikstrom (1991) reported a Gini coefficient of 0.35 for offenders committing all crime types. Wards contained around 5,500 inhabitants and as such are somewhere between the size of an LSOA and MSOA in England. Again, comparisons are difficult, but given the Gini coefficients of LSOA (around 0.36) and MSOA (around 0.3), this suggests that the degree of concentration in Birmingham is somewhat similar to that of Sweden. Such a contrast is being made across different cities, using different spatial scales and at different time points, therefore such a contrast is only tentative, but it is one worth acknowledging.

5.3.4 Multilevel variance partition

The descriptives and visualisations reported so far give a reasonable indication as to what extent the concentration of offender residences can vary by spatial scale. But to quantify the *variance* attributable to each level, and gauge the extent to which larger aggregations mask underlying variation, existing research in crime literature has deployed a multilevel variance partition model. As discussed in Chapter 4, to account for the relevant statistical assumptions, the variance partition is ran on a bootstrapped stratified sample (N = 500) whereby each sample consists of 50% of Output Areas *by* LSOA. The mean or median is then calculated from the estimates obtained, which are then converted into a proportion for ease of interpretation and comparison across scales. The estimates obtained from the bootstrapped models were normally distributed, therefore the mean was considered to be a good representation of the data. For computational efficiency, and to simplify the stratified bootstrapping code in R, cross-sectional models were ran for each year separately, rather than using random slopes of time from which to calculate the final proportions. In alignment with previous research, the positive skew in the dependent variable was addressed by using a log transformation. Results were similar even without using this transformation.

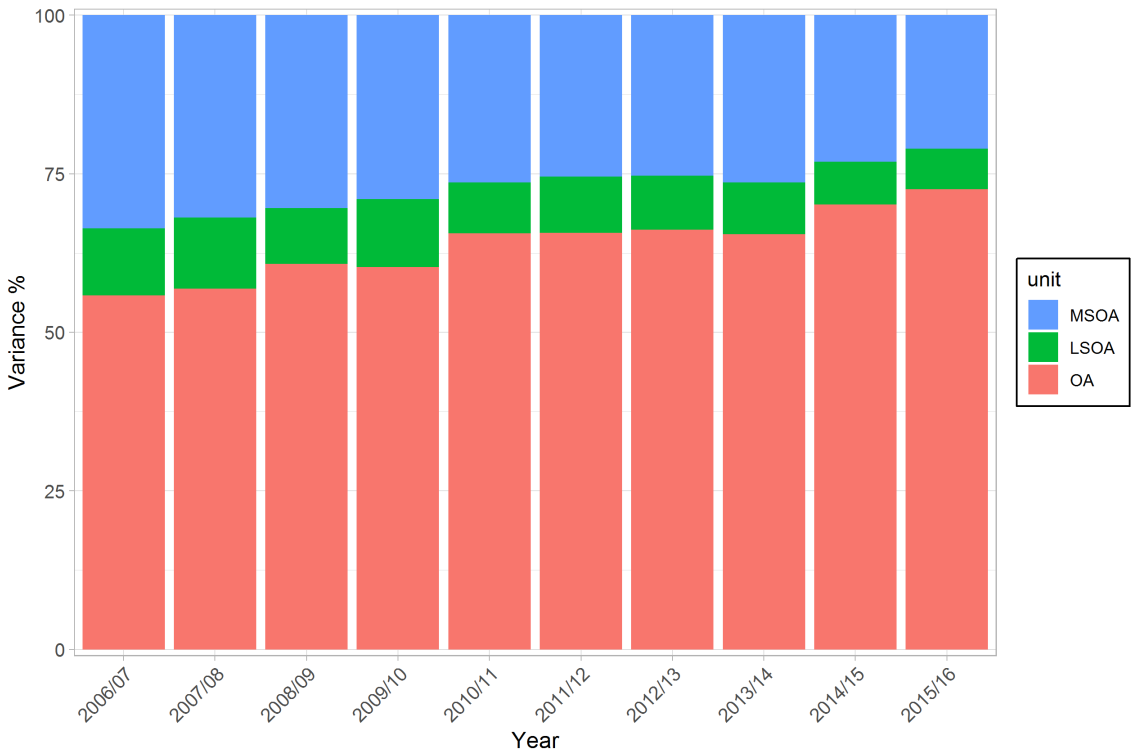

Figure 5.7: Multilevel variance partition for different spatial scales for each year.

Figure 5.7 reports the percentage of total variance in offender residences attributable to each spatial scale from 2006/07 to 2015/16 based on the mean bootstrapped estimates[2]. In the first study year, 2006/07, 56% of the variance in offender residence concentrations were attributable to Output Area level, 10% to LSOA and 34% to MSOA. By the final study year, 2015/16, 73% was attributable to OA, 6% to LSOA

[2]The construction of the aggregate-level offender measure is outlined in Chapter 4, in which it is described how adjustments were made to avoid repeat offenders (who appear multiple times in the data) over-inflating counts. Duplicate records were only counted more than once if the offender was known to have moved to a different Output Area within the same year. Following advice from Dr Wouter Steenbeek, the author of one of the papers which inspired this analysis (see Steenbeek & Weisburd, 2016), the cross-sectional multilevel variance partitions were also ran on data using a different aggregate-level measure. These included data sets in which (1) all offenders with duplicate records were removed, leaving only one-time offenders; (2) duplicate records were counted more than once if the offender was known to have moved house *at all* (i.e. just different easting-northing coordinates) within the same year, (3) duplicate records were counted more than once if the offender was known to have moved to a different LSOA within the same year; and (4) as previous, but for MSOA. The purpose behind running these additional models was to check that findings were not simply an artefact of the way in which duplicate records were handled. Findings did not differ substantially using these different data sets, suggesting that the results are fairly robust to the definition.

and 21% to MSOA. Between these years, change was relatively gradual for all spatial scales, with no stark fluctuations year-on-year. The results provide strong evidence to support the descriptive findings. Most variance in the spatial distribution of offender residences is uncovered when using Output Area. In other words, there is *most heterogeneity* at Output Area level. That said, it is worth noting that the variance was greater for MSOA than it was for LSOA, which differs from the descriptive results. However, it is worth noting in the crime literature studies deploying this variance partition method (Schnell et al., 2017; Steenbeek & Weisburd, 2016), the largest spatial scale (equivalent of MSOA) had the second highest variance i.e. a larger variance than the second smallest spatial scale (equivalent of LSOA). This raises the prospect that *larger* units do not necessarily equate to *more variance*, and thus, just as in the crime concentration, there is no rule-of-thumb that 'smaller is always better'.

5.3.5 Overview

The descriptive statistics, visualisations and multilevel variance partitions highlight three significant findings. Firstly, generally speaking, offender residences are more concentrated at smaller spatial aggregations. In this case, the greatest concentration is found at Output Area level, in comparison to LSOA and MSOA. This is consistent with the existing crime strand of research, which has consistently found that crime tends to be concentrated more in micro-places (such as street segments) compared to meso units such as large neighbourhood and community units. Secondly, and relatedly, the descriptive statistics suggest that offender residences appears to be *less concentrated* than crimes. Although comparisons are problematic across study regions and spatial scales, there is reasonable evidence to suggest that offender residences are more equally distributed across space. However, both the descriptives and the multilevel variance partition indicate that offender residence concentrations are *increasing over time*. Thirdly, the findings more generally suggest that studying the spatial patterning of offender residences at larger meso spatial scales, such as LSOA and MSOA, would mask a significant level of detail compared to Output Areas. This is consistent with contemporary research into crime concentrations which advocates the use of micro level spatial scales (e.g. Weisburd, Morris & Groff, 2009). That said, findings presented here also suggest that there is no infallible rule about whether larger aggregations increase between-unit homogeneity. However, these findings strongly suggest that using Output Areas as the spatial unit of analysis to tackle research questions 2 and 3 would be most appropriate, in order to unmask the maximum amount of detail in the data.

5.4 Research question 2: longitudinal stability

With the appropriate spatial scale selected, based on the theoretical (see Chapters 2 and 3) and empirical reasons (see previous section) outlined, the next stage is to establish the degree of longitudinal stability in offender residence concentrations at Output Area level during the study period. The analytical strategy serves to make both a methodological and substantive empirical contribution. Firstly, the general citywide trend in the number of known offenders is visualised. This sets the context from which more detailed analysis can be conducted and contrasted to gauge the degree of (in)stability and deviations from the citywide trend. Secondly, following a preliminary demonstration of the shifting rank orders of Output Areas, anchored k-medoids (ak-medoids) is deployed, with a final cluster solution decided by the Calinski Criterion. Next, an existing generic implementation of k-means is used which is entirely inductive. Although consideration will be given to the cluster solution decided by the Calinski Criterion, the final number of clusters will match those found using ak-medoids, for the purposes of a systematic comparison, with the alternative solution reported in Appendix A. The results generated by both methods will be visualised to facilitate this contrast, and descriptives reported in a tabular format.

5.4.1 The citywide trend

As outlined in previous chapters, a defining question in contemporary spatial criminology has been around the stability of crime concentrations at localised spatial scales, largely inspired by Shaw and McKay's (1942/1972) study on delinquency areas (where offenders lived) in Chicago. The interest in longitudinal (in)stability was revived, but with focus on crimes instead of offender residences, with the 'new wave' started by Weisburd and his colleagues (2004) and Griffiths and Chavez (2004). These studies widely deployed clustering methods (see Chapter 3) to establish the degree to which micro and meso areas deviate from the citywide crime trend. As such, the citywide trend (in this case, for known offenders) is an important backdrop from which the clustering can be conducted, in order to gauge the extent to which fine-grained spatial scales are experiencing the citywide trend in unison.

Figure 5.8a plots the yearly counts of known unique offenders in Birmingham during the study period (see Chapter 4). This shows that there were just over 20,000 unique offenders in Birmingham known to West Midlands Police in 2006/07 which decreased fairly consistently until a slight increase in 2012/13 and 2013/14, followed by a continued decline to around 8,000 in 2015/16. This downward trend is somewhat unsurprising given the nationwide fall in police record crime during the same time period (ONS, 2019). Figure 5.8b visualises the average number of known offenders per 100 resident population at Output Area level, which mirrors the citywide trend. This means that, even when accounting for fluctuations in resident population changes over time, on average, Output Areas have experienced a consistent drop in known offender residences.

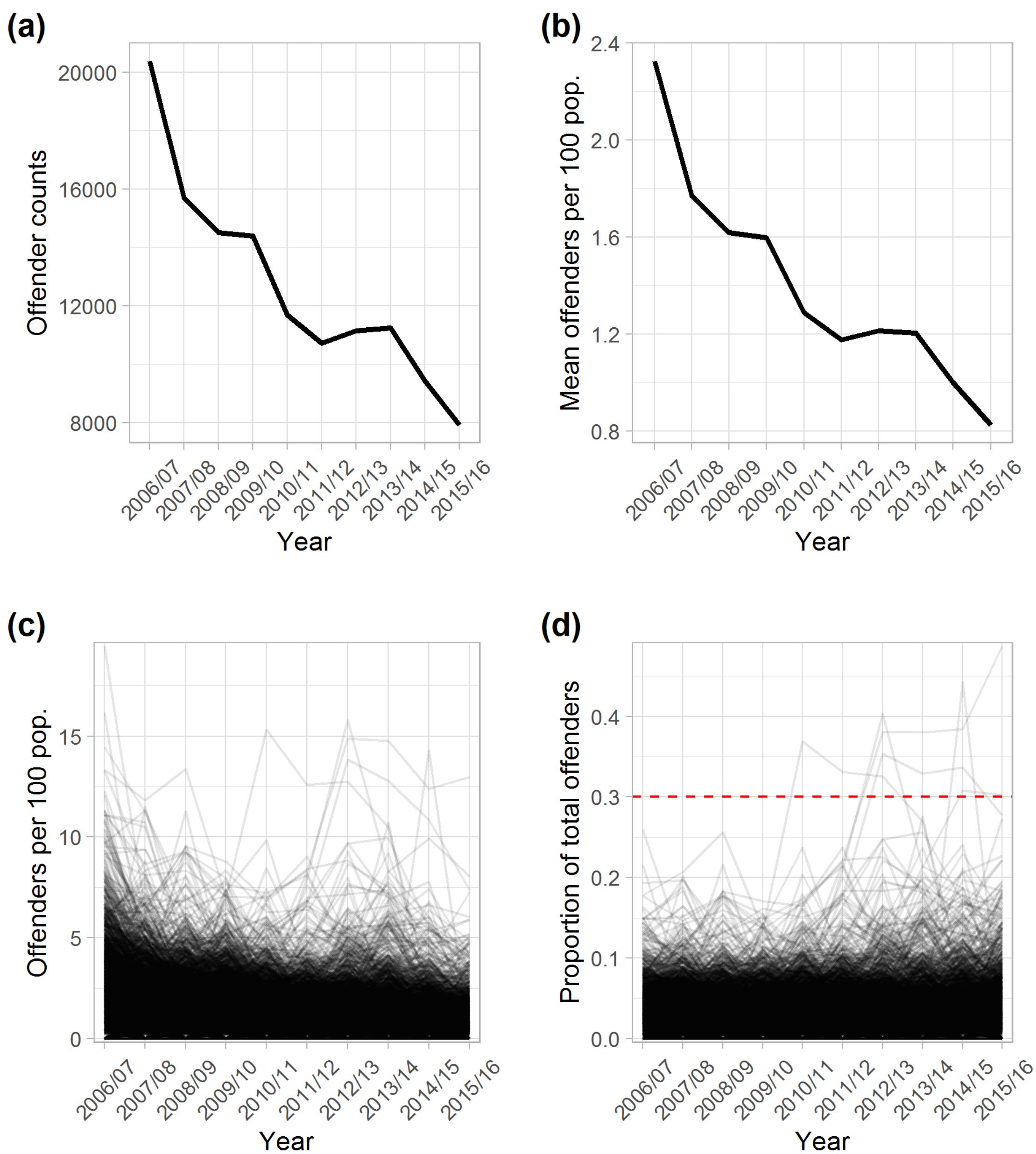

Figure 5.8: (a) Offender counts in Birmingham from 2006/07 to 2015/16; (b) Mean offenders per 100 residents at OA level; (c) Offenders per 100 residents for each OA (N = 3222); (d) Proportion of total offender counts attributable to each OA (N = 3222) with outlier threshold (in red).

The cluster analysis, conducted at Output Area level, is set against this backdrop. Have Output Areas experienced this drop in unison, or can the citywide fall be attributed to just a handful of local areas which are driving wider trends, with most areas remaining stable? The number of Output Areas is simply too large to draw conclusions from basic plots. Visualisations which show individual trajectories of offenders per 100 residents for each Output Area (N = 3222), as in Figure 5.8c, suffer from overplotting: there is too much information to derive any meaningful patterns. We can identify some outliers, and make out a broad downward trend, but little more. Existing crime studies in the 'new wave' have not reported such visualisations to demonstrate the motivation behind longitudinal clustering, but methodologically, this is the aim: to simplify complex data to such an extent that patterns emerge. Reference to Figure 5.8d is made later.

5.4.2 Rank order correlations

City-level descriptive statistics can provide us with some initial hints that there is some degree of instability and shifting amongst Output Areas which is obscured by the overplotted trends. Figure 5.9 visualises a Spearman's rank order correlation matrix of offender residence rates by year at Output Area level in the form of a heatmap. This is a quick, exploratory way of gauging the extent to which observations are shifting amongst one another as time progresses (see Long, 2011). In this case, a rank order correlation of 1 between time point t and $t + 1$ indicates that any changes that occurred in offender residence rates at Output Area level during the year were entirely uniform: the order of high to low Output Areas remained the same. Low correlation values indicate that there has been non-uniform change, with some areas increasing or decreasing at different rates.

Figure 5.9 indicates that there has indeed been a great deal of shifting amongst Output Areas during the study period. The correlation between consecutive years, for instance, 2006/07 and 2007/08, is fairly strong but imperfect (0.74, $p < 0.05$), and this similarity decays over time. By the final year, the rank order of Output Areas from 2006/07 to 2015/16 in terms of their offender residence rates has changed considerably (0.54, $p < 0.05$). Moreover, the correlation between adjacent years declines over time, with some fluctuations. For instance, whilst the correlation between 2006/07 and 2007/08 is 0.74, the correlation between 2014/15 and 2015/16 is 0.64, suggesting greater volatility and shifting over time. This provides preliminary descriptive evidence to suggest that there is some degree of instability amongst localised offender residence rate trends, and merits further examination and unpicking of the raw trajectories visualised in Figure 5.8.

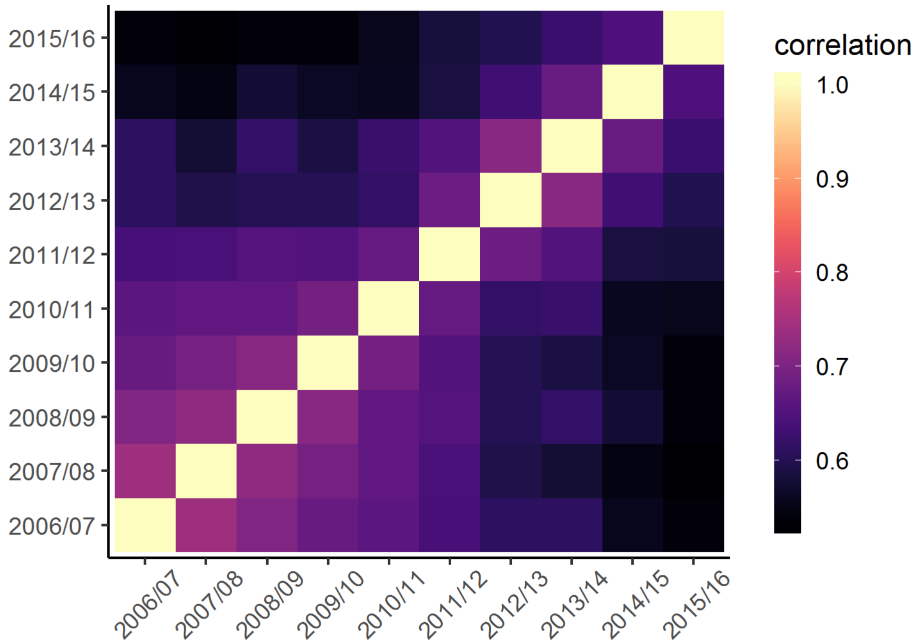

Figure 5.9: Spearman's rank order correlation of offender residence rates at Output Area level.

5.4.3 Relative versus absolute measures

As outlined in Chapter 4, a useful transformation of the raw offender residence rate is the proportional measure, whereby each Output Area is assigned a percentage of the total offender residence rate for that year. Stable proportional trajectories over time are therefore indicative of offender residence rate trajectories which are consistent in *relative* terms to the citywide trend (see Adepeju et al., *under review*). Conceptually, should Output Area offender residence rates (the absolute measure) decline in unison, the proportional trajectories (the relative measure) will remain flat, as each Output Area's share of the total remains static. As such, clustering on the proportional measure aids the derivation of meaningful results and discussion surrounding the extent of longitudinal stability in terms of change relative to the citywide trend.

Given this, the substantive aim is to deploy ak-medoids and k-means to disentangle meaningful patterns from the overplotted data in Figure 5.8d, which are the relative trajectories of each Output Area. This has the wider aim of gauging the degree of stability in offender residence concentrations over time. A decision was made to drop a small number of outliers before conducting this analysis, defined as any proportional (i.e. relative) trend which exceeded 0.3% during the study period (see red dashed line in Figure 5.8d). One of these outliers was the Output Area containing HM Prison Birmingham, which is of little empirical or theoretical interest to this study, and consistently had the highest 'offender residence' count for the study period. The remaining outliers were identified as such due to one-off years in which the offender count spiked, only to return to its previous trajectory the following year. Personnel from West Midlands Police noted that whilst some of these outliers might be erroneous, some of them may have been due to specific policing operations which resulted in a large number of offenders being apprehended in a short period of time. The decision to remove these outliers did not have a substantial impact on the clustering results, but it does make the visualisation of results clearer, as it permits a more limited Y-axis, which uncovers greater detail in the results. Only five Output Areas exceeded this threshold, leaving a total number of 3217 Output Areas on which clustering was performed. As noted in the analytical strategy (see Chapter 4) this analysis has two aims, (1) unpick localised trends in relative offender concentrations to answer research question 2, and (2) to contrast ak-medoids and k-means to demonstrate the different patterns disentangled by each method, in a similar manner to the associated working paper on crime concentrations using both methods (see Adepeju et al., *under review*).

5.4.4 Cluster solutions

To begin with, the results from ak-medoids are reported. Using the Calinski Criterion, an 8-cluster solution was found to be optimal. That is, the within-group variance was minimised, and between-group variance maximised, when the proportion trajectories are categorised into 8 clusters. However, the gain from using 8-clusters was only marginal compared to a 5-cluster solution, with the Calinski value falling (indicating a less optimal solution) for 6 and 7 clusters respectively, and then peaking at 8 clusters (see Appendix B). As such, in the interests of creating a meaningful and parsimonious cluster solution, 5-clusters is reported here. The combination of using model fit descriptive statistics and researcher judgement in combination, rather than one in isolation, is a strategy which is encouraged when deploying longitudinal clustering methods more generally (Nagin, 2005).

5.4.5 Ak-medoids

Descriptive statistics for ak-medoids are reported in Table 5.6, and the individual proportion (relative) and rate (absolute) trajectories, along with a median trajectory for each cluster, are visualised in Figure 5.10a and 5.10b respectively. These median trends are visualised in isolation in Figure 5.11. The most salient finding, evident in Table 5.6a immediately, is that there is indeed some instability in offender residence trajectories over time. As conceptualised in the previous chapter, Output Areas with relative trajectories which are stable and flat are experiencing a trend which is uniform relative to the citywide trend (in this case, a decline). Out of the five clusters identified by ak-medoids, only one matches this trend (Cluster C, in yellow), with the quartile classification (see Chapter 4) labeling Output Areas in this cluster as 'stable' (see Table 5.6). The relative median trend of this group is flat (see Figure 5.10a), and the absolute offender rate trend is steadily declining (see Figure 10b). This is the largest cluster (N = 1079), suggesting that many Output Areas are indeed relatively stable and decline in unison, in parallel with the citywide drop. That said, the cluster represents only a third of the sample, indicating that the majority of Output Areas are experiencing offender rate trends which are iniquitous, that is, non-uniform over time, and deviating from the wider decline in offenders.

Clusters D (in green) and E (in blue), for instance, are characterised by *increases* in their proportional trajectories (see Figure 5.10a, Figure 5.11a and the classification in Table 5.6). These are what Shaw and McKay (1942/1972) might have classified as 'delinquency areas', particularly Output Areas in Cluster E: those neighbourhoods which house an increasing relative proportion of known offenders, and fairly persistent offender rates, even over lengthy periods of time, and during wider falls. Together, Clusters D (N = 709) and E (N = 268) comprise 30% of the total sample, and therefore their contribution is by no means negligible.

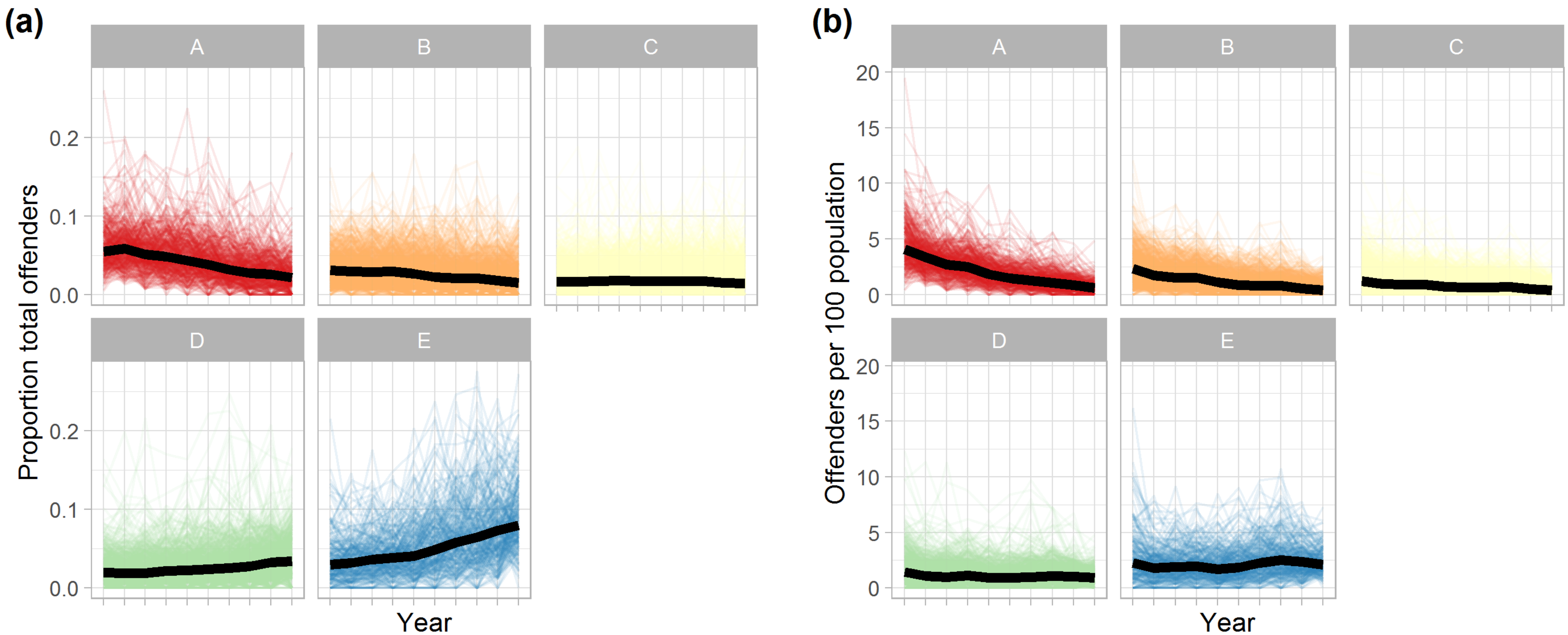

Figure 5.10: 5-cluster solution using ak-medoids on proportions for (a) proportional trajectories, (b) rate trajectories.

The remaining two clusters were classified as 'decreasing' (see Table 5.6). This decline in relative terms is reflected in the rapid drop of offender rates: the declines are so steep that they outstrip the citywide fall. In the crime literature, such groups are often defined as 'driving the citywide trend' (e.g. Andresen, Curman & Linning, 2017), and these results are comparable: a relatively small number of Output Areas are contributing disproportionately to the citywide decline in known offenders. Cluster A (in red), which comprise 12% of the sample (N = 387) demonstrates a decline in the relative measure over time (see Figure 5.10a) which translates to a steeply declining offender rate trajectory (see Figure 5.10b). Cluster B (in orange) is larger (N = 774) but experiences a less steep relative decline, which is mirrored in a shallower offender rate slope. Although this cluster still contributed disproportionately to the decline in known offenders in Birmingham, it is certainly less dramatic than Cluster A. Together, these two decreasing class clusters comprise 36% of total Output Areas used in analysis, and represent interesting cases of 'delinquency areas', which begin 'problematic' but experience overt declines over time.

Ak-medoids has demonstrated its capability of unpicking longitudinal trends in offender concentrations at fine-grained spatial scales. Using a 5-cluster solution, the method identified a large group comprising of around one third of Output Areas in Birmingham which demonstrate stability over time, both through visual inspection of proportional (relative) trajectories, and through the quartile classification. Two clusters were identified as having increasing relative trajectories. The remaining two clusters, classified as decreasing, were characterised by stark decreases in offender rates, outstripping the citywide trend. These increasing and decreasing classes comprise approximately one third of the total sample each (two thirds total). Accordingly, ak-medoids suggests that there is indeed some instability over time in offender residence concentrations, characterised by shifting, non-uniform offender trajectories at Output Area-level. This finding is consistent with the descriptive rank order correlation statistic reported earlier. That said, it still remains unclear to what extent ak-medoids differs from the generic implementation of k-means. To address this, results from k-means are now reported.

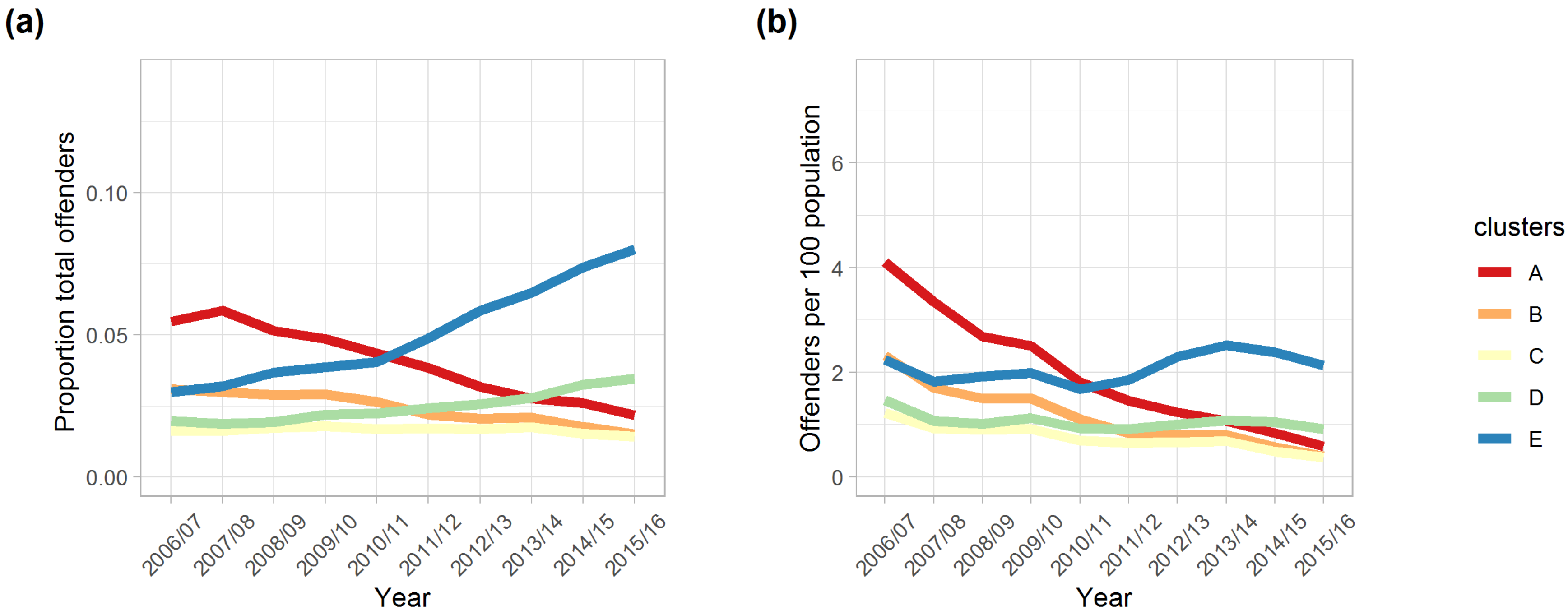

Figure 5.11: 5-cluster solution using ak-medoids with median trend lines for (a) proportional trajectories, (b) rate trajectories.

Table 5.6: Descriptives of ak-medoids cluster solution

Cluster	Size (N)	Size (%)	% +ve prop. traj.	% -ve prop. traj.	Class
A	387	12	0	100	Decreasing
B	774	24	0	100	Decreasing
C	1079	34	46	54	Stable
D	709	22	100	0	Increasing
E	268	8	100	0	Increasing

5.4.6 K-means

In the interests of comparison, a 5-cluster solution was also chosen for k-means, even though the Calinski Criterion indicated that a 3-cluster solution was optimal. The visualisations and descriptives for the 3-cluster k-means result are reported in Appendix A. Choosing 3 or 5-clusters did not impact on the findings significantly, but using the latter makes for a more systematic comparison. Descriptive statistics for the 5-cluster solution are reported in Table 5.7, with the individual trajectories with median lines of best fit for relative and absolute trajectories in Figure 5.12a and 5.12b respectively. Median lines in isolation are in Figure 5.13.

Again, the broader finding of longitudinal instability is evident from the individual trajectory visualisations in Figure 5.12a. Generally speaking, however, there appears to be more widespread evidence of stability compared to the ak-medoids results. For k-means, clusters A (N = 1147) and B (N = 1047) appear to have stable relative trends, suggesting that their offender rate trends (which are declining, see Figure 5.13b) were consistent with the citywide trend. This stability is evidenced more objectively with the quartile classification of 'stable' in Table 5.7. Together, these stable clusters make up 68% of the total sample. Cluster C (N = 650) is the only group identified visually, and through the quartile classification, as having a declining relative trend, which is steeper than the city as a whole.

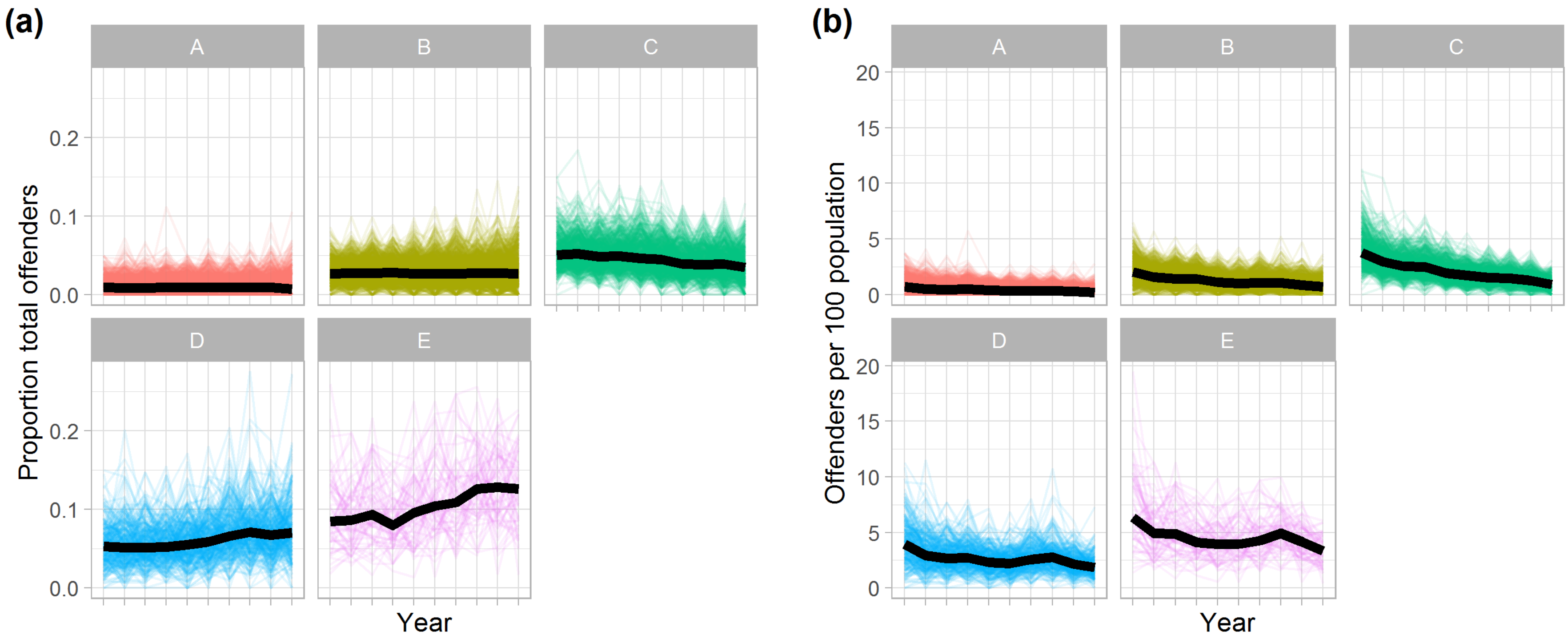

Figure 5.12: 5-cluster solution using k-means on proportions for (a) proportional trajectories, (b) rate trajectories.

Clusters D (N = 310) and E (N = 63) were classified as increasing in terms of their relative trends, which is also evident visually. Despite having an increasing relative trajectory, Cluster D has a declining median offender rate slope, which fluctuates during the end of the study period. Cluster E, whilst identified as increasing, has a volatile trajectory, and a small number of Output Areas (only 2% of the sample). One might expect, given the sharp increase in the median relative trajectory, that the corresponding median offender rate trend would either be characterised by an increasing trend, or perhaps a very shallow decline. However, it is a seemingly steep decline. This may be a result of k-means' sensitivity to short-term fluctuation, as evidenced most saliently with Cluster E's relative trajectory. It might also largely be a result of the small group size, which makes such trends problematic to summarise visually without introducing some degree of misrepresentation. The more balanced group sizes for ak-medoids avoid this potentially misleading issue. As outlined in Chapter 4, a benefit of offering the visuals with individual trajectories in Figure 12a and 12b (and Figure 10a and 10b for ak-medoids), mean that there is complete transparency in reporting the underlying data. By relying solely on mean or median trend lines in isolation, as has been the case for the vast majority of new wave crime concentration research (exception: Wheeler et al., 2016), the message being conveyed is confounded, and potentially misleading.

Table 5.7: Descriptives of k-means cluster solution.

Cluster	Size (N)	Size (%)	% +ve prop. traj.	% -ve prop. traj.	Class
A	1147	36	46	54	Stable
B	1047	32	49	51	Stable
C	650	20	25	75	Decreasing
D	310	10	70	30	Increasing
E	63	2	76	24	Increasing

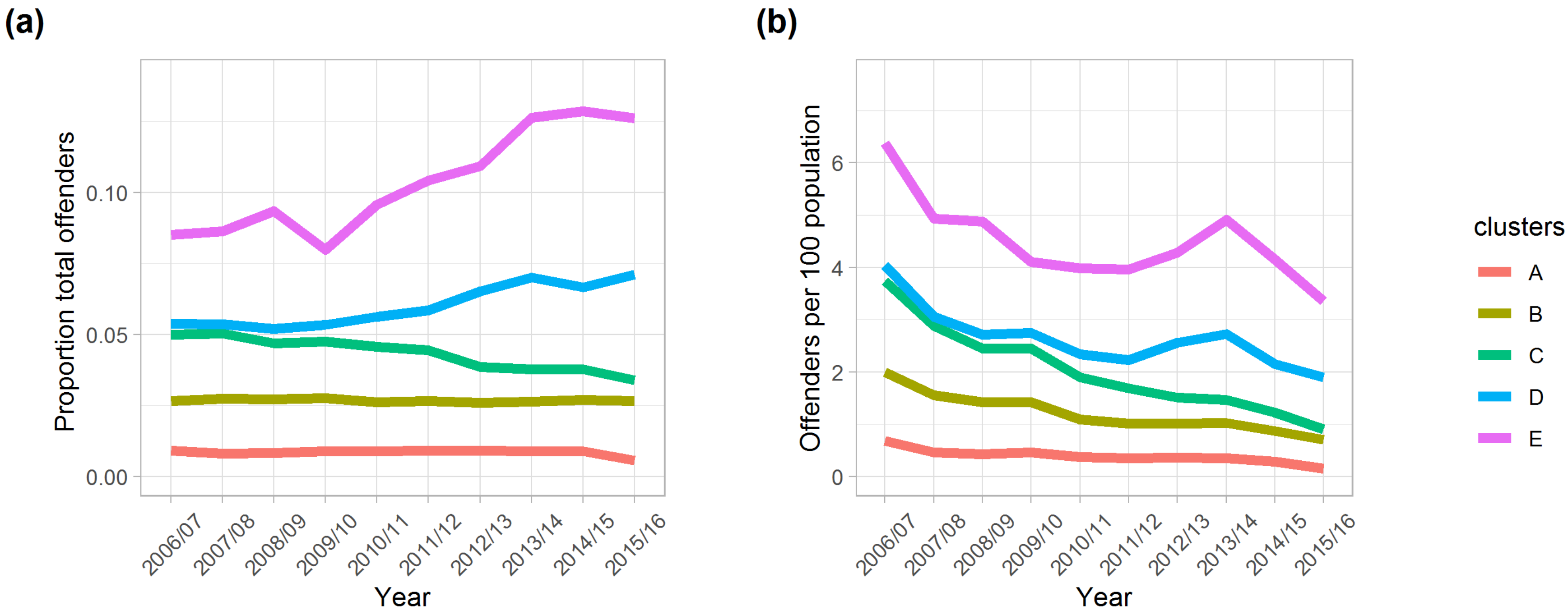

Figure 5.13: 5-cluster solution using k-means with median trend lines for (a) proportional trajectories, (b) rate trajectories.

Overall, the groups identified using the generic implementation of k-means, as used in the crime strand of spatial criminology to date, suggest that most Output Areas were characterised by relative stability in offender residence concentrations throughout the study period. Around two thirds of these localised areas were experiencing trends which were consistent with the citywide decline. This suggests that the macro-level trend was largely a result of widespread, uniform change at fine-grained spatial scales. That said, there was some evidence of instability, with a small number of Output Areas (12%) experiencing volatile increases in their relative share of offender residence concentrations, and around 20% characterised by declines.

5.4.7 Comparing ak-medoids and k-means

The broad findings from k-means aligns with that of ak-medoids: there is some evidence of instability in offender concentrations over time. That is, local areas in Birmingham have not experienced the decline in the number of known offender residences equitably. By unpicking subgroups within the data, characterised by similarity in their longitudinal relative trajectories of offender residence rates, both methods demonstrate capability in disentangling meaningful trends from the overplotted data presented at the beginning of this section. However, there are a number of key differences. It is worth emphasising for readers that all visuals, between ak-medoids and k-means, have been visualised *on the same Y-axis scale*, contrary to some existing crime concentration literature which has compared the findings from two different methods using two different scales (see Curman et al., 2015).

Firstly, the classification of the groups identified by ak-medoids and k-means differs considerably. Whilst ak-medoids identified only one stable cluster, which comprised of around one third of Output Areas, k-means identified two stable clusters, together comprising two thirds of Output Areas. The different conclusions drawn from this are quite drastic: using ak-medoids, most Output Areas are *unstable*, shifting amongst one another over time and deviating from the citywide trend, but using k-means, most Output Areas are *stable*. In the crime literature, a key finding has been that most small area crime concentrations remain stable over time, with only a small proportion of units driving citywide trends (e.g. Weisburd et al., 2004; Andresen et al., 2017). However, the use of ak-medoids appears to highlight how sensitive this finding is to the clustering methods deployed (see also Adepeju et al., *under review*). Plotting the proportion of total offenders attributable to each cluster highlights the difference in findings of stability in a different way (see Figure 5.14). These total proportions are characterised by gradual, linear change using ak-medoids, emphasising the dynamic nature of concentrations over time, but the k-means cluster solution demonstrates a remarkable lack of change, with many clusters differing little over time in terms of the total volume of offender residences attributable to each cluster.

Secondly, the size of the groups found differs significantly between methods. Ak-medoids generated one (stable) cluster which was around a thousand Output Areas (one third of the total), two clusters of around 700, with the remaining two containing approximately 300 Output Areas each. K-means, on the other hand, had two (stable) groups with a thousand Output Areas each, and the smallest group contained 63 Output Areas. This has a number of implications. Theoretically, it impacts on the degree to which one concludes that areas are remaining stable over time, as above. The identification of large, stable groups, with non-stable groups being small in number, inherently curbs conclusions towards those made in the crime literature: that most areas remain stable, and citywide trends are largely a result of a handful of areas which are characterised by more volatile trends. However, small groups can simply appear volatile due to data sparsity. Empirically, and in terms of policy relevance, the identification of small groups can be favourable, especially in an era of austerity. With limited resources available, police forces and local governments can only investigate or intervene in a small number of areas where it will be most effective. As such, there is no 'correct' answer of whether ak-medoids having larger, more balanced groups is an improvement over k-means, it is simply a point of discussion which has clear theoretical implications, as returned to in Chapter 6.

Regarding the clustering methods more generally, the relatively low number of clusters identified using k-means and ak-medoids aligns with previous crime research. Deploying k-means in isolation, Andresen and colleagues (2017) identified between three and five cluster solutions depending on the crime type. Curman and colleagues (2015) identified a four cluster solution using k-means, but seven using group-based trajectory modelling (GBTM) on the same data. In comparison with other studies deploying GBTM in previous crime concentration research, this is a consistent pattern (see Chapter 3), with GBTM identifying as many as 22 clusters (e.g. Groff, Weisburd & Yang, 2010). Again, this highlights the degree of sensitivity in the methods deployed, and tentatively highlights a benefit of k-means and ak-medoids, given that findings from GBTM sometimes have to be simplified by hand post-analysis to make meaningful interpretation possible. Explaining why the methods perform so differently is up for debate, but might largely be a result of the reliance on Bayesian Information Criterion (BIC) for deciding cluster solutions using GBTM. In the field, there has tended to be a lack of adjudication by the researcher when iteratively adding clusters to the model.

Thirdly, the degree of within-cluster homogeneity varies considerably between methods. Table 5.6 and 5.7 report the percentage of positive or negative trajectories within each cluster for ak-medoid and k-means respectively. Ak-medoids consistently achieves clusters which have homogeneous slopes for the increasing and decreasing categories. This is a result of the non-random intitialisation strategy, informed by a trajectory approximation, and subsequent medoid-based expectation-maximisation procedure, which 'guides' the forming of clusters towards clear delineations of long-term trends. The stable category, as intended by the ±25% quartile classification threshold, is characterised by a balanced mix of the two. K-means, on the other hand, which relies on generic, random starting points, and subsequently uses total distances and centroids, does not have any completely homogeneous clusters with respect to long-term slopes. The stable clusters are balanced in terms of positive and negative relative slopes, but the decreasing and increasing clusters continue to contain a mix, even though there is always a clear monopoly of the classified (increasing or decreasing) trend. This heterogeneity compared to ak-medoids raises questions about the theoretical relevance of the cluster solutions. Whilst subgroups identified using such clustering methods do not 'exist' in any real form, they should hold some meaning given the research questions and theoretical framework (Nagin, 2005). When the theoretical motivation is to gauge stability in long-term trends, and identify clusters characterised by directional homogeneity, ak-medoids holds advantage over k-means. A discussion on the implications of the differences between methods is returned to in the next chapter.

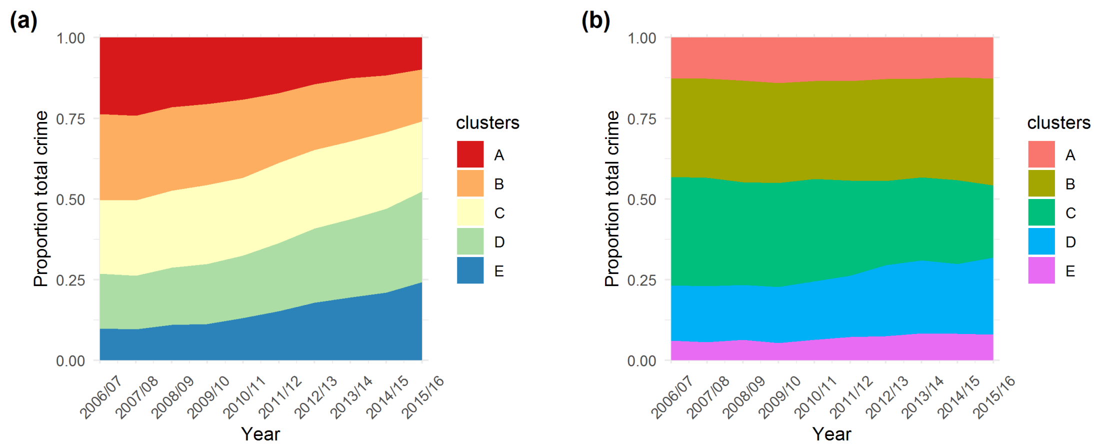

Figure 5.14: Proportion of total offender counts for each year attributable to each cluster for (a) ak-medoids and (b) k-means.

5.4.8 Spatial distribution of cluster solutions

A fundamental dimension of spatial criminology is the clustering of phenomena in space. The 'new wave' has made an effort to visualise the spatial distribution of longitudinal clusters identified in exploratory analysis. Doing so aids the interpretation of findings, and provides clues for how the observed longitudinal trends can be explained. The spatial distribution of the cluster solutions generated using ak-medoids and k-means are visualised using hexograms (see Chapter 4) in Figures 5.15a and 5.15b respectively. The outliers which were removed from analysis are included in the hexograms but coded in grey and treated as missing ('NA').

It is clear from Figure 5.15a that the ak-medoids cluster solution has a distinct geographic pattern. Output Areas grouped into Cluster A, identified as the most sharply declining group, tend to cluster around the outskirts of the city centre, especially the northern and western extents. However, there are also clustered pockets of this group elsewhere in the city. Members of Cluster B, the other group classified as 'decreasing', demonstrate a strong geographic pattern, often neighbouring one another, and frequently being proximal to other declining Output Areas in Cluster A. The stable Cluster C, representing a third of the sample, also tend to neighbour one another. Output Areas in Cluster A comprise most of the city centre, but are also commonly found to the south of the city, and the very north. Interestingly, the most sharply increasing Cluster E can be found neighbouring sharply decreasing Cluster A Output Areas around the city centre, although they also appear in isolation on the southern outskirts of the city.

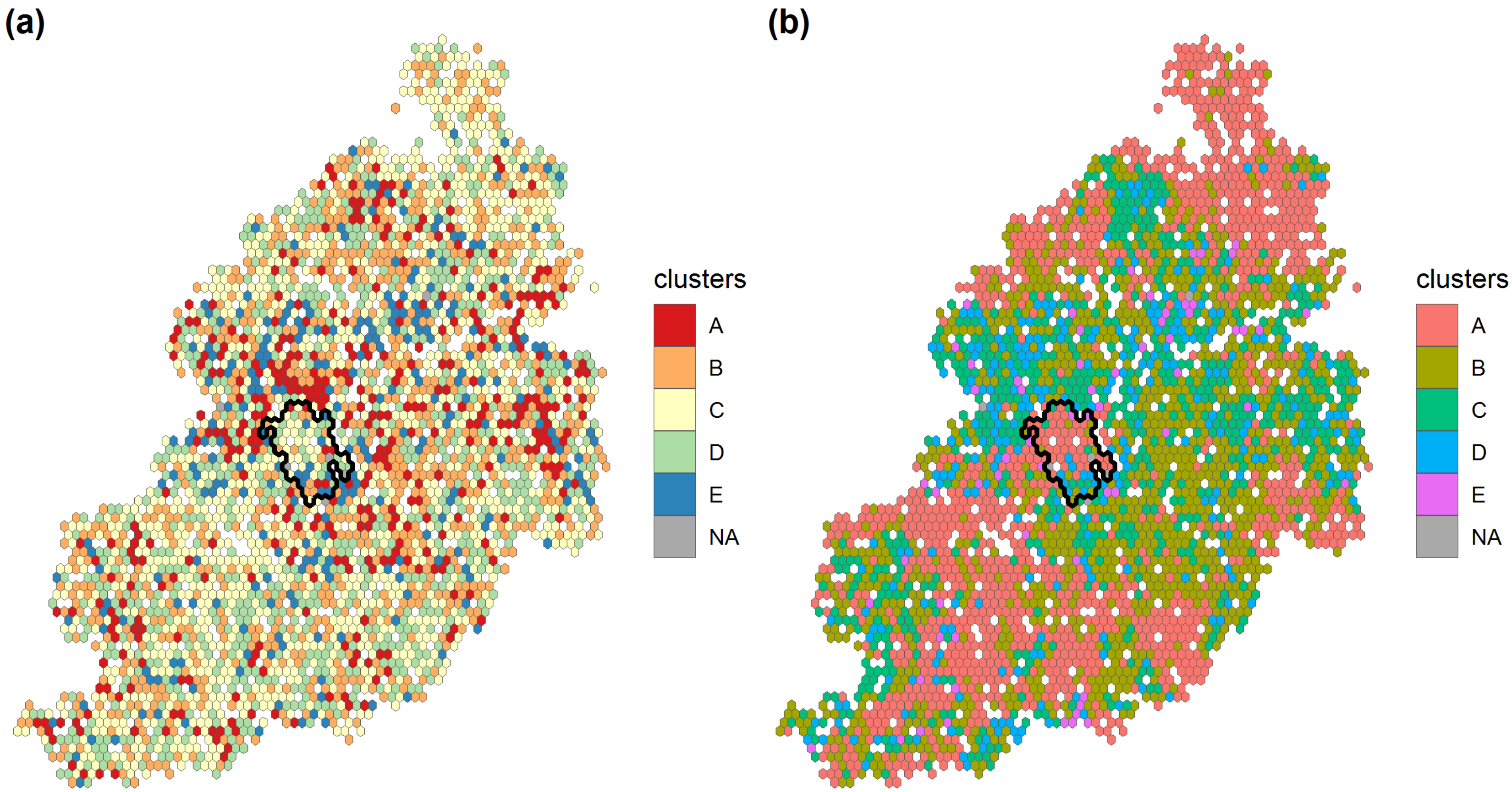

Figure 5.15: Spatial distribution of cluster solutions for (a) ak-medoids, (b) k-means. City centre boundry shown in black.

That said, the geographic pattern using the k-means solution in Figure 5.15b is even more salient. Output Areas belonging to any particular cluster rarely appear in isolation. Low and stable Output Areas in Cluster A dominate the city centre and suburbs to the north and south. Cluster B, which also primarily consists of stable Output Areas, are frequently found surrounding those in Cluster A, although they form their own congregation east of the city centre. Whilst they frequently form proximal groups, Output Areas in the increasing Cluster D feature across the city. The volatile, increasing Cluster E Output Areas are difficult to spot, as they are so few in number, but rarely appear in isolation, instead tending to neighbour one another, or neighbouring Output Areas in the increasing Cluster D.

The differences in spatial clustering between the two methods highlights a key point relating to the suitability of k-means. It raises an issue demonstrated in the crime literature when using simulated data (Adepeju et al., *under review*) which suggests that k-means is sensitive to the starting points or outright levels between Output Areas, rather than actual change over time. By way of example, the clusters identified by k-means (see Figure 5.13) are largely already evident in 2006/07 based on the starting point of each cluster, with only Clusters C and D starting similarly and then diverging. For ak-medoids, the clusters are not defined in 2006/07, with all clusters demonstrating some degree of shifting in order from the first year, or divergence/convergence over time. K-means demonstrates non-shifting behaviour in the crime papers of Andresen *et al* (2017) and Curman *et al* (2015), in which identified clusters largely remain in the same order from the first time point to the last. The result of this is that simply by using the relative offender measure for 2006/07 and categorising observations into five arbitrary thresholds, one can recreate a similar result (see Figure 5.16) to that which maps the k-means solution (see Figure 5.15b). Results using k-means are clearly heavily dictated by values in the first year. This calls into the question the benefit of conducting *longitudinal* analysis, and questions the meaningfulness of clusters identified by k-means when the primary interest is that of trends over time.

On the other hand, clusters identified using ak-medoids are highlighting patterns which can only be obtained through longitudinal analysis. Clusters derived from this approach do not demonstrate as strong spatial clustering, although it is clearly still evident. A consequence of this finding, and its contrast to the groupings identified using k-means, suggests that *change over time may be driven by highly localised* *factors*, with even neighbouring Output Areas behaving somewhat independent of one another.

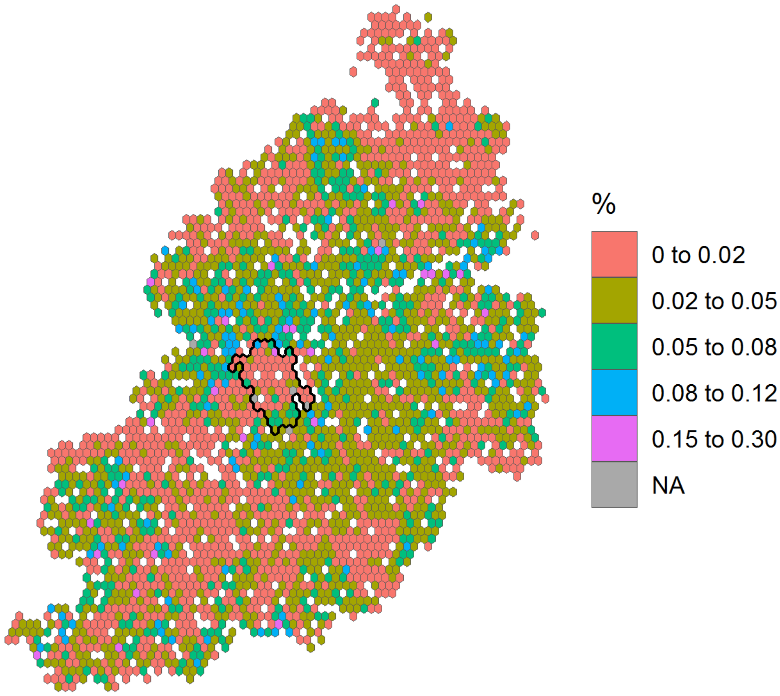

Figure 5.16: Proportional measure for 2006/07 categorised by arbitary thresholds. City centre guide is shown in black.

5.4.9 Overview

This section has sought to explore the question of longitudinal stability in offender residence concentrations. Following initial descriptives, a bespoke clustering method, termed ak-medoids (see Adepeju et al., *under review*), was deployed alongside an existing, generic implementation of k-means to disentangle instability in longitudinal trajectories at Output Area level. The aim was to establish the degree to which there had been local variation underlying the citywide decline in known offenders in Birmingham between 2006/07 and 2015/16. Both results confirmed that there has indeed been some instability in localised offender residence patterns over time, with some neighbourhoods characterised by fairly persistent concentrations, even amidst the citywide drop, and many declining more sharply, disproportionately contributing to wider declines. That said, the two methods differed in terms of the extent to which this stability was evident. Ak-medoids identified around a third of Birmingham as stable, suggesting a great deal of local variation in offender concentrations through time, whereas k-means identified two thirds as stable. In alignment with the aims of the method detailed in the previous chapter, ak-medoids generated more balanced, homogeneous groupings, which were less sensitive to starting points, in order to more deductively unpick long-term stability in offender residence trends. In alignment with existing crime research, k-means generated unbalanced groupings, some especially small, and often with heterogeneous long-term trends. Groupings identified by k-means were also found to be highly sensitive to cross-sectional levels of the outcome variable, rather than change over time. A result of this is highly spatially clustered groupings, which might overestimate the importance of meso or macro-level factors in driving local trends. This highlights how conclusions on the extent of longitudinal stability in offender residence concentrations might be sensitive to the methods deployed. The issues, and implications that arise from them, are discussed further in the next chapter.

5.5 Research question 3: explanation

5.5.1 Hypotheses recap

The previous section unpicked the degree of instability in offender residence concentrations over time at Output Area level, a spatial scale selected as theoretically and empirically appropriate. Findings indicated that there has indeed been a great deal of instability and local variation in offender residence concentrations, although the degree to which this holds true for large portions of the city varied by the cluster solutions identified using ak-medoids and k-means. That said, both methods uncovered two distinct groups characterised by 'increasing' relative offender residence trajectories over time. As discussed in Chapter 3, there are a number of key variables associated with social disorganisation theory which can be said to predict long-term trends in delinquency areas, namely, deprivation (measured as overcrowding), ethnic diversity (measured using a diversity index) and residential mobility (measured as rented accommodation). With this in mind, three hypotheses were proposed:

- H1: The higher the proportion of overcrowded households, the more likely Output Areas are to fall into the increasing relative offender residence classification

- H2: The higher the ethnic diversity index, the more likely Output Areas are to fall into the increasing offender relative residence classification
- H3: The higher the proportion of rented households, the more likely Output Areas are to fall into the increasing relative offender residence classification

As per the data and analytical strategy detailed in the previous chapter, these three hypotheses will be tested using the relevant census data measures at Output Area level, along with the controls of risky population and a spatial lag (given the clear clustering demonstrated using Local Moran's I earlier in this chapter), to predict the odds of Output Areas falling into the 'increasing' classifications identified using both ak-medoids and k-means, in separate models. The descriptives relating to each of these independent variables is reported in Appendix C.

Before that, however, some descriptive analyses are reported which address individual-level residential populations flows. So far, the question of longitudinal stability in offender residence concentrations has been answered using data at Output Area level, which has been constructed from individual-level data. Micro-neighbourhood-level analysis is the focus of this project, aligning with existing research (theoretically and empirically) in spatial criminology. However, as discussed in Chapters 2 and 3, using aggregated data has a number of drawbacks. In the case of longitudinal stability, the use of data aggregated to Output Area level might mask more complex, underlying processes. Long-term trends in offender residence concentrations may be a result of a number of factors, including the onset and desistence of individuals, but also the residential population flows of repeat offenders, whose persisted offending is coupled with frequent moves of residence. A relative increase of offenders in an Output Area might not be a result of individuals onsetting or persisting, but rather, an influx of already-active offenders who are moving from another Output Area (which might, in turn, experience a decreasing relative trajectory). This brings about an issue of selection: when we think we are examining onset or persistence, for instance, we are actually just examining underlying flows between areas. Whilst this section's main aim is to report results from the spatially lagged logistic regression analysis (to test H1, H2 and H3), it will first begin with a comment and description of residential population flows. Whilst this is substantively interesting in its own right, as has been demonstrated in recent work in the United States (Kirk, 2019), it also helps the interpretation of the theoretically-driven logistic regression models.

5.5.2 Residential population flows

The first point of note is that even at the individual-level, there appears to a reasonable amount of volatility in individual-level offender residence concentrations. Of the total number of known individual offenders in Birmingham between 2006/07 and 2015/16 (N = 105,664) there were 38,158 repeat offenders (36%). Essentially, these were individuals who appeared more than once in the data, having been identified as an offender in more than one crime. Of these repeat offenders, 24,318 (64%) were only known to have lived in the same Output Area. In other words, each time the police identified these offenders for an offence, they reported to be living in the same Output Area as the time previously. This leaves 13,840 repeat offenders who were known to have moved house to a *different* Output Area during the study period. This is 1 in 3 repeat offenders. It means that out of the total number of known individual offenders in Birmingham between 2006/07 and 2015/16, 13% were repeat offenders who were known to have moved house to a different Output Area during the time period.

Whilst this proportion appears relatively small, it worthwhile emphasising that these 13% are those most known to West Midlands Police. We only know that these offenders have moved house during the study period for the very reason that they were identified as a defendant for multiple offences. Given the known relationship between where offenders reside and where offences are committed more generally, but also specifically in Birmingham, as outlined earlier in this chapter, these house moves of repeat offenders might be having a significant impact on long-term crime trends. Personnel at West Midlands Police were especially interested in these descriptive statistics, despite their simplicity, on the basis of this point, given that the main focus of their spatial analysis is *crime locations* as oppose to *offender residences.* As noted in the next chapter, it is hoped that a key product of this thesis is to prompt a more balanced approach in academic research and police analysis.

That said, when it comes to explaining offender residence concentrations, 13% remains a relatively small proportion of the total offender population. The localised relative increases in offender concentrations identified using ak-medoids and k-means are still likely to be largely driven by onset or persistence (amidst citywide desistence), as offenders appearing in time point t continued to appear in $t + 1$, or newly appear as first-time offenders (given other factors, such as policing strategies or shifts in the criminal justice system, discussed in the next chapter). The consequence of this is that models seeking to explain increases in relative offender trajectories at Output Area level are assumed largely (but not exclusively) to be explaining area-level onset and persistence, rather than inflows of already-active offenders. This is worth bearing in mind when discussing the implications of findings. However, as noted above, these population flows are potentially highly significant when it comes to long-term crime trends, and as such, the following section reports on some preliminary descriptives which specifically attempt to visualise these flows over time. The section will then proceed to the explanatory models using the cluster solutions derived from ak-medoids and k-means.

5.5.3 Characteristics of origin-destination areas

Figure 5.17 visualises the origin (residence in time point t) and destination (residence in time point $t + 1$) population flows of the 13% (N = 13,840) of offenders between 2006/07 and 2015/16 in relation to Townsend deprivation deciles at Output Area level, calculated using 2011 census data. A decile of 1 represents the most deprived, and 10 is the least deprived. The spatial distribution of these deciles is also mapped out for contextual reference. It is clear from these visuals that there are indeed meaningful patterns in the resident population flows of offenders in Birmingham, with individuals tending to move to and from similarly deprived areas. The most common moves were from one most deprived decile Output Area to another (7.5%), followed by the second most deprived to the most deprived (3.9%) and then the most deprived to the second most deprived (3.8%). The lighter blue and yellow values in the bottom left quartile of the heatmap demonstrate that most offender population churn is occurring in deprived areas, which cluster around the city centre and in small suburban conurbations. In all, 22% of moves were to and from like-for-like deprived areas (the sum of the diagonal).

Beyond deprivation measures, Figure 5.18 visualises these origin-destination offender population flows for the 2011 Output Area Classification (OAC). These percentages are normalised to account for the unbalanced number of Output Areas in each classification. Again, there are distinct patterns in the flows during the study period. Output Areas classified as multicultural metropolitan ('Multi. Metro.') experienced major inflows during the study period from ethnicity central Output Areas (16%). Interestingly, this most common origin-destination flow for offenders means that potentially prolific individuals might be moving increasingly further away from the city centre, as most ethnicity central Output Areas cluster around the city centre limits (see Figure 5.18a). This would be consistent with research in the United States which has found that offenders returning to civilian life have increasingly been moving away from the city centres (Kirk, 2019). Such patterns over time might be attributed to wider trends in the suburbanisation of poverty identified in the United States (Chaskin & Joseph, 2015; Tach & Emory, 2017), returned to in the next chapter.

This finding is consistent with the descriptive results relating to the journey to crime, presented earlier in this chapter. It was demonstrated in the first section that the distance traveled by offenders from home to offence location has been increasing over time. This finding now becomes intuitive, with high crime rate areas continuing to cluster in the city centre, and offenders potentially living further away from the city centre, the distances being travelled are increasing. This apparent willingness to continue offending in the same areas, despite living further away, suggests that crime hotspots may not be that sensitive to offender residence patterns. It is also consistent with findings which suggest that offenders continue to offend in their old, familiar neighbourhoods, even after moving house (Bernasco, 2010). Further analysis would be needed to verify the suburbanisation of offender residences, and the potential impact of this on crime hotspots, but the descriptives presented here are certainly suggestive of important patterns which speak to both offender residence and crime concentration strands of research[3].

[3] Some preliminary attempts were made to verify more definitively whether offenders were moving further away from the city centre. This involved plotting count population flows in and out of each Output Area for the study period. A map visualising these flows is reported in Appendix D. This is not reported here, largely because the results are so sensitive to the definition of a 'city centre'. Birmingham's size means that many other areas within the city boundaries can be considered smaller urban conurbations (e.g. Sutton Coldfield), making definitive statements about 'suburbanisation' somewhat problematic. However, the map certainly suggests that many suburban areas have experienced *inflows* of known offenders during the study period.

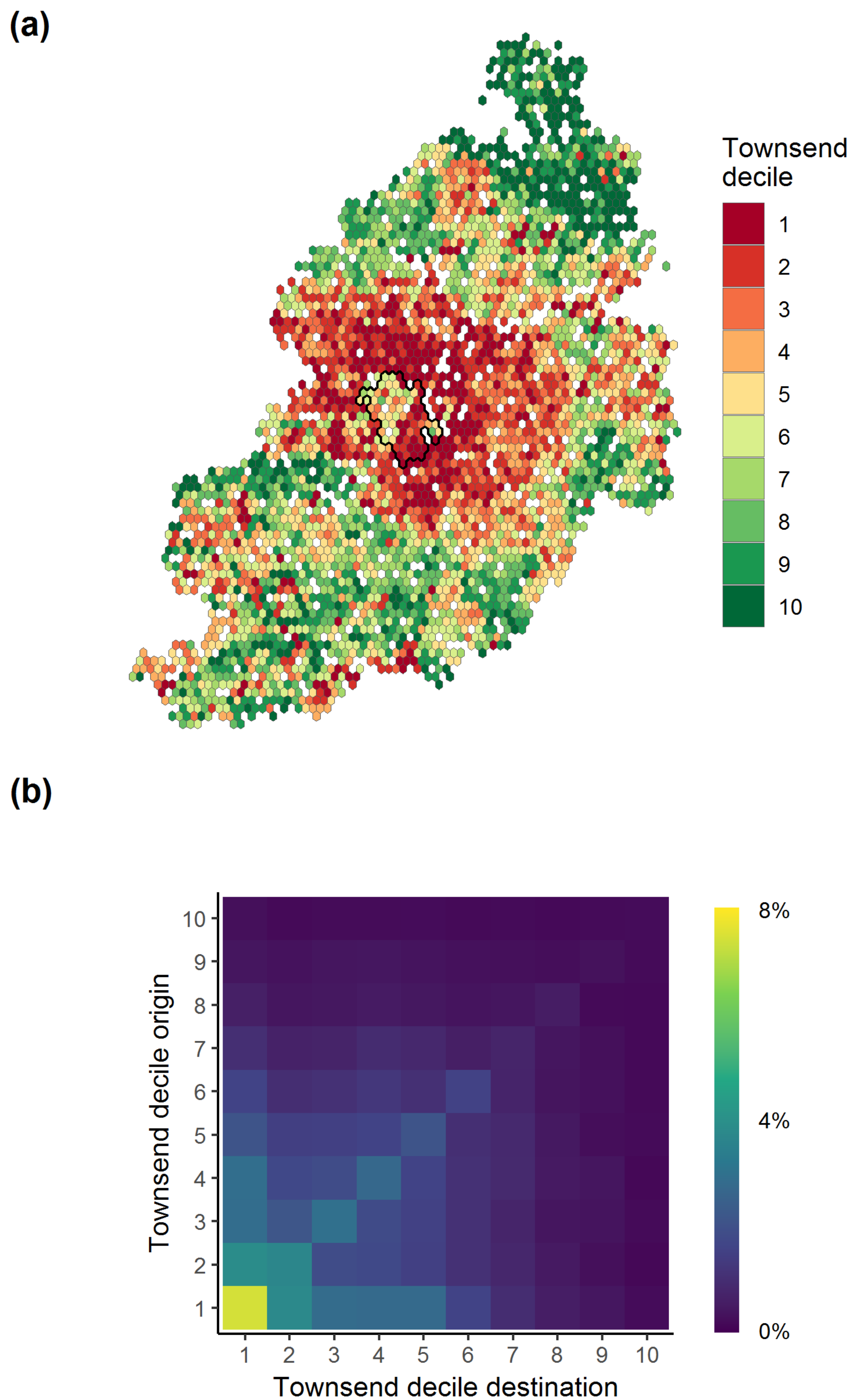

Figure 5.17: (a) Townsend deprivation (2011) deciles (1-most deprived, 10-least deprived) with city centre guide shown in black, and (b) Offender residential origin-destination population flows from 2006/07 to 2015/16 by decile.

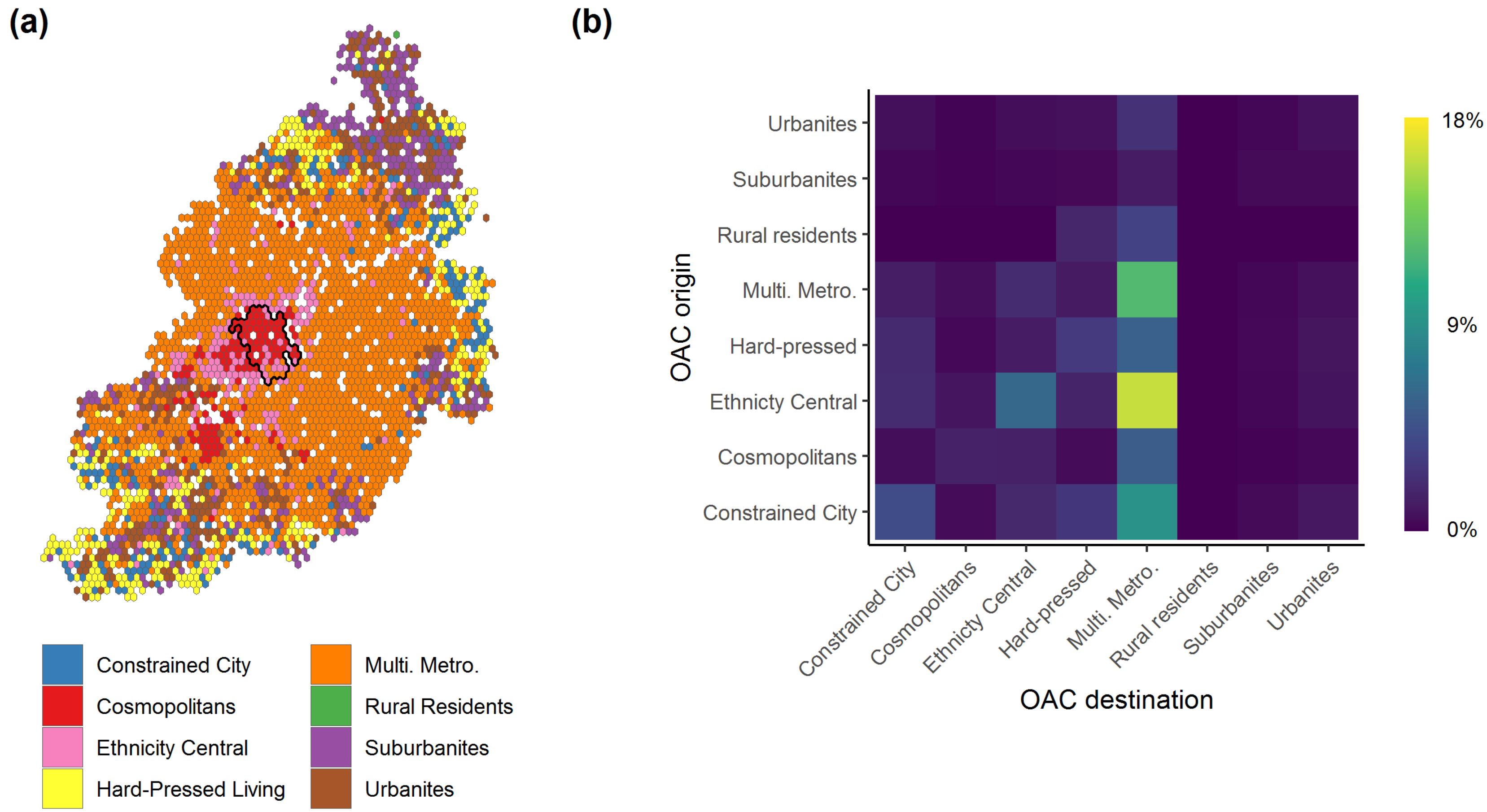

Figure 5.18: (a) Output Area Classification supergroups (2011) with city centre guide shown in black, and (b) Offender residential origin-destination population flows from 2006/07 to 2015/16 by supergroups.

5.5.4 Spatially lagged logistic regression results

As detailed in the analytical strategy, three key theoretically-driven independent variables were identified from the 2001 census to test hypotheses stated above. Deprivation is measured through the proportion of households identified as overcrowded. Ethnic diversity is the Simpson's index of diversity for all ethnicity categories. Residential mobility/rented accommodation is measured with the proportion of households which are rented. Two controls are used for the risky population (proportion of residents aged 15 to 24), and a spatial lag (mean relative offender proportions of neighbouring areas) to account for the dependence between observations. Two models were run: one using the increasing classifications from ak-medoids, and one using the increasing classifications of k-means. All independent variables were standardised to permit comparisons of effect sizes. 95% confidence intervals are reported in all visualisations and tables, and p-values are rounded to three decimal places.

Figure 5.19a visualises the odds ratio estimates for the spatially lagged logistic regression analysis using the ak-medoids increasing classification. Table 5.8 reports the full estimates in tabular format. Overall, there is support for two out of three hypotheses[4]. Interestingly, findings suggest that the higher the proportion of overcrowded housing in 2001, the less likely Output Areas are to fall into the relative 'increasing' classification (OR 0.77, $p < 0.001$). Not only does this provide evidence to reject H1 but the statistically significant estimate is the opposite direction to what was hypothesised. The higher the ethnic diversity measure in 2001, the more likely Output Areas are to fall into the increasing class (OR 1.16, $p < 0.01$), providing evidence to reject the null hypothesis that there is no relationship between ethnic diversity and increasing relative offender residence concentrations. The higher the proportion of households which are rented, the more likely Output Areas are to fall into the increasing class (OR 1.15, $p < 0.01$), so we can also reject

[4]There were no issues of multicollinearity in these models. Correlation matrices of all independent variables gave largely weak associations, with the highest correlation being between ethnic diversity and overcrowding (0.46) which was not considered an issue. Post-analysis examinations using the variance inflation factor (VIF) also did not reveal any issues based on the thresholds used by Field (2012). Testing whether independent variables were linearly related to the log odds of the dependent variable was carried out using a method advocated by Kassambara (2018), which visualises the relationship. On the whole, this did not raise any issues, although the results suggested that there was a non-linear relationship for *overcrowding* in the k-means model. A viable remedy for this was not found, but a recode (to categorical) of overcrowding, or an alternative measure, could be considered in extensions of this analysis.

the null hypothesis that there is no relationship between rented accommodation and increasing relative offender residence concentrations. As such, we can tentatively reject H1 and accept H2 and H3.

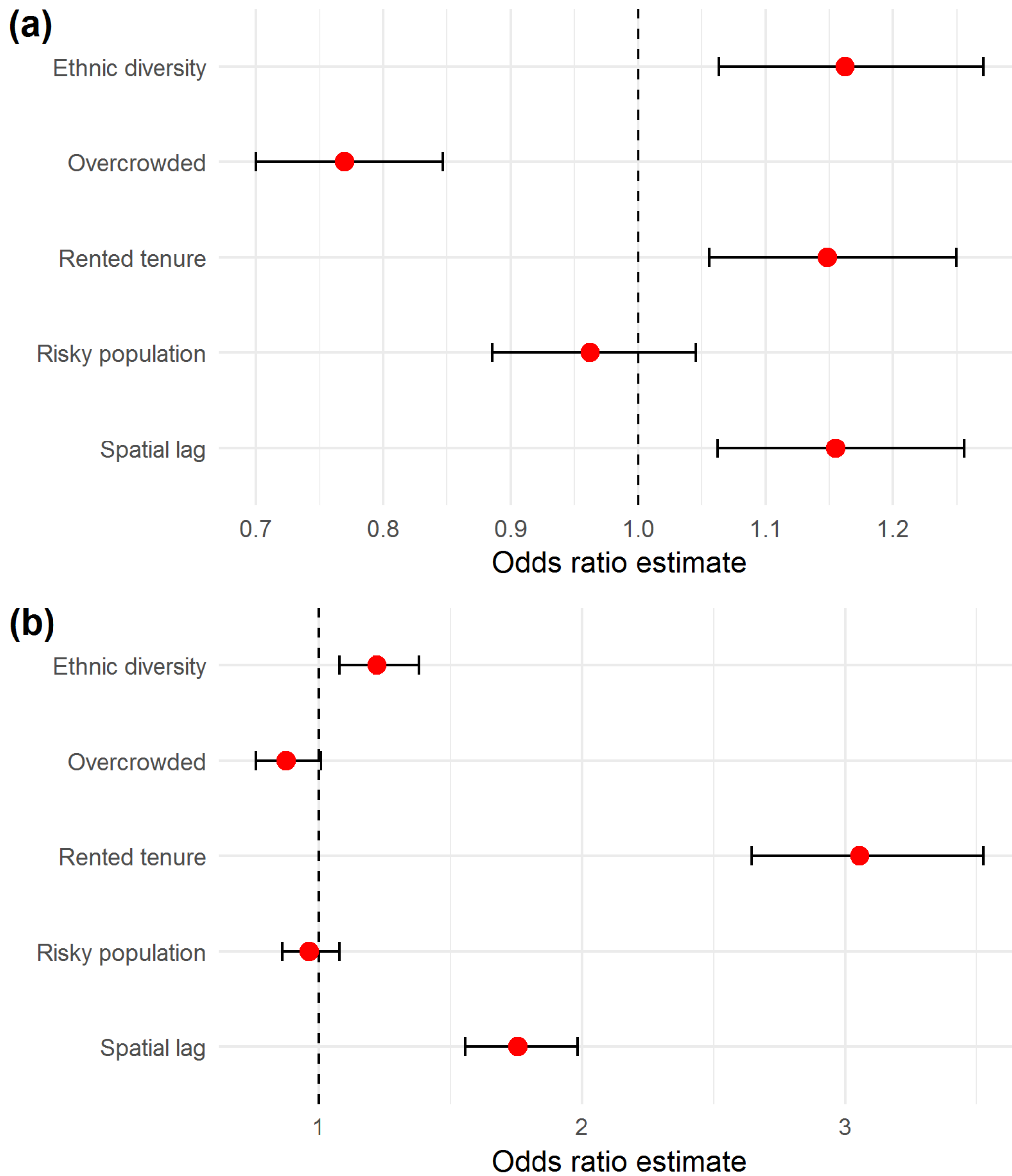

Figure 5.19: Logistic regression result for (a) ak-medoids, (b) k-means with dependent variable as increasing (1), decreasing or stable (0). 95 percent confidence intervals reported.

Similarly, Figure 5.19b visualises the odds ratio estimates using the k-means 'increasing' classification, with the full results in Table 5.9. The broad findings are similar to the analysis using the ak-medoids classifications: there is support for two out of three hypotheses. This time, there was no statistically significant association between overcrowding and the likelihood of Output Areas experiencing an increasing relative trajectory (OR 0.87, $p > 0.05$). As such, the data does not provide enough evidence to reject the hypothesis that there is no association between overcrowding and the increasing classification. However, findings suggest that Output Areas with greater ethnic diversity are more likely to fall into the increasing group (OR 1.22, $p < 0.01$), providing evidence to reject the null hypothesis and accept H2. There is also evidence to reject the null hypothesis for H3, as there is a statistically significant relationship between the proportion of rented households and the increasing class (OR 3.06, $p < 0.001$). The results using the k-means cluster solution therefore broadly align with those of ak-medoids, with insufficient (if not, contradictory evidence) to accept H1, and evidence to support H2 and H3.

Interestingly, though, the effect sizes between the two dependent variable constructions (for ak-medoids and k-means) differ considerably. Without exception, the effect sizes of the main (statistically significant) independent variables using the 'increasing' categories identified by k-means are larger than the equivalent for ak-medoids. The number of observations categorised as increasing does differ between ak-medoids (N = 977) and k-means (N = 373) although this does not explain the discrepancy. More likely, this finding is a result of the starting points of clusters. As demonstrated earlier in this section, and in a recent comparison between ak-medoids and k-means in the crime concentration literature (see Adepeju et al., *under review*), k-means is much more sensitive to starting values and outright levels than ak-medoids. A result of this is that the starting values of k-means' increasing clusters are substantially higher than the equivalent for ak-medoids, which are low. This is because ak-medoids focuses specifically on change over time, irrespective of starting values. As has been demonstrated, this holds advantage when examining dimensions of longitudinal stability, but when coupled with data availability issues, which limit independent variables to the 2001 census, it becomes difficult to disentangle the explanatory model. Here, perhaps the regression model using the ak-medoids cluster solution suffers because between-cluster differences are simply not apparent in 2006/07, the year closest to the explanatory variables measured in 2001. This highlights the limitations of such quantitative analysis, and is returned to as a discussion point in Chapter 6.

Table 5.8: Logistic regression results for ak-medoids cluster solution, coded increasing (1), stable or decreasing (0). 95% confidence intervals reported. N = 3215. Likelihood-ratio Model Chi Square: 66.766 ($p < 0.001$).

Predictor	Odds ratio	CI low	CI high	Std error	P-value	Z-value
Ethnic diversity	1.1626671	1.0634739	1.2711123	0.0454987	0.001	3.3125500
Overcrowded	0.7698635	0.6997515	0.8470006	0.0487193	0.000	-5.3683443
Rented tenure	1.1487377	1.0559782	1.2496455	0.0429580	0.001	3.2278875
Risky population	0.9622636	0.8858668	1.0452488	0.0422058	0.362	-0.9114129
Spatial lag	1.1550802	1.0621159	1.2561815	0.0428104	0.001	3.3676377

Table 5.9: Logistic regression results for k-means cluster solution, coded increasing (1), stable or decreasing (0). 95% confidence intervals reported. N = 3215. Likelihood-ratio Model Chi Square: 538.286 ($p < 0.001$).

Predictor	Odds ratio	CI low	CI high	Std error	P-value	Z-value
Ethnic diversity	1.2206387	1.0793881	1.380373	0.0627460	0.001	3.1774810
Overcrowded	0.8747436	0.7593479	1.007676	0.0721803	0.064	-1.8540297
Rented tenure	3.0552058	2.6469005	3.526495	0.0731940	0.000	15.2587180
Risky population	0.9636664	0.8604881	1.079217	0.0577793	0.522	-0.6405416
Spatial lag	1.7556634	1.5551296	1.982056	0.0618827	0.000	9.0953784

5.5.5 Overview

The population flow descriptives and logistic regression models presented in this section give us a number of insights into how we can seek to explain offender residence concentrations over time. Firstly, between-Output Area offender residence moves were explored through descriptive statistics and visualisations. It is clear that there is indeed some instability over time, with around a third of repeat offenders moving to different Output Areas during the study period. However, this group only accounts for 13% of all known individual offenders in Birmingham. So, whilst it is problematic to disentangle this selection in aggregate-level analysis of offender residence patterns, long-term trends at Output Area-level are likely to largely be a result of onset or desistence events, rather than population flows. Of those who do move, there is evidence that moves are made between similarly deprived areas, with many moving to areas further away from the city centre. These findings may reflect wider patterns in the surburbanisation of poverty, and long-term could have an impact on shifting crime concentrations. There is partial evidence for the three hypotheses derived from social disorganisation theory using the cluster solutions generated using ak-medoids and k-means. It remains unclear whether overcrowding as a measure for deprivation is associated with increasing relative offender residence trajectories. In fact, the only evidence is contradictory to the proposed hypothesis. However, there is evidence to suggest that high ethnic diversity and a high proportion of rented accommodation is associated with increasing trends in relative offender residences. The regression model using the cluster solution derived from k-means appears to hold greater explanatory power compared to ak-medoids, although this might be a consequence of the limited independent variables and temporal lag, which better explain outright differences between clusters, rather than changes over time. More detailed discussion of these findings, with particular attention on the implications, are returned to in the next chapter.

5.6 Conclusion

This chapter has presented results relating to four main dimensions. Firstly, the empirical distinction between crime and offender residence locations was demonstrated. As Chapters 2 and 3 have argued, there are theoretical reasons and (some) empirical evidence to justify treating the two as related (but distinct) phenomena. Using the data from Birmingham, it was shown that crime and offender residences are indeed empirically distinguishable. At the aggregate level, the two have weak to moderate correlations and distinct spatial clustering across all spatial scales. These associations and patterns are especially salient at fine-grained units. Moreover, offenders appear to be quite mobile when choosing targets, with the majority of crimes being committed outside of the offenders' home neighbourhood. The distance from home to crime location is roughly 1 mile (straight line), and appears to be increasing over time. Demonstrating these distinctions augments the strong theoretical reason, and moderate existing empirical reasons, for reviving the offender residence strand of longitudinal research, and ceasing to assume that offender and crime concentrations are synonymous.

Against this backdrop, results were presented to answer the first research question, namely, the question of spatial scale, through the replication of methods used in crime concentration literature. The use of descriptive tables, visuals and a multilevel variance partition, confirmed that offender residences tend to be more concentrated, and have greater variance, at the most fine-grained spatial scale. That said, in alignment with existing crime research, there is no 'rule of thumb' to suggest that smaller units always uncover greater nuances in the data. Based on these findings, the smallest census block unit, Output Area, was selected for future analysis.

Next, descriptive statistics and longitudinal clustering methods were deployed to examine the degree of (in)stability in offender residence concentrations over time, in answer to research question 2. Basic rank order correlations indicated that the citywide decline in the number of known offenders has been non-uniform at Output Area level. More detailed analysis using a novel technique, anchored k-medoids (ak-medoids), and an existing technique, k-means, were presented to unpick meaningful patterns in Output Area-level relative offender residence trajectories. Both methods confirmed that there has indeed been instability over time, with many Output Areas experiencing increasing or decreasing trends which deviate from the citywide decline. That said, k-means appeared to identify a much larger proportion of the city as stable. Ak-medoids demonstrated an ability to disentangle subgroups characterised by directional homogeneity, which were more balanced in size, compared to k-means. Both methods generated cluster solutions which were spatially proximal, although k-means appeared more sensitive to outright levels, rather than change over time.

The final research question for which results were reported related to explanation (RQ3). First, a brief descriptive evaluation was reported on the extent to which longitudinal trends in offender residence at Output Area level are being determined by individual-level residential population flows i.e. offenders moving house from one neighbourhood to another. A number of findings emerged from this. Firstly, only a relatively small proportion of the known offender population in Birmingham were repeat offenders who moved residence to different Output Areas during the study period. Most offenders either only appear once in the data (one-time offenders) or appear more than once, but do not move house. This suggests that long-term, aggregate-level trends are largely being driven my onset, persistence or desistence (or other factors, such as policing, discussed in Chapter 6), rather than offenders moving to and from particular areas. That said, since these are repeat offenders, this could be having an important impact on shifting crime hotspots. The population flow descriptives also suggested that offenders are moving to and from similarly deprived areas, with some actively moving away from the city centre. Finally, spatially lagged logistic regression results were reported using the cluster solutions derived from ak-medoids and k-means respectively. These models found mixed support for the three hypotheses posed based on social disorganisation theory. There was no evidence to suggest that highly deprived areas subsequently experience increasing relative offender residence trends. However, areas characterised by high ethnic diversity and a high proportion of rented accommodation were more likely to experience increasing relative trends. The model using the cluster solution from k-means appeared to hold greater explanatory power compared to ak-medoids, although this might be as a result of shortcomings in the data and model, rather than the ak-medoids clusters per se. This demonstrates the limitations of conducting such quantitative analysis in isolation. This, along with the other findings reported above, are returned to and discussed in more detail, including caveats and the wider empirical, theoretical and policy implications, in the following chapter.

Chapter 6

Discussion: implications and future research

6.1 Introduction

Findings from analyses reported in this thesis serve to answer the three main research questions derived relating to spatial scale, longitudinal stability and explanation. Firstly, what is the most appropriate spatial scale to study offender residential concentrations? Secondly, to what extent do offender residential concentrations demonstrate stability over time? And thirdly, how can we explain the longitudinal (in)stability of offender residential concentrations observed? A review of existing methodologies deployed in the offence concentration field was conducted to identify suitable methods, with adjustments and improvements made where appropriate. Findings were reported set against the back drop of an initial demonstration of why the spatial patterning of offender residences and offences are not only theoretically, but also empirically distinct (yet related) phenomena. Data was sourced from West Midlands Police Force and open census data for Birmingham, England. This chapter begins with a re-cap of the findings from the analyses conducted to answer these research questions. The theoretical implications are then outlined, followed by a discussion on the data used, including the merits and shortcomings, and the impact this might have had on findings. The methodological and policy implications of findings are then detailed, which leads into a discussion on the limitations of the study, and with these in mind, proposals for future research are then put forward.

The chapter concludes with a summary of the key discussion points.

6.2 Re-cap of findings

Findings from the journey to crime literature demonstrate that offenders tend to commit offences relatively close to where they reside. Although the theoretical distinctions are clear, the empirical differences are not completely understood, especially when considering the impact of spatial scale. Here, descriptive analysis was conducted to demonstrate that they are indeed empirically distinct in Birmingham, even across multiple spatial scales. The correlation between offender residence and offence rates in Birmingham was weak to moderate across the entire 10-year period. The degree to which each phenomenon clustered in space also varied, with fine-grained spatial scales making such distinctions more stark. These aggregate-level findings were scrutinised further using individual-level journey to crime descriptives. Offenders were shown to typically commit crime *outside* of their resident neighbourhood, and travel around 1-2 miles to do so. There was evidence of increased mobility over time. Findings were consistent with the *distinct* theoretical explanations for why crimes and offender residences are non-randomly distributed in space. With these findings in mind, along the theoretical argumentation and existing findings from the journey to crime literature, there is clearly plenty of justification for reviving interest in offender residences.

The spatial scale at which researchers have examined the geography of both offences and offender residences has, generally speaking, been decreasing over time. The 19th Century pioneers mapped out criminal activity at the nationwide level, using large regions as the unit of analysis. The Chicago School made analysis more local, using pinpoint locations of offender residences, as well as aggregate-level neighbourhood units considered to be theoretically meaningful. Contemporary studies have deployed a number of different methods to demonstrate the empirical benefit of using small areas to study crime concentrations. Doing so has been found to increase between-unit heterogeneity, and uncover more detail in the data which would otherwise be masked with larger units. By way of a replication, a number of descriptive and model-based statistics were deployed to examine whether this holds true for offender residence concentrations using nested census block units in Birmingham. Findings suggested that offender residence concentrations *increase* as the geographic resolution becomes more fine-grained. Smaller units, in this case Output Areas, were found to expose more detailed longitudinal trends, suggesting that offender residences are becoming *more concentrated* over time. A multilevel variance partition also found that the largest proportion of total variance was attributable to Output Areas. There is some evidence to indicate that, generally speaking, offender residences are less concentrated than crimes. Following these findings, Output Areas were selected as the most appropriate scale going forward, so as to ensure that as much detail as possible was unmasked in further analyses.

The context for examining the longitudinal stability of offender residences was set through a series of descriptive statistics on the citywide trend in Birmingham. The absolute citywide count and mean Output Area rates of known offenders has consistently fallen during the study period. Rank order correlation matrices suggested that this decline has been non-uniform across space. Two longitudinal clustering methods were deployed to unpick the degree of instability and uniformity in these trends over time, one being a generic implementation of k-means, and another being a bespoke method termed anchored k-medoids (ak-medoids) developed as part of this thesis. Clustering was ran on a *relative* measure of offender residences to better identify deviations from the citywide trend. Both methods found evidence of instability in offender residence concentrations over time, but differed in the degree to which this was true. Findings suggested that the usage of k-means in isolation might result in researchers *overestimating* the proportion of cities which are mimicking the citywide trend and experiencing stable relative trajectories. Ak-medoids demonstrated an ability to unpick meaningful groups from the data, characterised by distinct longitudinal trends and within-group homogeneity, which k-means was unable to identify. Both methods were capable of identifying clusters with meaningful spatial patterns, although the groupings identified using k-means were highly clustered in space, and appeared overly sensitive to outright levels in relative offender concentrations, rather than change over time.

The final step was to try and explain the longitudinal patterns observed. A preliminary attempt was made to disentangle the extent to which fluctuations in relative offender concentrations over time were simply a result of some offenders moving house between Output Areas. Although only a small proportion of offenders were known to have moved house during the study period, those that did demonstrate a degree of residential mobility. Generally speaking, offenders moved between neighbourhoods with a similar level of deprivation, and with specific demographic characteristics. There was some descriptive evidence that offenders are tending to live increasingly further away from the city centre. Spatially lagged logistic regression models, using predictors based on social disorganisation theory, were then deployed using the 'increasing' clusters as the dependent variable, derived from k-means and ak-medoids respectively. Findings suggested that neighbourhoods characterised by high ethnic diversity and a high proportion of rented households increase the odds of Output Areas experiencing *increasing* relative trends in offender residence concentrations. This is consistent with social disorganisation theory. However, there was no evidence to suggest that overcrowding, as a proxy for deprivation, is associated in increasing trends. In fact, the only evidence suggests that the relationship was the opposite to what was hypothesised. Although the overall findings were similar, whether using the cluster solution derived from k-means or ak-medoids, findings suggest that explanatory models are sensitive to how clusters are obtained.

The findings generated from analyses have a number of theoretical, methodological and policy-orientated implications. Each of these dimensions are now dealt with in turn, along with a comment on how the data used for this project may have impacted on the results, and consequently, the conclusions.

6.3 Theoretical implications

The development of a novel theoretical framework was not a primary aim of this thesis, but the substantive findings have a number of implications for existing theories. Firstly, the empirical distinction between offender residences and crimes highlights how problematic it is for social disorganisation to have become a theory for two distinct (but related) phenomena. Secondly, the identification of delinquency areas in Birmingham suggests that some of the mechanisms at work in Chicago for Shaw and McKay (1942/1972) are also present in an English urban setting. However, the fact that the apparent stability of these areas differs depending on the methods deployed also raises questions about the fragility of empirical support for this stability. Thirdly, evidence that deprivation, ethnic diversity and rented accommodation (as a proxy for residential mobility) play an important role in explaining offender residence concentrations over time provides support for the claims made by social disorganisation theory, and related work which emphasised the importance of housing (Bottoms and Baldwin, 1976). Fourthly, findings suggest that the field could benefit from widening its theoretical remit to include the suburbanisation of poverty, which to date, has played no part in the 'new wave' of research examining longitudinal concentrations of crime, or in this case, offender residences.

6.3.1 Offender-crime distinction

The finding that crime and offender residence locations are distinguishable across multiple spatial scales, across multiple years, is a novel empirical result that has important theoretical implications. Broadly, it provides strong reason to develop and test theoretical frameworks for crimes and offender residences separately, whilst acknowledging that the two are related. There has been a tendency, likely due to early findings of empirical similarity (e.g. Schuerman & Kobrin, 1986) to adopt social disorganisation theory for use in the crime concentration literature, despite it being developed as a framework to explain the persistence of delinquency areas i.e. where offenders live (Bottoms & Wiles, 1986). It is unlikely, given the findings presented here, and more generally in the journey to crime literature, that social disorganisation theory is suitable for explaining both crimes and offenders at fine-grained spatial scales. However, historical accounts of the literature have tended to brush over these distinctions (see Weisburd, Groff & Yang, 2012).

Instead, should the findings presented here spark a revival of the offender residence strand of research, perhaps social disorganisation theory can be reclaimed from the offence literature to fulfill its original intention, namely, to explain the persistency of delinquency areas over time. The theoretical frameworks generated to explain crime concentrations are plentiful, such as routine activities, rational choice, opportunity, crime pattern and optimal foraging theory, and are often intertwined. Although the offender residence location plays a fundamental role in some of these theories, thus emphasising the importance of offender residences in explaining crime concentrations, they do not seek to explain why offenders tend to live in particular areas, or why concentrations of offender residences might shift over time. Reclaiming social disorganisation to fulfill this role, or developing more contemporary explanations around modern obstacles like the suburbanisation of poverty (Kirk, 2019), can only serve to advance our understanding of crime, given the theoretical (and empirical) links. It would take a concerted effort of researchers in spatial criminology to acknowledge and act on this, but such calls for a refocus in the field have also been made elsewhere (see Bottoms, 2018).

6.3.2 Persistency of delinquency areas

The finding that delinquency areas can persist over time, irrespective of wider changes in the city, is consistent with expectations from social disorganisation theory (Shaw & McKay, 1942/1972). Although the contemporary new wave (see Chapter 2) claims to have found such evidence, these studies have mainly done so using police recorded crime data, not offender residence data. As such, the evidence presented in this thesis, gathered through the deployment of descriptives, visualisations, existing and (new) bespoke clustering methods, using offender residence data, represent an important theoretical contribution to the new wave. Coupled with evidence about the distinctions between crimes and offender residences, it is also represents a critique, which questions whether the new wave's findings, summarised in Chapter 2, really are in support of social disorganisation, or instead in support of crime-specific theories like routine activities. As it stands, the new wave has attempted to keep both in play simultaneously.

The use of a generic clustering method (k-means), which is entirely inductive, and a novel, bespoke method (ak-medoids), which is partially deductive, may also have important implications for theory. Here, the degree of (univariate) support for social disorganisation theory varied quite considerably by the findings generated from the two methods. Firstly, this finding might scupper the momentum that has been building throughout the new wave literature, which through the use of univariate clustering, claims to have been garnering empirical evidence to support for a variety of theories which are consistent with longitudinal stability in crime concentrations (see Chapter 3). It remains unclear to what extent these findings are an artefact of the methods being deployed, which until this project and related paper (Adepeju et al. *under review*), have been generated using only exploratory, atheoretical methods. Secondly, in contrast to this, the introduction of deductive longitudinal methods may accelerate theoretical advance in spatial criminology. It permits the theoretically-driven interrogation of data which, to date, has not been undertaken in the field. Specific hypotheses derived from theoretical frameworks such as social disorganisation and routine activities can be tested. It remains unclear which direction, and to what extent, the demonstration and contrast between deductive and inductive methods will impact on the development of theories in spatial criminology, but it will likely have implications for both offender residence and crime concentration research.

6.3.3 Explaining delinquency areas

Findings from the explanatory models are fairly encouraging of further examination into social disorganisation theory as a framework to explain offender residence concentrations in England. That said, there is still plenty of room for discussion. High ethnic diversity and a high proportion of rented households increased the odds of neighbourhoods experiencing increasing relative offender residence trajectories, as hypothesised. There was no evidence to suggest as such for overcrowding. As discussed, this could be because overcrowding is an imperfect or outdated proxy for deprivation. However, it could also signal a shift in the way in which social disorganisation operates in an era and welfare system far removed from that of pre-World War II Chicago.

As stated in earlier chapters, high ethnic diversity and high residential mobility are largely thought to be responsible for creating socially disorganised neighbourhoods. It is simply that ethnic minorities tend to move to deprived areas upon arrival, and then proceed to leave such areas as soon as it is economically viable. In Birmingham, the correlation between overcrowding and these measures was low to moderate, suggesting that those areas characterised by overcrowding are not necessarily characterised by a large proportion of rented houses or high ethnic diversity. Whilst there is evidence for a relationship between ethnic minority populations and overcrowding at the area-level (Lymperopoulou & Finney, 2017), it does not necessarily follow here that *diverse* areas have an overcrowding problem. Instead, it is plausible that social disorganisation is manifesting in English neighbourhoods through means other than deprivation, with ethnically diverse and residentially mobile populations converging for other reasons. Such a scenario would render the causal mechanisms underpinning social disorganisation theory somewhat irrelevant, at least in its original form, in the context of English cities today. Comparable points have been made by Anthony Bottoms upon reflection of his Sheffield case studies, in which it became clear that "the single concept of social disorganisation [could not] adequately explain offending in all the varied types of high offender neighbourhood" (2018, p. 139-140). Future research might benefit from a more nuanced and context-specific approach to explaining delinquency areas given the study region and time period, drawing inspiration from the Chicago School, rather than seeking to mimic it.

That said, findings from the population flow descriptives show that offenders tend to move house to and from highly deprived areas when using the Townsend Index (rather than overcrowding in isolation) as a measure. This suggests that deprivation is still playing a major role in explaining delinquency areas, but perhaps not in the way which was hypothesised. Further analysis would be required to understand the mechanisms behind these relationships. Research in the United States has demonstrated that the criminal justice system plays a significant role in determining the residential mobility of offenders following their release from prison (Kirk, 2009; Harding, Morenoff & Herbert, 2013). That said, there is certainly still strong evidence to suggest that social disorganisation can manifest and explain offender residential patterns at neighbourhood level in the context of an English city. This is somewhat conflicting with existing findings by the likes of Baldwin and Bottoms (1976) who questioned the relevance of social disorganisation in the UK. However, that analysis was conducted on cross-sectional data, missing the *dynamic* dimension of the theory which is so crucial (see Chapter 2), on larger spatial units, and without descriptives on origin-destination population flows on known offender house moves. There is certainly good reason not to dismiss the relevance of the theory in the English context quite yet.

6.3.4 Population flows

As reported above, the descriptive findings reported using origin-destination data on offenders moving house during the study period may hold significant value for our understanding of social disorganisation theory, but there are also wider implications for future theoretical development. As it stands, the field of spatial criminology has not formulated a formal theoretical framework around offender residential population flow patterns. A handful of studies have examined the residential patterns of incarceration, but not over an extended time period (e.g. Sampson & Loeffler, 2010) and few have specifically described residential moving patterns over time spatially. However, those that have in the United States have found evidence to suggest that offenders are living increasingly further away from city centres (Kirk, 2019). This is consistent with the findings presented here in Birmingham, although preliminary, and align with what might expect from the suburbanisation of poverty (see Kneebone & Garr, 2010). With the suburbs said to be the areas characterised by the faster growing poor populations, and many offenders coming from and residing in deprived communities, this finding is a novel but (retrospectively) an expected one. There is scope for these findings to contribute to the development of a theoretical framework around the residential patterns of offenders, drawing upon existing understandings of social disorganisation theory and the suburbanisation of poverty. Advancing these dimensions of spatial criminology could also hold substantial merit for crime concentration research, given what is known about the journey to crime.

6.3.5 Final comments on theoretical implications

A number of theoretical implications emerge from the findings generated in this thesis. Firstly, the empirical demonstration that crimes and offender residence concentrations are distinct (but related) phenomenon strongly suggests that each demand unique theoretical frameworks. Offender residence and crime locations are intrinsically linked through the journey to crime literature (and associated theories) but the current trend of adopting social disorganisation theory to explain *crime* concentrations appears misguided. At fine-grained spatial scales, it seems implausible that the theory is applicable to both strands of research. More likely, there are different mechanisms driving offenders to reside and offend in particular areas. An acknowledgement of the theoretical and empirical distinctions between offender residences and crimes will ultimately further the field, with the journey to crime literature (and associated theories, such as optimal foraging) providing the conceptual link between the two strands.

Secondly, the finding that persistently high offender residence neighbourhoods, 'delinquency areas' (Shaw & McKay, 1942/1972) are evident in Birmingham, and that deprivation (but not overcrowding in isolation), ethnic diversity and rental housing play an important role in explaining them, suggests that social disorganisation theory is applicable to neighbourhoods in English urban areas. This finding, in contrast with existing cross-sectional case studies in English cities (e.g. Morris, 1957; Baldwin & Bottoms, 1976), confirms the benefits of adopting a longitudinal approach to re-examining the work of the Chicago School. Thirdly, and relatedly, the introduction of theoretically-driven longitudinal clustering methods opens up fresh questions for the crime concentration new wave literature. Whether the use of ak-medoids verifies or contradicts existing findings, and their support for theories like social disorganisation and routine activities, remains to be seen.

Fourthly, findings that offender residence population flows are consistent with expectations from the suburbanisation of poverty and elements of social disorganisation suggest that there is opportunity to merge these two currently unmarried strands of research. To date, spatial criminology has not formulated a formal, global theoretical framework to explain and derive hypotheses about offender residential mobility (origin-destination) patterns, but there would be clear merits to doing so. Advancing explanations of long-term trends in offender residential movements might have important implications for the crime concentration literature, and our understanding of poverty in urban areas.

6.4 Data caveats and implications

The appropriateness and quality of data is an important component to consider when discussing the findings presented in this thesis. As outlined in Chapter 4, police recorded data in general is subject to a number of caveats relating to recording practices, for instance, but there are also specific issues relating to census data which demand discussion. Three dimensions are focused on here. Firstly, the bias in police recorded crime and offender data, and the implications this might have had on findings. Secondly, the implications of aggregating offenders across crime types and individual characteristics. Thirdly, issues surrounding the measures and causal arguments in the explanatory models. Each of these is now considered in turn. In doing so, the aim is not just to provide a self-assessment of the findings from this thesis, but also to illuminate paths for future research.

6.4.1 Police data issues

Chapter 4 summarises the unavoidable shortcomings of using police recorded data for examining offender residence concentrations. These are issues common to all studies which utilise such data in spatial in criminology and have been acknowledged for some time (Myers, 1980), but these pitfalls may have impacted on the findings presented in this thesis.

There is plentiful evidence to suggest that police recorded crime data, and consequently police recorded offender data, is not a true representation of crime and victimisation in England and Wales, largely due to the varying propensity of victims to report crime to the police, which can differ due to a number of factors, especially crime type (ONS, 2015; Tarling & Morris, 2010; Hope, 2014). People's reporting of crime varies by their age and gender, and there is weak evidence to suggest that it also varies by deprivation (Tarling & Morris, 2010). Other characteristics known to be associated with trust in police, such as immigration status and experience with police contact (Bradford, Sargeant, Murphy & Jackson 2015), will likely impact on individuals' willingness to report offences to the police. Given that a number of these characteristics, such as immigration status and deprivation, as well as crime type concentrations (Andresen & Linning, 2012), can vary significantly across space, variations in the reporting of crime across neighbourhoods, and consequently, the recording of known offenders in Birmingham, might in part by driven by these spurious factors. With much of the evidence about this topic coming from the Crime Survey for England and Wales (CSEW), which is not available (and would not be reliable) down to the fine-grained spatial scales used in this study, the impact is problematic to verify. However, it is certainly worth bearing in mind with the data presented in this thesis, even if it is an issue common to nearly all studies in spatial criminology.

Beyond this, policing practices also play a role in dictating the spatial distribution of crimes and offender residences. For instance, there is evidence to suggest that police forces disproportionately approach ethnic minorities to exercise stop and search powers, even when controlling for other factors (Medina Ariza, 2014). Again, with demographic characteristics such as ethnic composition varying considerably across space in Birmingham at fine-grained spatial scales, such practices might impact on police recorded crime data. Specifically, areas characterised by a disproportionately high volume of crime (and as such, matched known offender records in that area, or elsewhere) might not be so because there is actually more crime, but because there are larger ethnic minority populations (resident or ambient) who are being subject to stop and searches. The targeting of specific groups by police, based on characteristics like age, class background and ethnicity, has historical and wider economic roots (see Choongh, 1998). Contemporary empirical research continues to demonstrate that police forces may be unjustly targeting particular groups who are considered ‘permanent suspects’ (McAra & McVie, 2005). In Scotland, where much of this research has been conducted, these groups have become the ‘usual suspects’: individuals from deprived backgrounds, often young men, recycled through the youth justice system, as “the deeds of their more affluent counterparts are often overlooked” (McAra, 2017, p. 962). In the United States, researchers have made theoretical arguments to assert that individuals from deprived, marginalised communities are more likely to be stigmatised, and subsequently identified as offenders, in comparison to similarly criminal individuals living in wealthier areas (Sampson, 2009).

One can only speculate as to the implications these biases in police recorded data are having on the findings from this project, but it is worth exploring these briefly for discussion. Firstly, fluctuations in known offender residence concentrations at fine-grained spatial scales like Output Areas might be influenced by the widespread decline in the use of stop and search tactics in England since 2011/12 (Lennon & Murray, 2018), around half-way through the study period. Should the decline in the use of stop and search have occurred inequitably across space in Birmingham, the trends observed might partly be a result of these factors. Whilst important, this would be a confounding factor given the aims of the project. Secondly, and relatedly, some of the independent variables used in the explanatory models, for instance the ethnic diversity measure, may also be associated with distrust in police and the under-reporting of crime, as well stop and search tactics. As such, it is plausible that the associations observed in answering research question 3 (explanation) might partly be a result of these factors, rather than the mechanisms outlined in social disorganisation theory. That said, such comments can only be made with speculation. A thorough examination of these issues in Birmingham would merit a study in its own right.

6.4.2 Aggregating across crime types

There was a strong argument in favour of examining offenders irrespective of crime type for this thesis in order to provide a baseline from which future research can be contrasted. That said, this decision will have had important implications. As outlined in Chapter 3, the new wave has tended to aggregate crime types together when examining offence concentrations, although recent studies have found that examining crime concentrations irrespective of type can mask important differences (Andresen et al., 2017). Comparable comments can be made here. For instance, there has been evidence to suggest that the distance traveled from offender residence to offence location varies by crime type at least as far back as Baldwin and Bottoms' study in Sheffield (1976). Recent research, for instance, has found that offenders are willing to travel more (around 1.5 miles further) to commit property crime compared to say, violent crime (Ackerman & Rossmo, 2015). By aggregating crime types together, the journey to crime descriptives presented in this thesis will be an amalgamation of these distances. Although findings indicated that crimes and offender residences were empirically distinct across multiple spatial scales, it is plausible that the degree to which this holds true will vary by crime type[1].

Personnel from West Midlands Police also raised further points regarding the aggregation of crime types. For instance, most cases of domestic abuse occur in the home (Dobash & Dobash, 1984) and as such, there is no meaningful 'journey to crime'. Theories often deployed in the journey to crime literature, such as optimal foraging theory, tend to be used to explain target selection in crimes like burglary (Johnson & Bowers, 2004), and arguably bear little relevance to domestic abuse. An implication of *including* crimes like domestic abuse in this analysis is that the mean and median journey to crime distances are *underestimated*. The finding that offenders tend to travel around 1-2 miles to commit crimes in Birmingham would probably increase, should we only include crimes where there has been any form of travel (i.e. excluding crimes that occur in the home, such as family violence and domestic abuse). Research making this exclusion has found that the distance traveled from origin to destination is higher than in much previous research, with a median distances of around 5 miles (Ackerman & Rossmo, 2015)[2]. This would not scupper the finding that the spatial patterning of crimes and offender residences are distinct, rather, it would make the distinctions even more salient. However, it remains unclear to what extent longitudinal trends in offender residence concentrations have been driven by changes in offending patterns in relation to specific crime types, or whether key social disorganisation theory variables can better explain the spatial patterning of offender residences who specialise in specific crime types.

[1]Towards the tend of this thesis, some attempts were made to explore the journey to crime by crime type. These descriptives are reported in Appendix E for interest.

[2]It is worth adding that this study calculated distances using street networks, rather than straight-line distances, which is what most previous research has done, including this thesis. Using street networks inevitably increases the estimates of the distances traveled.

However, by reporting findings irrespective of crime type, a baseline has been set from which future research, using a more specific subset of data, can be contrasted, in a similar manner to how the crime strand of research progressed in the new wave (see Chapter 2). It is hoped that the iterative manner in which crime concentration research has progressed, starting with 'total crime' and narrowing down to specific crime types, will be mimicked in offender residence literature, in order to fully gauge how findings might differ.

6.4.3 Aggregating across individual characteristics

A decision was made early on in the project to include all records of known offenders irrespective of age and sex. Whilst largely justified on the basis that it creates a yardstick for future research (see Chapter 4) the decision will have had a number of implications which deserve acknowledgement and discussion. Offending patterns are known to vary by age and sex. For instance, young offenders have been found not to travel as far as older offenders (Baldwin and Bottoms, 1976), and there is some evidence to suggest that women travel less far than men (Groff & McEwen, 2006) although evidence around this is disputed (Townsley, 2017). The use of age would also open prospect to unpick the degree to which aggregate-level trends in offender residence concentrations, within any given city, are a result of a cohort effect consistent with the age-crime curve, rather than causal mechanisms at the neighbourhood level. The crime types committed by men and women also vary, with the vast majority of burglars being men (Vandeviver, Neutens, Van Daele, Geurts & Vander Beken, 2015) and most welfare fraud offenders being women (Prenzler, 2017), for instance. There is also evidence to suggest that in many Western countries the crime gap between men and women is narrowing (Matthews & Minton, 2018), which given their different behaviour regarding crimes types, might partially shape long-term trends and (in)stability at small spatial scales. The exact implications of aggregating across age and sex for known offenders in Birmingham is unclear, but it is certainly an avenue which demands further exploration.

6.4.4 Measures and causation

As outlined in Chapter 4, the variables used to predict increasing relative offender concentrations were largely derived from key social disorganisation theory variables. Overcrowding, ethnic diversity and rented tenure were obtained from the 2001 census and used to predict the increasing trends beginning in 2006/07 and ending in 2015/16. In doing so, an assumption was made that the causal mechanisms of social disorganisation theory were lagged by that temporal gap. This is not implausible, given the glacial nature with which social disorganisation is considered to take effect (Griffiths & Chavez, 2004), but it is one that deserves scrutiny. In the closing stages of this thesis, a renewed data sharing agreement with West Midlands Police Force gave access to offender residence data back to 2001/02. As such, further robustness checks will need to be ran in order to establish the extent to which this lag was reasonable.

Although the census data remains the best source of open data available for the relevant time period, containing variables commonly used to predict offender residence concentrations in previous research, it is not without flaws. The overcrowding measure was used in isolation as a proxy for deprivation, despite the Townsend Index being available, so as to disentangle the effect of deprivation and rented housing. However, findings were not as hypothesised, with the only strong evidence suggesting that areas characterised by overcrowding were actually *less* likely to experience increasing relative trajectories. This might be because overcrowding is simply an insufficient measure for poverty. A more thorough examination, incorporating more nuanced (qualitative) data on deprived communities in Birmingham during that time period might shed some light on the lack of finding in this area, and explain the discrepancies in findings between the dependent variables derived from ak-medoids and k-means respectively.

6.4.5 Final comments on data

In highlighting the caveats of the data used for this project a number of issues and potential implications have been highlighted. Firstly, like most studies in the field, the data provided by West Midlands Police suffers from the biases of police recorded crime data, in terms of key dimensions like recording practices, underreporting and police bias in targeting certain individuals. Secondly, the definition of offender is broad, in the sense that crime types have been aggregated together, despite there being evidence from the crime literature, and theoretical frameworks, to suggest that offenders should be examined by crime type. The same can be said for individual characteristics like sex and age. Thirdly, the causal argument in explanatory models is imperfect due to the measure of deprivation and temporal lag.

That being said, there are a number of positives which demand acknowledgement. The offender data provided by West Midlands Police has permitted a rich examination of the spatial distribution of known offenders at (multiple) fine-grained spatial scales, in a manner which has not been conducted before. As detailed in Chapter 4, despite the known issues surrounding police recorded data, there is evidence to suggest that the data used for this project is a representative picture of offenders in Birmingham. Secondly, the use of aggregated crime types, whilst subject to criticism, is the only way in which a meaningful benchmark can be set for future research. Most of the analyses relating to spatial scale, longitudinal stability and explanation in this thesis has never been conducted before on offender data. Future research examining offenders who commit specific crime types is certainly recommended, and would benefit immensely from these findings as a yardstick, just as the new wave iteratively made analyses more nuanced and specific as the field progressed. Thirdly, the ongoing data sharing agreement with the police, and continued sharing of data which can be used to extend the current time period, means that many of the issues raised and questions generated from this thesis can be rectified and explored further in future research, as outlined later in this chapter.

6.5 Methodological implications

The substantive findings from this thesis, along with specific attempts to improve upon existing longitudinal clustering methods, have significant methodological implications. Firstly, the importance of spatial scale when examining offender residences has been demonstrated, with notable similarities and distinctions with the crime concentration literature. Secondly, the successful usage of hexograms for the first time in spatial criminology has showcased the ability of researchers to accurately visualise and publicly disseminate findings with privacy concerns. Thirdly, the sensitivity of findings to the clustering methods deployed, demonstrated through the use of a new method, highlight issues which may have ramifications for new wave crime concentration literature, as well as future research into offender residences. Fourthly, the usage of relative and absolute measures of offender residences when performing cluster analysis has introduced a novel method for evaluating stability over time. Each of these is now considered in turn.

6.5.1 Spatial scale is fundamental

In the crime strand of literature, which as discussed, is much more methodologically advanced, contemporary research has made a concerted effort to highlight the importance of spatial scale (see Weisburd et al., 2009), with recent studies demonstrating the empirical benefits of using fine-grained units (Weisburd & Steenbeek, 2016; Schnell, Braga & Piza, 2017; Gerell, 2017). Here, findings have highlighted that spatial scale is also an important dimension to consider when studying offender residence concentrations.

Although there was strong evidence to indicate that crimes and offender residences are empirically distinguishable in Birmingham, the relationship between the two was sensitive to the unit of analysis being used. The relationship was *more similar* with larger aggregations. This is likely a result of the distance-decay between the offender residence and crime location (see Rengert, Piquero & Jones, 1999) whereby offenders appear less willing to travel long distances to get to a suitable target. With a typical straight-line origin-destination distance for crime being around 1-2 miles, based on findings in Birmingham, but also in previous reviews of literature (Ackerman & Rossmo, 2015), the likelihood of masking the distinction between origin and destination increases as the spatial scale increases. As such, it is perfectly plausible that previous research has found a legitimately strong relationship between the two phenomena using aggregated data. Assuming that this does not matter would still be misguided, given the distinction in theoretical frameworks, and because the two could still be disentangled using individual-level journey to crime data, or smaller aggregations. It is also perfectly plausible that such findings were an artefact of spatial scale and the Modifiable Areal Unit Problem. The same could be said for studies which found no relationship between crimes and offender residences. It is challenging to retrospectively verify the extent to which this proposition is true in previous research (unless through replication using the same data) but the findings presented here raise a fundamental point that must be considered in future research, either when conducting new analyses, or when reviewing previous literature.

Evidence that offender residences are increasingly concentrated, and changes in concentration more evident, at fine-grained spatial scales, also has important implications for the choice geographic unit of analysis. It emphasises the importance of choosing a unit that is sufficiently small to unmask important patterns in which would otherwise remain masked. Existing studies which have examined the geography of offender residences have rarely offered an empirical demonstration of why their choice of unit was appropriate, even though, as discussed in Chapter 2, early pioneers such as Henry Mayhew (1851/1862) and John Glyde (1856) were aware of its importance. That said, a decision to use small units should reflect the aims of the research. Units of analysis can become as small as the raw point data is accurate: some crime studies have used grid cells as small as 50x50 metres (see Bowers, 2014). However, such units are unlikely to hold significance to residents, or reflect physical boundaries on the ground, making them theoretical irrelevant for concepts like social disorganisation theory. Moreover, to augment synthetic square grids with other data, such a resident population numbers, or demographic characteristics for explanatory analysis, one would need geocoded household-level data, which is rarely publicly available, if at all. As such, the finding that offender residences concentrate at smaller aggregations does not render large geographic units redundant, but it is a worthy consideration, in balance with the aims of the study at hand.

This point is supported by the finding that there is a higher variance of offender residences between Middle Super Output Areas (MSOA) compared with Lower Super Output Areas (LSOA), despite the latter being smaller. The finding that larger units do not necessarily have a lower share of total variance is one consistent with the crime literature[3] (see Steenbeek & Weisburd, 2016; Schnell et al., 2017), even though the highest proportion of variance has always been attributable to the smallest unit, as was found here with Output Area. Depending on how unit boundaries are defined, it is perfectly plausible that larger units will unmask higher between-unit heterogeneity. High between-unit *homogeneity* would give little prospect for explanation, as there would be no variation to explain. It is this variability which has led researchers to claim that street segments hold greater prospect for explanation in the crime strand of literature (Rosser, Davies, Bowers, Johnson & Cheng, 2017). With this in mind, the findings from this study give strong reason to question any proposed

[3] In the crime concentration literature, the variance partition was entirely consistent with the Gini coefficient, with regard to the ordering of nested spatial scales (Steenbeek & Weisburd, 2016; Schnell et al., 2017). The finding from the current study, using the offender data in Birmingham, showed that the two methods can be inconsistent (albeit not significantly). This demonstrates the importance of using multiple methods to examine spatial scale, and to consider which method is most relevant given the aims and research questions of the study. The Gini coefficient describes the degree of inequality in concentrations, and the variance partition estimates between-unit heterogeneity.

rule-of-thumb that 'smaller is better' in spatial criminology (see Oberwittler & Wikstrom, 2009). The choice of spatial scale should be considered with the aims and research questions of the study in mind, ideally with some empirical examination of concentration and variance, rather than based on assumptions about the merits of each from their geographic size.

6.5.2 Stylised maps in criminology

A challenge that emerged during this project was to sufficiently anonymise spatial visualisations to ensure confidentiality, whilst maintaining geographic accuracy. This was coupled with the known challenge of misrepresentation in spatial data when using traditional mapping techniques, caused due to large variations in the sizes of areas being mapped. Failing to ensure anonymity would mean some results would have been reported through written descriptions, rather than through maps, severely limiting the accessibility and transparency of results. To avoid this, a novel implementation of cartograms and tiled hexagons (see Harris, Charlton & Brunsdon, 2018), termed 'hexograms' were deployed. Hexograms have been shown to convey spatial clustering in area-based data more accurately than original boundaries (Langton & Solymosi, 2019). In doing so, a degree of anonymity is also introduced. This method was deemed acceptable for reporting by personnel from West Midlands Police Force. To date, hexograms have not been used in spatial criminology. The demonstration of this method for visualising the geographic distribution of highly sensitive phenomena may have important implications for the field, facilitating the distribution of findings which would otherwise have remained too sensitive to report visually. Even in cases where the data is not confidential, hexograms can mitigate against the misrepresentation introduced when mapping raw boundaries, and therefore might hold merit beyond spatial criminology.

6.5.3 Clustering sensitivity

Studies which present novel clustering methods, and review existing implementations of such techniques, have acknowledged that clustering can be considered both an art and a science (Guyon, Von Luxburg & Williamson, 2009). There are a number of methods to choose from, each of which has strengths and weaknesses, and all suffer from the problem of choosing a 'cluster solution' which is empirically supported and theoretically meaningful. In spatial criminology, little attempt has been made to review the impact of different clustering methods (exception: Curman, Andresen & Brantingham, 2015), and until the development of anchored k-medoids as part of this thesis, no attempt had been made to develop bespoke methods for the field.

The implementation of an existing, generic method (k-means) and a novel, bespoke method (ak-medoids) in this thesis is one which has highlighted the sensitivity of findings to the clustering method deployed. The computational efficiency and relaxed statistical assumptions around k-means made it an ideal candidate to tailor for the examination of longitudinal trends in offender residence concentrations, as detailed in Chapter 3. The prospect of further comparisons to group-based trajectory modelling (GBTM) is discussed later this chapter, but for now, the only definitive conclusion from the findings presented here is that one should be hesitant about the recent excitement over the suitability of k-means in spatial criminology (see Andresen et al., 2017). Findings presented in this thesis suggest that the method may be overestimating the proportion of areas characterised by stability in offender residence concentrations, corroborating the equivalent findings in recent literature relating to crime (Adepeju et al., *under review*).

This has important theoretical implications, noted earlier, but methodologically, there are two significant implications. Firstly, it implies that the field should consider implementing more robust and transparent approaches to longitudinal clustering. For instance, *at least two* methods should be deployed and reported upon to ensure that findings are not simply an artefact of the method being used. This has only occurred once in spatial criminology using GBTM and k-means (see Curman et al., 2015) with other studies in the new wave using one method in isolation (see Chapter 3). Secondly, more positively, the successful implementation of non-random starting points and an outlier-insensitive expectation-maximisation procedure suggests that k-means can be successfully tailored to derive more theoretically suitable cluster solutions. This raises the prospect of replicating existing new wave studies to examine the extent to which previous findings were robust, and whether more meaningful clusters could be disentangled using ak-medoids. The development of an R package with accompanying open source code to implement ak-medoids (see Adepeju et al., 2019) means that other researchers can further tailor it to test their expectations about the longitudinal stability of crime and offender concentrations, or related phenomena, such as emergency calls-for-service. As such, the findings from this thesis may have methodological implications beyond research into offender residences.

6.5.4 Strengths of relative measures

The use of relative and absolute measures of offender residence concentrations has provided a degree of insight that could have important implications for how longitudinal stability is examined more generally in spatial criminology. To date, the crime concentration literature has only clustered on absolute measures of criminality, such as crime counts or rates for each time point. Here, the use of a relative proportional measure made interpreting results more meaningful, given that the key aim was understanding deviations from the citywide trend. Deploying clustering methods on the relative measure, then reporting the findings using both relative and absolute measures, provides a more specific and transparent picture of longitudinal stability at fine-grained spatial scales. The conceptualisation that flat relative trajectories translate to absolute trajectories which mirror the citywide trend, is one that also resonated with personnel from West Midlands Police Force, especially when visualised in the manner reported in Chapter 5. The approach is one that has been deployed in the crime concentration literature specifically to examine inequalities in the crime drop (see Adepeju et al., *under review*), and as such, it is one that is already having implications for methodologies in the new wave beyond that of the findings presented here.

6.5.5 Final comments on methodological implications

The substantive results and methodological advancements in this thesis have a number of implications for existing and future research. Firstly, inspired by advancements in crime concentration literature, issues relating to spatial scale have been empirically demonstrated using offender residence data for the first time. This serves as a guide for future research examining where known offenders live, but also provides insight into the interpretation of existing findings. Secondly, a novel method for visualising confidential data has been introduced to spatial criminology in the form of a hexogram, improving representation of irregularly sized polygons and permitting visuals of data which would otherwise go unreported due to confidentiality. Thirdly, the systematic comparison of longitudinal clustering methods has not only demonstrated theoretically-relevant findings relating to stability in offender residence concentrations, but also highlights the sensitivity of findings to the methods deployed. This serves as a cautionary word for fields relying heavily on findings from one method in isolation, as has tended to be the case in 'new wave' crime concentration literature. Fourthly, the use of both relative and absolute measures of offender concentrations has provided a novel insight into how to effectively visualise the stability of longitudinal trajectories, particularly when examining the degree to which small areas deviate from a given citywide trend.

6.6 Policy implications

Spatial criminology tends to be thought of as an academic discipline, with much of the cutting-edge research being published in journals, often behind paywalls. Outputs are presented more often at conferences than at police force headquarters or in front of key stakeholders outside of academia. However, the findings from this thesis can have important implications for local government policy and policing. Firstly, the insight gained from this examination of offender residences has stimulated interest from West Midlands Police Force, and encouraged future research in this area which would otherwise have gone unexplored. This largely came about due to the presentation of findings to personnel within the Force. Secondly, and relatedly, findings can contribute to a growing evidence-base which assists police forces in understanding the crime-based demand for their services. Leading from this, thirdly, the empirical examination of offender residence concentrations at fine-grained scales presented here, coupled with existing findings in the crime strand of research, may help in developing a more nuanced approach to the police funding formula used by local and central governments. Fourthly, evidence suggesting that shifting offender residence patterns are closely related to city centre urban development highlights the importance of housing policy in determining the spatial distribution of known offenders, and in turn, crime patterns, in Birmingham.

6.6.1 Highlighting offender residences

The findings presented in this thesis, and the insight obtained from the results and visualisations, have played an important role in garnering interest in the spatial distribution of offender residences at West Midlands Police Force. As outlined in Chapters 2 and 3, spatial criminology has been largely dominated by research demonstrating and explaining the non-random distribution of *crime*. West Midlands Police conduct in-house analyses, but personnel reported that the offender residence data is underused. This is also reflected in academic literature. Inevitably, the neglect of empirical research into the geography of offender residences has meant that, in a recent review of how theories and substantive findings in the field have impacted on practice, there is no specific reference to offender residence locations as a strand of research in its own right (see Welsh & Taheri, 2018). This shortcoming, or at least, the lack of evidence to justify its omission in research and in turn policy making, was recognised by the Force when the proposal for this thesis was first drafted. Although some members of their geospatial team had made initial attempts to examine the spatial distribution of offender residences, they had many questions that remained unanswered due to a lack of resource, training and software. As such, whilst the project has academic significance, the analysis presented here also serves as a demonstration to the police about the insight that can be gained from examining geocoded offender residence data using software like R, and to help stimulate ideas as to how future research can assist police practice. The R training conducted for West Midlands Police, as an unexpected by-product of this thesis, noted in Chapter 4, showcased the interest and potential impact of such approaches.

In presenting to the Force, it also became clear that the findings generated from this project were of interest to personnel in numerous roles, including active officers, geospatial analysts, evidence-based practice specialists and offender management leads. Some of the analysis conducted was actually led by comments and feedback from these personnel. In particular, the empirical link between offender residences and crime locations, and the offender residence origin-destination population flows, were guided by discussions with a senior geospatial analyst. Linking offender residence and crime data to examine the journey to crime, and modeling spatial patterns in offender residence moves, had been an area of interest for analysts within the Force for some time. This was in recognition that shifting offender residence concentrations, and the demographic factors driving these changes, are important determinants of the police's crime-based demand.

6.6.2 Police demand

In an era of austerity cuts to police services, the efficient allocation of limited resources has never been so important to ensure public safety and the well-being of police force personnel (Turnbull & Wass, 2015). Although countless cities have benefited from a fall in recorded crime and victimisation, there is evidence to suggest that this fall has not been equitable across space (Bannister, Bates & Kearns, 2017) or across society (McVie, Norris & Pillinger, 2019). In the face of funding cuts, this raises questions about the ability of police forces to maintain public safety fairly, and emphasises how forces must react to shifting spatial patterns in the demand for their services. The findings from this project strongly suggest that (1) the geography of known offender residences in Birmingham is dynamic, with concentrations shifting over time, and (2) known offenders in Birmingham tend to commit offences relatively close to where they reside. Consequently, long-term shifting patterns in where offenders reside, and what factors repel, force or attract known offenders to live in particular areas, are a fundamental component for police forces to consider when seeking to understand the crime-base demand for their services: there are strong empirical and theoretical reasons for doing so. It would be a welcome approach given the concern over how well police force's understand their crime-based demand, including planning for future trends (HMIC, 2017).

The significance of this point is compounded by evidence which indicates that existing offenders can generate newly-criminal populations by a process of neighbourhood socialisation (Livingston et al., 2014). In this manner, it is plausible that the shifting patterns of known offender residences, as observed in Birmingham, could inspire new offending populations, even in previously unproblematic areas of the city. An implication of such a scenario is a change in the volume and nature of demand for police services. The police play an active role not just in tackling the crime that may arise from these newly active offenders, but also the management of offenders in the community, including housing resettlement in collaboration with private partners. With this in mind, police forces might consider mitigating against the neighbourhood socialisation of new offenders through considered usage of their geocoded offender records. This was a point recognised by offender management leads at West Midlands Police, and leads us to the implications for funding.

6.6.3 Police funding

The primary source of funding for police forces comes from a 'needs based' assessment by central and local government. Although the formula used to estimate the needs of each force has evolved over time, it is largely determined by key population predictors of crime, such as unemployment amongst young men (Crawford, Disney & Simpson, 2018). Since funding is allocated based on an assessment which is meant to be a preemptive estimate of demand, longitudinal trends are a fundamental component of this assessment. As such, findings relating the shifting patterns and trends in offender residence concentrations, and their relationship with key demographic characteristics, can contribute to the refinement of this formula. For instance, the finding that offender residence concentrations change non-uniformly over time, with change being relatively linear and slow, and that changes are associated with key demographic characteristics, such as ethnic diversity and rented housing, raises the prospect for the predictive forecasting of demand through the use of offender data. The potential for individuals to become engaged in criminal activity following contact with prior offenders, brought about by shifting residential concentrations, coupled with the spatial relationship between residence and crime location, makes this point particularly pertinent. Longitudinal trends in known offender concentrations, whether examining neighbourhood-level trajectories or individual-level population flows, as demonstrated in this thesis, are likely to hold explanatory value in predicting future offending populations, shifting crime hotspots, and in turn, crime-based police demand.

The variation in longitudinal trends observed at fine-grained spatial scales also demonstrates the detail which is masked when conducting analysis at larger aggregations, such as police force regions, which is the level at which the funding formula analysis is conducted, to some criticism (Ludwig, Norton & McLean, 2017). Even within Birmingham, the findings reported in this thesis highlight the diversity of trends, and complexity of underlying patterns, which would simply be aggregated out of the picture using city or region-wide analysis. A police force area characterised by heterogeneity in longitudinal trends would be poorly represented by such aggregated data, for example. Perhaps realistically, analysis will continue to be conducted at police force area level. In that case, as a minimum, findings here demonstrate the potential of using data at fine-grained spatial scales to construct useful measurements at the region-wide level. For instance, quantifying the degree to which the offending population and offence locations are spatially clustered in a police force area might improve estimations of Activity Based Costing. A highly concentrated offending population which is longitudinally stable would likely be more easily and efficiently managed than a sparsely distributed and volatile one. It is perfectly realistic to construct such measures at police force area level, and include these measures in the regression models which currently determine funding from central and local government. As such, the findings from this thesis, perhaps with additional guidance on the specifics of useful measures from police personnel, could assist in the improvement of the funding formula not just for West Midlands Police, but for other police forces in England and Wales.

6.6.4 Housing policy

Findings that steep declines in relative known offender residences appear to be occurring on the outskirts of Birmingham city centre, and that some offenders are moving towards the suburbs, might have implications for local government policy. In particular, the role of the housing market, as far back as Baldwin and Bottoms (1976) has been emphasised as a key determinant of offender residence geographies in the UK. This was also recognised by the Chicago School in formulating social disorganisation theory, since it was cheap housing which attracted ethnically diverse populations to certain communities, who would leave at the first opportunity, creating high residential turnover, and in turn, social disorganised communities and delinquency areas. Accounts of housing sector development in Birmingham between the 1990s and present day go some way in explaining the longitudinal patterns observed, and emphasise how the findings from this thesis may have important implications for public policy on housing.

In the UK, the role of social housing has changed substantially since Baldwin and Bottoms' 1976 study, and Birmingham is no exception. Since the 1980 Housing Act, the Right To Buy scheme in England has resulted in a dramatic decline in the housing stock owned by local authorities. At the same time, the centres of many cities outside of London, including Birmingham, have been transformed, with rising resident populations on the back of new housing developments. At the beginning of the 1990s, the city centre of Birmingham was dominated by council housing, often in close proximity to manufacturing areas, with high levels of deprivation (Hall, Lee, Murie, Rowlands & Sankey, 2003). These conditions mimic those described by Shaw and McKay in Chicago (1942/1972) which are said to give rise to delinquency areas.

However, a detailed review of Birmingham's city centre housing development by Austin Barber (2007) reported that by 2004, the proportion of privately rented or owner occupied properties in the city centre had more than doubled, and council housing had halved. By 2006, many council estates had been pushed to outskirts of the city centre. Barber noted that this change was largely driven by redevelopment of non-residential land, rather than the revival of old housing stock, making Birmingham distinct from more classic cases of gentrification elsewhere in Europe, whereby existing residents are displaced. However, even by 2007, there was evidence that new-build city centre development was pressuring neighbourhoods beyond the city centre, towards the inner suburbs, with new resident populations in the city centre consisting of young professionals willing to pay higher living costs. By 2017, large-scale regeneration of city centre flats had been completed, raising questions about whether the transformation was "simply planned gentrification" (Murie, 2018, p. 138).

These accounts of Birmingham's development may go some way in explaining the shifting spatial patterning of offender residence concentrations in Birmingham, in particular, the steep declines experienced by some areas, but it should also highlight to local governments the potential ramifications for their policies. As noted above, these changes could have a long-term impact not just on crime concentrations, given the relatively short distances traveled, but also on the future offending population (see Livingston et al., 2014). Just as Baldwin and Bottoms (1976), Bottoms and Wiles (1986) and more recently Bottoms (2018) have been arguing, the housing market can play a fundamental role in determining shifting offender residence patterns, but to date, these claims been made without the depth of analyses using longitudinal data reported in this thesis. These findings may inspire some reflection within local governments on the wider impact housing policy can have on the distribution of offender residences, and in turn, crime concentrations.

6.6.5 Final comments on policy implications

It is hoped that this thesis will have useful implications for policy amongst police forces and local government, especially through the collaborative element with West Midlands Police Force. Findings have highlighted the importance of offender residence concentrations for the Force, which may have wider implications for how police forces understand their crime-based demand, and demonstrate the benefits gained from academic/force collaborations. Evidence gathered through this examination can also feed into improvements to the police funding formula, especially when considering the usefulness of fine-grained spatial scales, and long-term patterns in offender residence and crime concentrations. Finally, given that there is evidence to suggest that housing policy has played an important role in shaping the geography of offender residences in Birmingham, findings merit full consideration from local governments whose role it is guide and facilitate housing development.

6.7 Limitations summary and future research

In discussing the implications of the findings from this project, and outlining the data and methods used, a number of limitations have been highlighted which warrant more detailed acknowledgement. In doing so, suggestions for future research are made.

Firstly, whilst it might be reasonable to aggregate across crimes types in this initial study, outlined in Chapter 4, future research should undoubtedly explore the extent to which findings differ by the offence committed. A first step might be to examine crime types for which there is a strong theoretical basis for the journey to crime, such as residential burglary (see Bernasco & Nieuwbeerta, 2005; Langton & Steenbeek, 2017). The choice of specific crime types would ideally be driven by guidance from police forces, to ensure relevant impact. That said, some personnel suggested an examination of domestic abuse in isolation, given that it is a crime which commonly occurs at home, or at the home of a family member or partner. A systematic comparison between crimes types would certainly uncover variations and details which are masked by the current findings. This would mimic the iterative advancement of the new wave literature (see Chapter 2), which has recently found that the degree of instability in longitudinal crime trajectories varies by crime type (Andresen et al., 2017). The same can be said for the aggregation of data across individual characteristics: a wealth of insight could be gained from subsetting data by age and sex.

Secondly, although the comparison between k-means and ak-medoids provoked useful discussion on the sensitivity of clustering methods, and the benefits of bespoke approaches, there is still a great deal of room for improvement. At the moment, ak-medoids has only been implemented to unpick *linear* trends. Whilst this is beneficial for disentangling slow, long-term change over time, in other circumstances, a more complex polynomial (e.g. quadratic, cubic) might be more suitable. The benefit of the ak-medoids code being open source is that anyone who is inclined to do so can make this contribution. As such, it is likely that this addition will be made in the near future, making ak-medoids more widely applicable to different scenarios, maybe even outside of spatial criminology. An additional point to consider is that, to date, the performance of ak-medoids has only been systematically compared to k-means, largely due its successful demonstration in recent research and malleability using the *kml* package in R (Genolini et al., 2015). This does not, by any means, render GBTM redundant. It remains a popular method for longitudinal clustering both in spatial criminology (see Chapter 3), and individual life-course research (see Piquero, 2008). As has been demonstrated in the latter, the method holds some advantage with its model fit statistics, and independent variables can still be used to explain group membership (for a recent example see Girard, Tremblay, Nagin & Cote, 2019). Before we can come to any consensus on the suitability of longitudinal clustering methods more generally, further comparisons including GBTM would be a necessity. To facilitate this endeavour, a useful contribution will be to revive maintenance of the *CrimCV* package in R (Nielson, 2018).

Thirdly, a full consideration of how housing policy in Birmingham has impacted on offender residence concentrations would demand the use of additional data. The census data available at this time does not permit a thorough examination of changes in tenure, ownership and social housing during the 2006 to 2016 study period. Future research could consider two dimensions. Firstly, the use of Points of Interest (POI) data from Ordnance Survey could permit a quantifiable insight into urban development in Birmingham over time. POI data goes back to 2002, thus covering the entire study period, and contains geocoded information on public and private businesses, leisure and education facilities on an annual basis. From this, longitudinal measurements about land use and urban growth (and demolition) could be generated and used to augment existing explanatory models. This would revive Shaw and McKay's interest in urban development and building demolitions (see Shaw & McKay; 1942/1972, p. 28), which has had some interest in recent crime concentration literature (see Wheeler, Kim & Phillips, 2018). Secondly, there is a growing effort to measure urban development using crowd-sourced data on building construction dates (see Hudson, Dennett, Russell & Smith, 2019). This would allow one to model building construction during the study period on an annual basis, which could in turn become a key explanation for the offender residential patterns observed, especially when augmented with data on rental or house prices. However, data collection is currently only underway in London, so it may be some time before this becomes viable[4]. Nevertheless, it is worth bearing in mind for the future.

An attempt to rectify these issues bring us to the fourth suggestion for future research: the use of mixed-method case studies. Insight gained from quantitative analysis is invaluable, but even augmenting the analyses presented with POI data and (eventually) crowd-sourced building construction data would still fail to capture local nuance. Relying solely on quantitative analysis makes findings highly sensitive to the shortcomings in police recorded data and census information (see Chapter 4). In the spirit of the Sheffield study which inspired much of this thesis (see Baldwin & Bottoms, 1976), future research might consider conducting case studies on a handful of neighbourhoods which have experienced starkly different offender residence concentration profiles over time, to understand longitudinal instability and deviations from citywide trends. Using rich, qualitative data, collected from interviews with local residents, housing associations and police personnel with an intimate knowledge of these areas during the study period could unmask patterns and explanations which simply cannot be captured using quantitative data in isolation. The fact that the Sheffield study, which was conducted using both quantitative methods and qualitative case studies, is still discussed and written about today (see Bottoms, 2018) not only demonstrates how sparse such research is (despite its value) but also how valuable mixed-method approaches are to studying offender residences in spatial criminology.

6.8 Conclusion

This chapter has sought to offer a discussion on the findings and implications of the thesis along four main themes: theory, data, methodology and policy, and concluded with remarks on the limitations of the study and especially pertinent suggestions for future research.

In terms of theory, findings relating to the empirical distinction between crime and offender residence locations raise questions around the suitability of social disorganisation theory as a 'one theory fits all' for crimes *and* offenders. Findings that delinquency areas in Birmingham can persist over time, irrespective of wider

[4] Data on the year buildings are constructed does exist for the UK via organisations such as UKBuildings, and the Valuation Office Agency holds data on property values, but data tends to be behind a paywall and is subject to restrictions on its usage.

declines in known offenders, and that this stability can be explained to some degree by deprivation, ethnic diversity and rented accommodation, suggests that the theory holds relevance in 21st Century England. Linking with methodology, it was highlighted how the choice of methods, in particular, the use of longitudinal clustering techniques, can have a substantial impact on the degree to which findings are consistent with theoretical expectations. A number of caveats on the data were outlined, and the implications of these shortcomings discussed, primarily relating to the use of police recorded data, aggregating across crime types and individual characteristics, and measures for independent variables. Methodological implications included discussions on the importance of spatial scale, the first demonstration of hexograms in spatial criminology, the sensitivity of findings to the clustering method deployed, and the usefulness of both relative and absolute measures of offender residences.

By demonstrating the importance of offender residence locations in collaboration with West Midlands Police Force, this research may hold significance for policy. Findings highlight how the role that offender residence data, and spatial criminology more generally, can usefully inform police force's understanding of demand, and in turn, the police funding formula, in an era of austerity. For local government, findings which suggest that the housing market has played a fundamental role in shaping offender residence patterns over time may hold particular significance, emphasising how the spatial patterning of offenders and crimes is not just a matter for police, but for local public policy more generally. In discussing the shortcomings, a number of limitations and suggestions for future research were made, but a number were highlighted as especially pertinent. This included the need to examine different crime types and individual offender characteristics, extending the use of anchored k-medoids to permit modelling non-linear trends, a more comprehensive examination of urban development in Birmingham using new data sources, and the incorporation of mixed-methods to gain a more nuanced insight into explanations for the patterns observed.

Chapter 7

Conclusion

7.1 Introduction

The overarching aim of this thesis has been to advance understanding into the geographic distribution of offender residences. This strand of research emerged amidst the earliest studies in spatial criminology, with pioneering European cartographers and American sociologists mapping out the spatial distribution of where known offenders lived. With time, the interest in this strand of research waned. Instead, contemporary research has long since favoured examinations into the geographic distribution of *offences*. As a result, the field has become a one defined by *where crimes occur* rather than *where offenders live* (Bottoms, 2018). This has occurred despite there being strong empirical and theoretical reason for examining both strands of research.

In seeking to advance understanding into the geographic distribution of offender residences, this thesis has sought to revive the subject along three key dimensions: spatial scale, longitudinal stability and explanation. Findings open prospect for the geography of offender residences to once again became a key topic of interest in spatial criminology. This chapter primarily serves to summarise the chapters comprising the thesis. No new information or discussions are raised here, but instead, the summary reminds readers of the narrative that has been traced, the key findings reported and the discussion points raised. The chapter is brought to a close with a final comment on the original contributions of the thesis.

7.2 Chapter re-cap

Following an introductory first chapter, Chapter 2 traced the history of spatial criminology since its origins in the 19th Century to the present day. Rather than claiming to offer a comprehensive review and critique of the whole field, the chapter served to highlight the contrasting development of research into the spatial patterning of offender residences and offences along three key themes, namely, spatial scale, longitudinal stability and explanation. In doing so, it demonstrated how, despite these dimensions having their foundations in early studies examining offender residences, the field has increasingly favoured their examination for offences. Consequently, developments in data and methods have largely been exploited to examine the spatial patterning of offences, much to the expense of offenders. This has occurred despite there being strong theoretical and empirical reason to treat the two has distinct (but related) phenomena. The chapter concluded by posing key research questions along the three key dimensions of spatial scale, longitudinal stability and explanation. In answering these questions, it is hoped that the long-since neglected strand of research into offender residences can be revived and once again form an integral component of spatial criminology. With this in mind, the chapter concluded by posing the following research questions. These were designed to flow linearly: once the most suitable spatial scale was selected, the degree of longitudinal stability could be examined, and then subsequently explained.

- RQ1: What is the most appropriate spatial scale to study offender residential concentrations?
- RQ2: To what extent do offender residential concentrations demonstrate stability over time?
- RQ3: How can we explain the longitudinal (in)stability of offender residential concentrations?

Chapter 3 picked these three research questions up for further examination with a focus on considerations of data and methods. In doing so, particular attention was paid to contemporary research into offences, which has made significant methodological advance in the examination of spatial scale and longitudinal stability, in particular. Commonly used methods were reviewed to assess their suitability for deployment on offender residence data. In doing so, a number of concerns were identified, and shortcomings in existing methods highlighted, for consideration when adopting comparable approaches on offender residence data. Generally speaking, existing methods used to examine spatial scale, such as descriptives statistics, visualisations and variance partitions, were considered appropriate for answering RQ1. To examine longitudinal stability (RQ2), specific focus was placed on the influential use of clustering methods in spatial criminology. These methods were outlined and critiqued to establish their appropriateness, methodologically and theoretically, for examining stability in the spatial patterning of offender residences. Despite the merits of using clustering to examine stability, a number of shortcomings were identified which were earmarked to address when deploying comparable methods in this thesis. Finally, a review of the frameworks used to explain offender residence concentrations was conducted, largely inspired by social disorganisation theory (RQ3). Attention was paid to how theoretically-relevant dependent and independent variables have been operationalised in existing research. The chapter concluded with summary remarks on the key issues to consider when drawing inspiration from advancements in the offence strand of research, in particular, the areas in which improvements can be made for use in this thesis.

With these considerations in mind, Chapter 4 detailed the data and methods deployed to answer the three key research questions posed. The suitability of offender data obtained through an Information Sharing Agreement with West Midlands Police Force was described, including ethics, variable descriptions, bias and reliability. Details of the study region, Birmingham, were reported, including an account of the different spatial scales available. Attention then turned to the socioeconomic data derived from the census, with a focus on the theoretical relevance of variables constructed from the raw data, and associated issues relating to census years and boundary changes. Based on the discussions from Chapter 3, the methods deployed for answering each respective research question were described with specific reference to the offender residence data from Birmingham. Analytical strategies were proposed. Descriptive statistics, visualisations and a multilevel variance partition were chosen to answer the question of spatial scale (RQ1). With a suitable unit of analysis identified, two longitudinal clustering techniques were identified to answer the question of stability (RQ2), namely, k-means and a novel technique termed anchored k-medoids, developed as part of the thesis. Its implementation was designed to remedy the shortcomings identified in Chapter 3. Descriptive statistics regarding individual-level population flows, and spatially lagged logistic regression models based on social disorganisation theory, were then proposed to answer the final research question of explanation (RQ3). An initial demonstration of the empirical distinction between offender residences and offence locations in Birmingham was also proposed, as a preamble to the main results.

Chapter 5 reported the findings generated following the execution of these analytical strategies. The chapter began with a series of descriptives to showcase the distinct spatial patterning of offender residences and offence locations, in terms of correlation, spatial clustering and the journey to crime. This augmented the theoretical distinctions discussed in Chapter 2, demonstrating that offender residences and offences are indeed empirically distinguishable, with offenders tending to offend relatively close to their own residence, but not in the immediate vicinity. Findings using descriptives, Lorenz curves, Gini coefficients and a multilevel variance partition, in answer of the question of spatial scale (RQ1) were then reported. These suggested that the degree to which offender residences concentrate, and the extent of between-unit heterogeneity, varies depending on the spatial scale used. Generally speaking, these findings demonstrated the benefits of using micro-scale units of analysis, and as such, the smallest census block in England, Output Areas, were selected as the spatial scale for subsequent analysis. K-means and anchored ak-medoids were then deployed to unpick the degree of instability in offender residence concentrations at Output Area level (RQ2), following an initial description of the citywide drop in the number of known offenders in Birmingham. Findings suggested that, although many local areas have declined in unison, there has been some instability in concentrations over time, with many Output Areas experiencing trajectories which deviate from the citywide trend. A comparison between k-means and anchored k-medoids highlighted the sensitivity of findings to the method deployed, with the latter, a novel approach developed alongside this thesis, holding some merit over k-means. Population flow visuals and spatially lagged regression models were then reported to address the final research question of explanation (RQ3). Findings suggested that high ethnic diversity, and a high proportion of rented housing, increase the likelihood of Output Areas experiencing an increase in relative offender concentrations, in alignment with expectations from social disorganisation theory. Offender residential population flow descriptives suggested there was also some instability at the individual-level, with offenders tending to move to and from highly deprived areas, and many moving away from the city centre over time.

Chapter 6 primarily offered a discussion on the implications of these findings in terms of theory, data, methodology and policy. Theoretically, findings supported the notion of reviving the offender residence strand of research, and adopting and developing unique theoretical frameworks to explain the shifting spatial patterning of offender residences. It was argued that these frameworks should be distinct from explanations of offence concentrations, but aim to reconcile the close relationship between the two phenomenon. Issues relating to the use of police recorded crime data, aggregating across crime types and individual characteristics, and causation, were detailed, and potential implications discussed. Methodologically, the importance of spatial scale when studying offender residences was highlighted, along with the value of novel ways of visualising area-based data. The merits of bespoke approaches to longitudinal clustering through the use of anchored k-medoids demonstrated the sensitivity of findings to the choice of method, and promoted the benefit of more inductive approaches to examining stability through the use of the new method. This, and the use of relative and absolute measures to unpick longitudinal stability, may have positive ramifications for spatial criminology more broadly. In terms of policy, it was suggested that this project serves as a showcase for examining the spatial patterning of offender residences, especially for West Midlands Police, who have requested further work in this area. The implications of findings for needs-based police demand, police force funding and housing policy, were also outlined. The chapter concluded with some summary remarks on shortcomings which were then used to inform suggestions for future research.

7.3 Original contributions

Given the content of the chapters detailed above, the key original contributions of this thesis fall within five principal dimensions. These contributions directly address the aim of this thesis, that is, to advance understanding into the geographic distribution of offender residences.

Firstly, clarity has been provided on the development of offender residence and offence concentration research in spatial criminology through extensive literature reviews and accompanying empirical demonstrations. Although the importance of the 19th Century scholars and Chicago School is widely acknowledged, with many contemporary studies focusing on offences, reviews tend to brush over their focus on offender residences. This has occurred despite many of these early studies explicitly recognising the theoretical distinctions between where offenders live and where offences are committed, and the merit in examining the spatial patterning of offender residences. Although this point has been made periodically in existing literature (e.g. Bottoms & Wiles, 1986), in tracing this narrative, a review of contemporary methods used in the (more advanced) offence strand of research has been conducted, and their suitability gauged for deployment on offender residence data, along with an empirical demonstration of how offender residences and offence locations are distinguishable across multiple years and spatial scales. This represents significant advance over recent reviews which emphasise the importance of offender residences in spatial criminology, in constrast to offences, with minimal empirical demonstration.

Secondly, this thesis has provided a detailed (longitudinal) examination of the impact of spatial scale when studying offender residence concentrations. To date, thorough investigation of spatial scale using longitudinal data, in pursuit of the most theoretically and empirically suitable geographic unit of analysis, has only been conducted using police recorded *offence* data. In this thesis, a series of descriptive statistics and visualisations showcased the degree to which offender residences concentrate across three nested English census block units. Multilevel variance partitions then estimated the variance attributable to each spatial scale in order to disentangle the degree of heterogeneity between units at different aggregations. In doing so, the findings from this study demonstrate, for the first time, the merits of using micro-scale units of analysis when studying the spatial patterning of offender residences longitudinally. Specifically for study regions in England, the results strongly suggest that the smallest census unit, Output Areas, are the most appropriate.

Thirdly, findings from this thesis have contributed to our understanding of longitudinal stability in offender residence concentrations. Although this was of central interest to seminal studies conducted by the Chicago School, to date, only the offence strand of research has benefited from recent advances in longitudinal clustering methods, which are commonly deployed to unpick meaningful patterns from small area trajectories. This study has provided the first demonstration of the insight gained from such techniques in unison when using data on known offender residence locations. In doing so, the degree of stability in these concentrations has been quantified, visualised and mapped at fine-grained spatial scales for the first time. As such, a key component of the Chicago School has been revived with the benefit of contemporary advances in data and methods.

Fourthly, and relatedly, following an extensive review of existing approaches to longitudinal clustering, a new method was implemented, termed 'anchored k-medoids' (ak-medoids), along with a relative (rather than absolute) measure of concentration. Ak-medoids was specifically designed with consideration to the theoretical frameworks and empirical aims of the study. The merits of ak-medoids were showcased through a systematic comparison with a generic implementation of k-means, both of which were deployed on a relative proportional measure, which permits easier interpretation of (in)stability and uniformity in localised trends. Findings were reported using descriptive statistics and visualisations which offer greater transparency on the suitability of cluster solutions compared to existing studies. In doing so, this thesis has made a methodological contribution which may have wider implications for the field (e.g. Adepeju et al., *under review*).

Finally, this thesis has shed new light on potential explanations for the longitudinal spatial patterning of offender residence concentrations using both individual-level population flows and aggregate-level visualisation and analysis. Findings suggesting that there are indeed meaningful patterns to the origin-destination house moves of known offenders, and that these might be explained by key demographic characteristics and urban development, representing significant advance over existing studies in England. The deployment of spatially lagged logistic regression models to explain the relative (in)stability of offender residence concentrations observed have also provided novel insight. This more nuanced approach to explanatory models, unmasking individual-level origin-destination flows of known offender house moves, and explaining shifting patterns using longitudinal data, open prospect for the offender residence strand of research to make an impactful revival in spatial criminology.

Appendix A

Three cluster k-means solution

As detailed in Chapter 5, the Calinski Criterion indicated that a 3-cluster solution was the most optimal grouping when deploying k-means on the relative offender residence measure. In the interests of a systematic comparison, a 5-cluster solution was selected as per the ak-medoids solution, with the 3-cluster solution reported here. The descriptives and visuals mimic those reported in Chapter 5.

Even when using this alternative solution, the broad findings are comparable to those reported in Chapter 5, with some minor disparities. The individual trajectories are reported in Figure A.1 and accompanying median trends in Figure A.2. The 3-cluster solution fails to identify a stable cluster, instead finding two decreasing (clusters A and B) and one increasing (cluster C), each characterised by heterogeneous long-term trends (see Table A.1). Consistent with the findings reported in the main body of this thesis, and in comparable crime concentration literature (see Chapter 4), the clusters obtained are sensitive to the outright levels, rather than change over time. This renders the spatial clustering similar to those that could have obtained through cross-sectional analysis.

Table A.1: Descriptives of k-means 3 cluster solution

Cluster	Size (N)	Size (%)	% +ve prop. traj.	% -ve prop. traj.	Class
A	1572	49	48	52	Decreasing
B	1333	41	40	60	Decreasing
C	312	10	63	37	Increasing

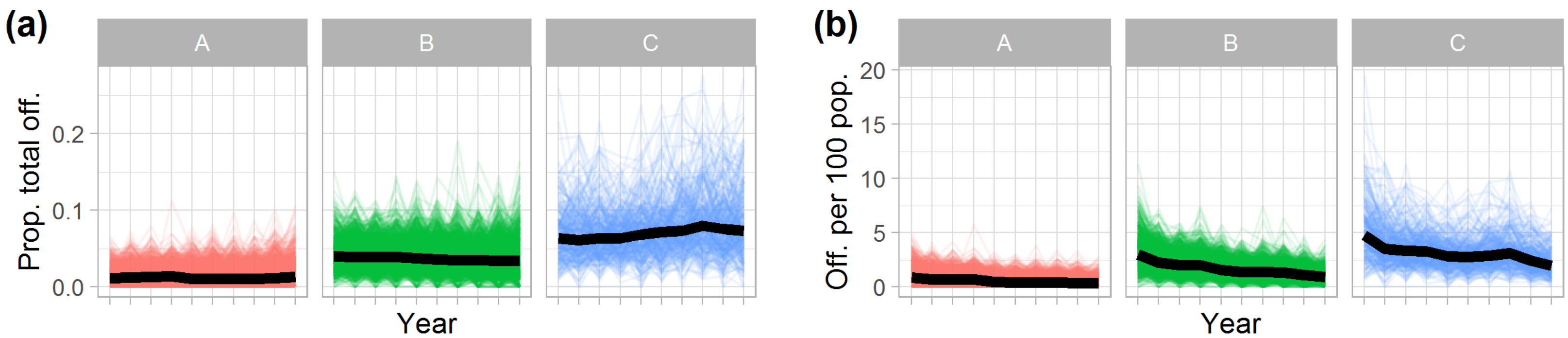

Figure A.1: 3-cluster solution using k-means on proportions for (a) proportional trajectories, (b) rate trajectories

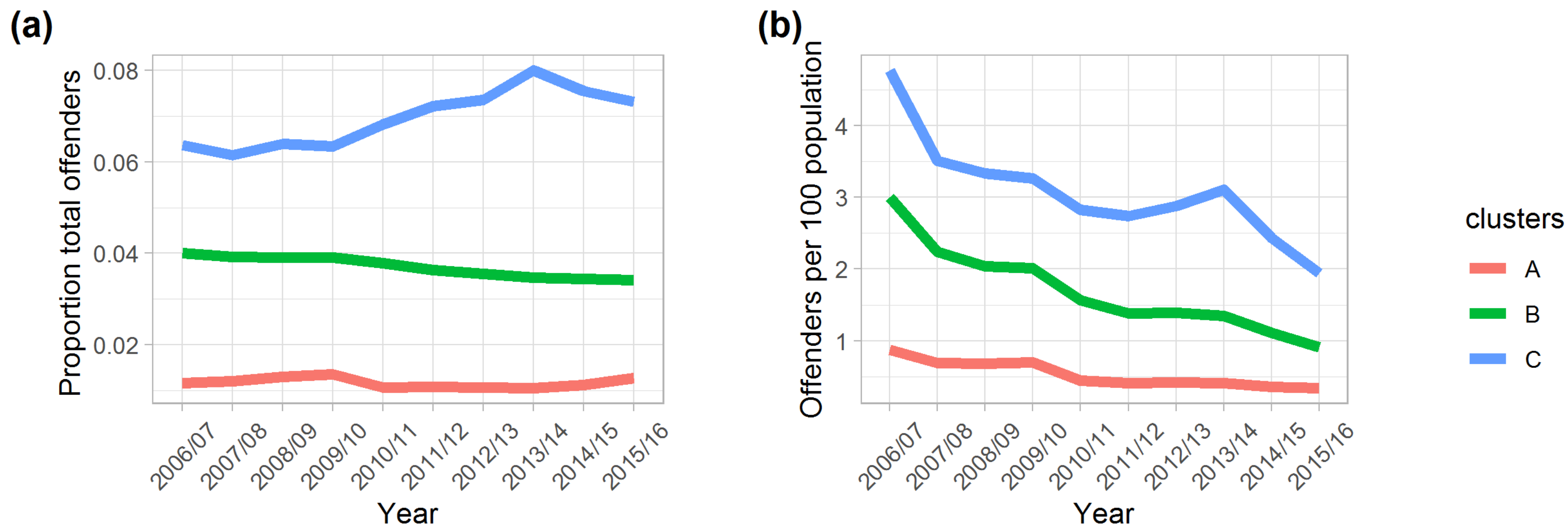

Figure A.2: 3-cluster solution using k-means with median trend lines for (a) proportional trajectories, (b) rate trajectories

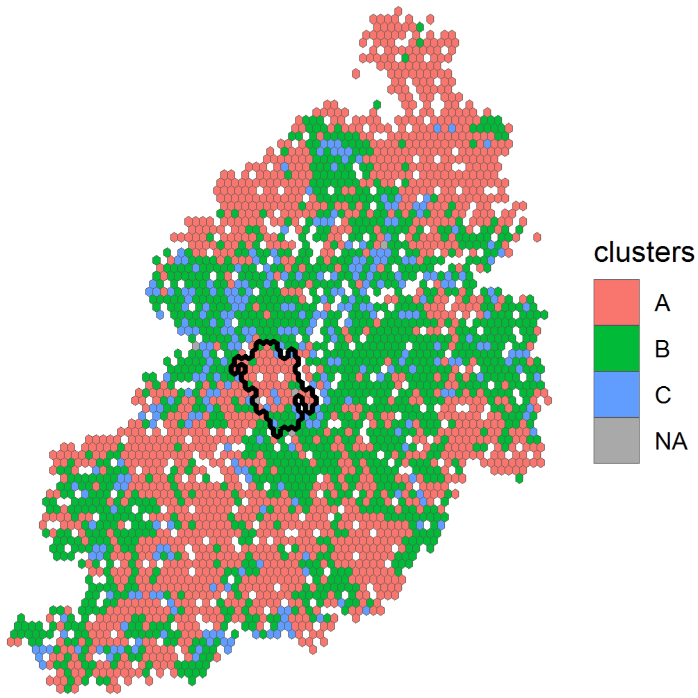

Figure A.3: Spatial distribution of 3 cluster k-means solution

Appendix B

Calinksi Criterion results

The analytical strategy (see Chapter 4) and results chapter (see Chapter 5) detailed how the final cluster solutions were obtained. This included a comment on the balance between determining solutions using metrics and researcher judgement. As detailed in the main body of this thesis, the Calinksi Criterion was used as the metric to guide the final cluster solution selection for ak-medoids (and consequently, k-means). In doing so, the metric indicated that an 8-cluster solution was optimal (see Figure B.1). However, the benefit obtained by using such a solution, over a 5-cluster solution, was not deemed too minimal, given the increased complexity and lack of parsimony in an 8-cluster solution. As such, a 5-clusters were selected.

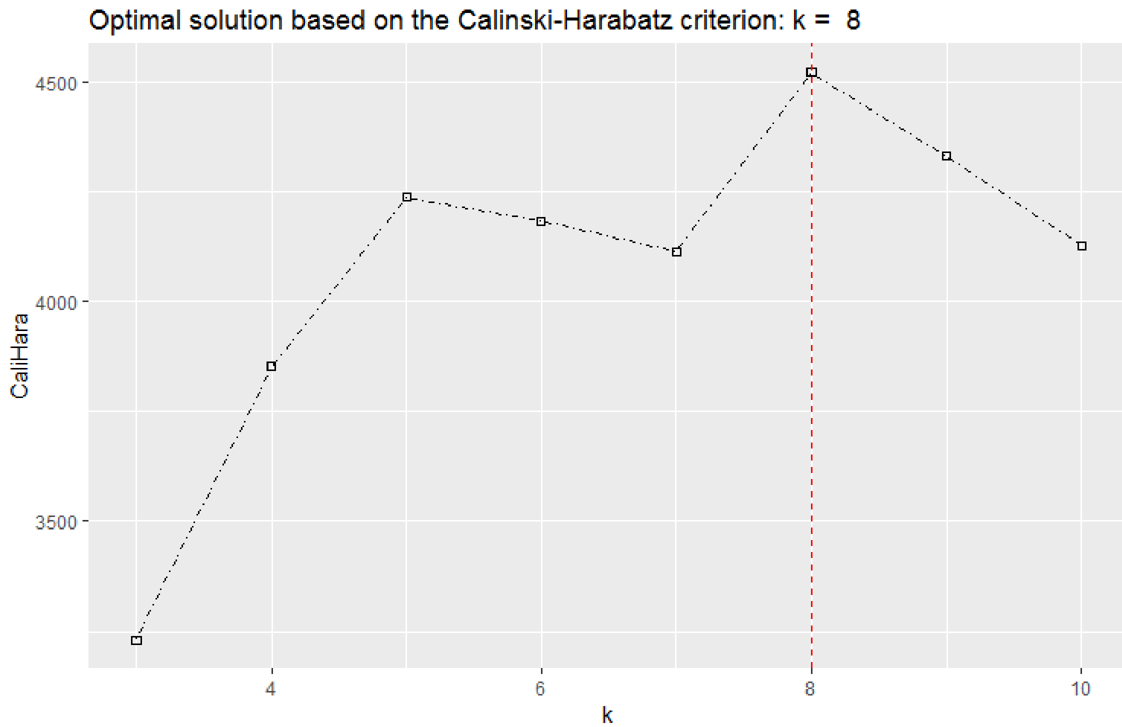

Figure B.1: Ak-medoids Calinski Criterion results

Appendix C

Independent variable descriptives

As outlined in Chapter 4, the independent variables used in the regression models were derived from the 2001 census, and adjusted for the 2011 changes in Output Area boundaries. The descriptives of these variables are reported in Table D.1. 'Overcrowding' is defined in alignment with existing research (Yousaf & Bonsall, 2017), representing the proportion of households with more occupants than rooms. 'Risky population' is the proportion of residents aged between 15 and 24. 'Rented accommodation' is the proportion of households who rent their accommodation in any form. 'Ethnic diversity' is the Blau index of residents using all ethnicity categories. The 'spatial lag' was calculated as the mean relative offender proportion of neighbouring Output Areas using the queen adjacent matrix. All variables were standardised before analyses was conducted.

Table C.1: Descriptives of independent variables

-	Mean	Std. Deviation	Minimum	Maximum
Overcrowded	3.68	4.70	0.00	28.26
Risky population	14.26	8.61	0.00	94.21
Rented accommodation	35.69	23.77	0.00	95.83
Ethnic diversity	1.49	0.29	0.84	2.29
Spatial lag	0.03	0.02	0.00	0.14

Appendix D

Net population flows

Descriptives and visualisations relating to the residential mobility of known offenders is detailed in Chapter 5. Particular attention was paid to ~14,000 offenders who were known to move house between 2006/07 and 2015/16, including the demographic and deprivation characteristics of their origin and destination moves. In examining these patterns, an attempt was made to visualise the net flows (inflows minus outflows) of house moves amongst offenders during the study period. This was calculated for each Output Area. The distribution of these net flow counts at Output Area level is plotted in Figure C.1. This suggests that there is some stability in these net flows over time, with 640 Output Areas experiencing zero net flows (whereby inflows equals outflows), and a total of 852 experiencing either one net inflow or outflow, together representing nearly half the city. However, there is also a great deal of instability, with many Output Areas experiencing dramatic out or inflows throughout the study period (as many as 23 net outflows, and 29 net inflows). As noted in Chapter 5, many of those areas experiencing inflows are in the suburbs and towards the edges of Birmingham, with is further visualised in Figure C.2. These findings, and their consistency with the surburbanisation of poverty, are certainly worthy of further examination.

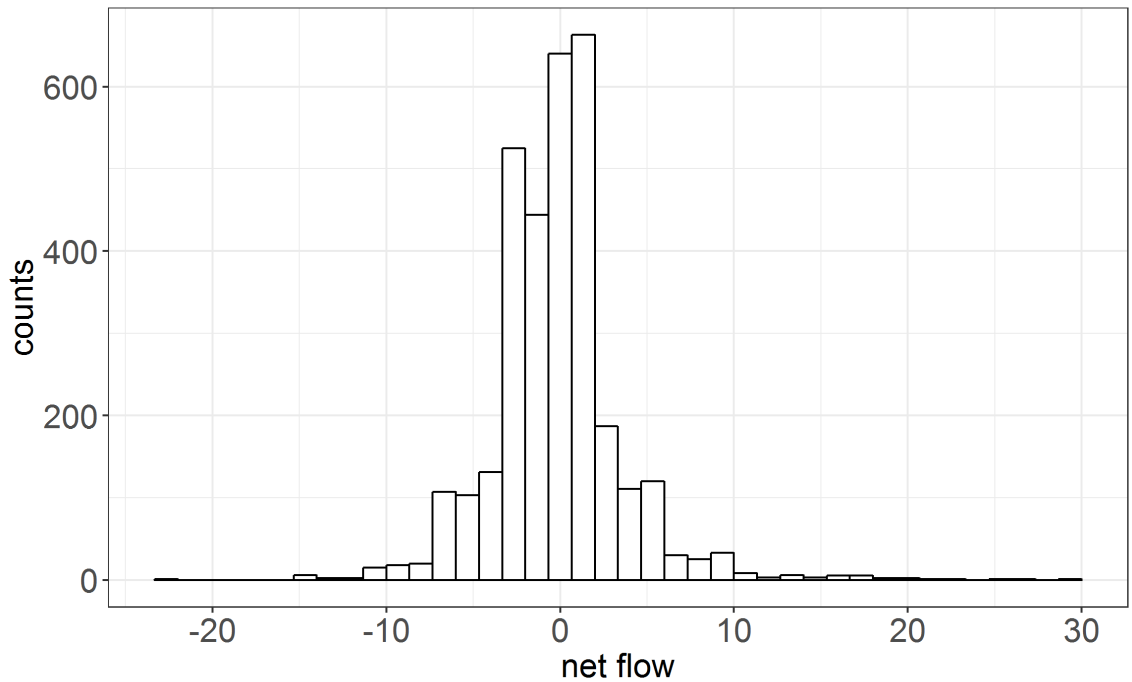

Figure D.1: Net offender residential flow histogram for Output Areas

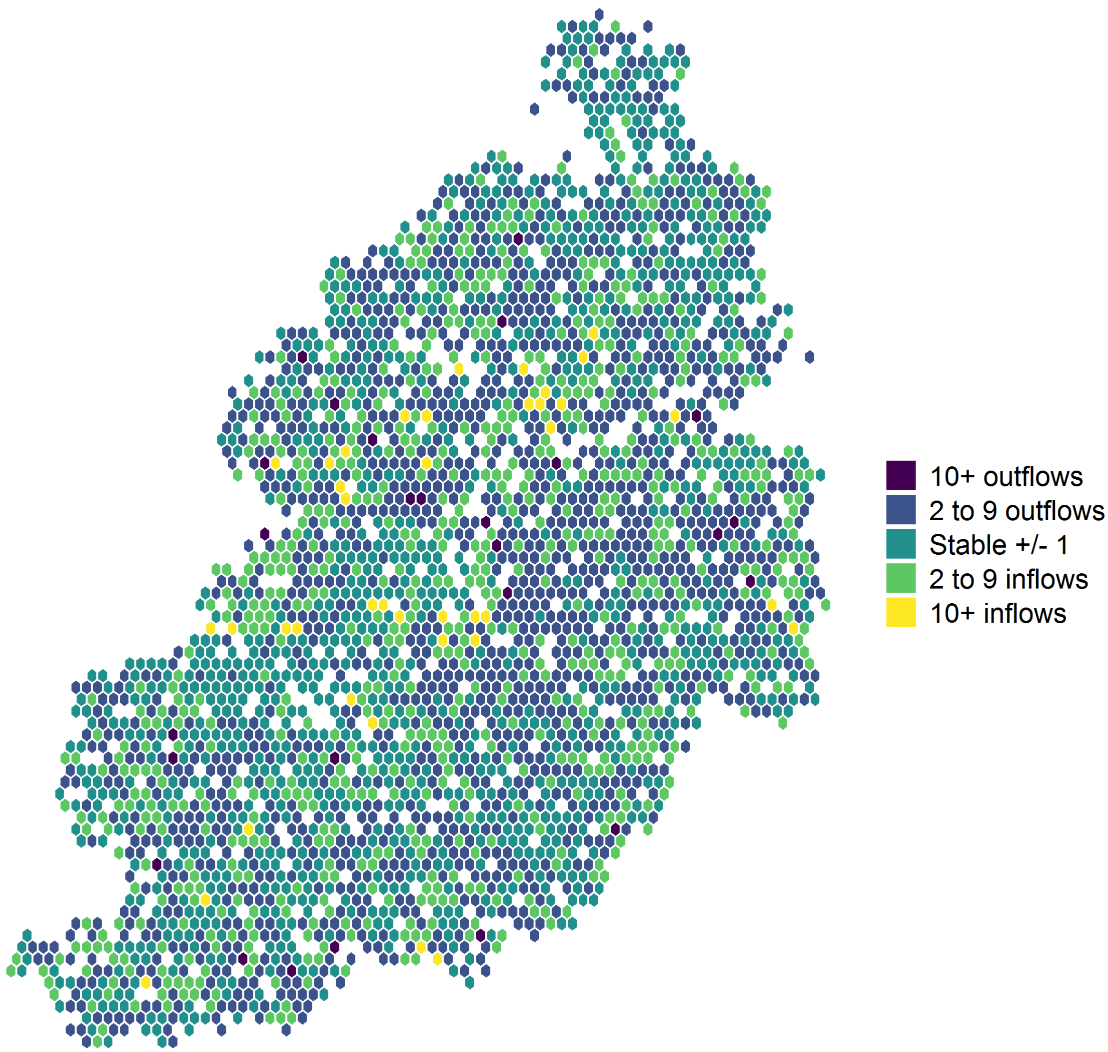

Figure D.2: Spatial distribution of net offender residential flows at Output Area level

Appendix E

Journey to crime by type

Although there are strong theoretical reasons to treat offender residences and offences as distinct (see Chapter 2), there are also clear empirical reasons for doing so, as detailed in the journey to crime literature. Findings from this thesis demonstrate the empirical distinctions between where offenders live, and where offences are committed, using longitudinal data (see Chapter 5). However, it does so using data aggregated by crime type. The impact of this can be showcased using descriptive statistics for each crime type. Doing so demonstrates that the empirical distinction between the two phenomena holds for all crime, burglary, assault and shoplifting, although there are distinctions between them. Figure E.1 visualises the proportion of offences committed in an offenders' home Output Area for each year of the study period, and Figure E.2 visualises the straight-line distances from residence to offence location. The statistics reported here include offences committed in the offender's own home. For crimes like shoplifting, this has no impact, but it is likely to *overstate* the proportions and *understate* the distances respectively for crimes like assault, many of which are domestic.

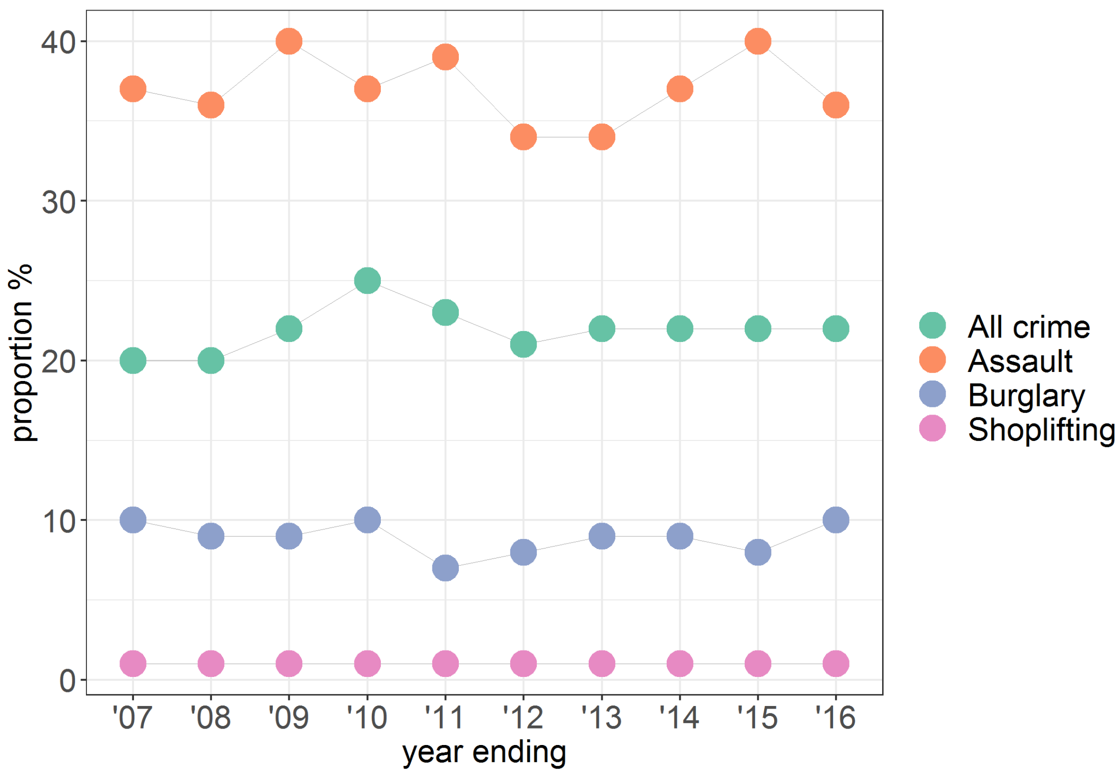

Figure E.1: Proportion of offences committed in an offender's home Output Area, by crime type

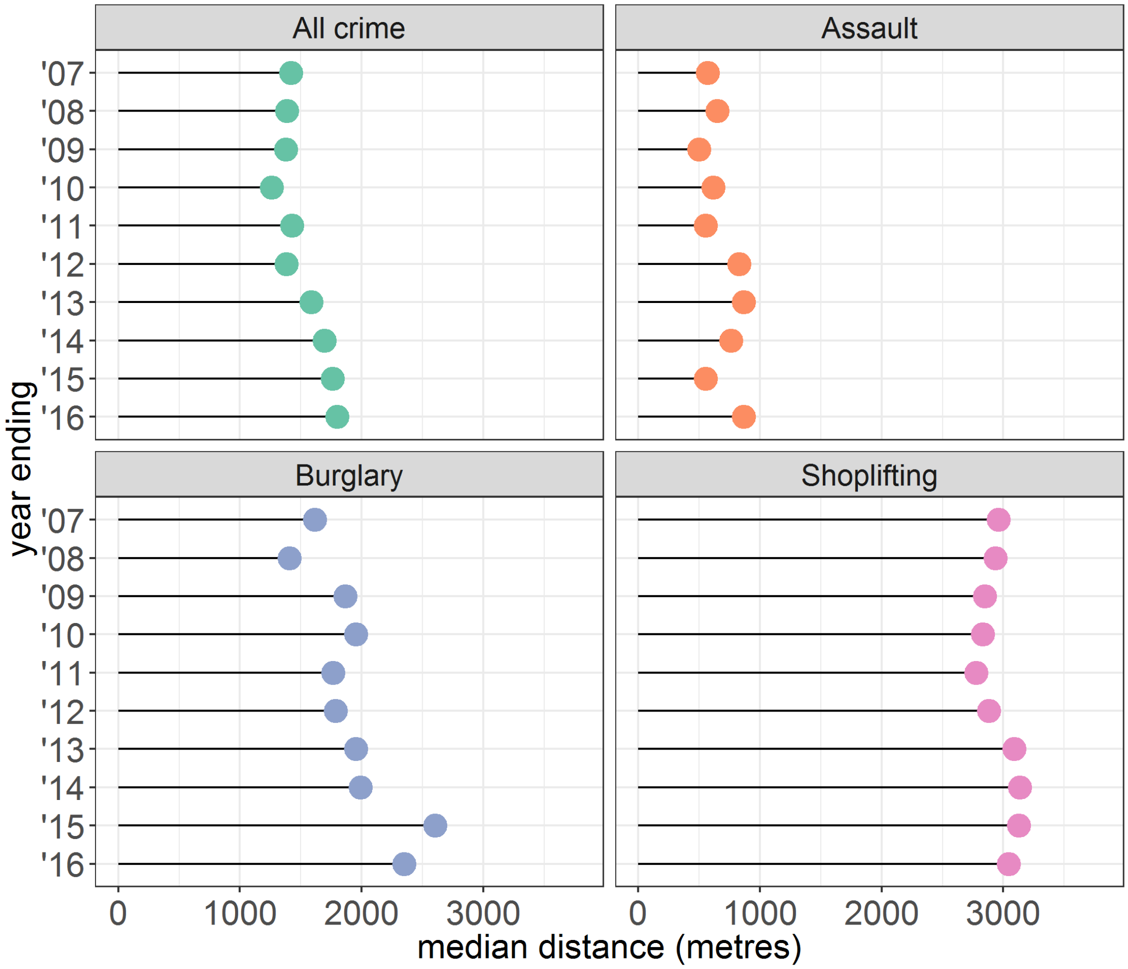

Figure E.2: Journey to crime descriptives by crime type

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