Please cite the Published Version

Additional Information: This is an open access article which will appear in Journal of Spatial Information Science

Offender residence locations: exploring the impact of spatial scale on variability and concentration

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Abstract: In recent decades, the analysis of different geographic scales for studying the spatial patterning of crime has profoundly deepened our theoretical grasp of crime dynamics. However, a similar investigation is lacking when it comes to the patterning of offender residences, despite there being clear theoretical and empirical reasons for doing so, among them, the close relationship between where offenders live and where their corresponding crimes are committed. This paper delves into the concentration and variance of offender residences across different levels of spatial aggregation. The data used contains the locations of residence for known offenders in Birmingham between the years 2006 and 2016. Resident locations are aggregated to Output Areas (OA), nested within Lower Super Output Areas (LSOA), further nested within Middle Super Output Areas (MSOA). Descriptive and model-based statistics are deployed to quantify concentration and variation at each spatial scale. Results suggest that most variance (48%) in offender residence concentrations is attributable to the largest spatial scale (MSOA level). Output Areas capture approximately 38% of the variance. Findings open up discussions on the role of urban development in determining the appropriateness of spatial scale.

Keywords: offenders, geography, crime, spatial scale, hierarchical model

1 Introduction

Recent years have seen a considerable rise in studies which utilize micro-geographic units of analysis to study spatial concentrations of crime and related phenomena such as emer-

gency calls-for-service [1, 22, 28, 66]. This surge of interest was, in part, driven by a series of influential descriptive studies which document the degree to which crime concentrates at micro-places in urban areas [48, 56, 65]. In 2015, Weisburd synthesized much of these findings into the 'law of crime concentration,' evidenced by the persistence of crime concentration at micro-places even amidst wider fluctuations in the absolute level of recorded crime [62]. These 'global' descriptions of concentration were augmented with endeavors to classify crime trajectories of micro-places [1, 15, 24, 64, 68], identifying that a small number of micro-places, such as street segments, drive much of the macro-level trends in police-recorded crime [1].

Acknowledging the micro-place as a theoretically appropriate and practically relevant scale to study crime, but also that street segments are nested within larger neighborhoods, recent efforts have sought to estimate the degree of concentration and variance attributable to different (nested) spatial scales simultaneously. [60] deployed descriptive statistics and a multilevel variance partition using street segments, neighborhoods and districts in The Hague, the Netherlands. They found that the largest proportion of variance was attributable to micro-places, suggesting that meso-level aggregations might mask underlying between-unit heterogeneity. This study inspired investigations in Chicago [53] and Stockholm [21] which reported findings consistent with the idea that more 'action' was occurring at fine-grained micro spatial scales. These studies, in concert with the substantive demonstrations of longitudinal stability and hotspot policing strategies, served to further reinforce the notion that crime demanded investigation at highly localized geographic resolutions.

That said, these recent investigations into the importance of fine-grained spatial scales and crime have neglected the complimentary strand of research which examines where known offenders live. This has occurred despite there being strong theoretical and empirical reasons for establishing the degree of concentration and variance in offender residences across different levels of aggregation. Rather than place-based opportunity structures, offender residence concentrations are thought to be determined by wider urban characteristics such as housing type (e.g., purpose-built public housing, owner-occupied properties) and residential redevelopment initiatives [5]. Indeed, empirical studies have demonstrated that the causal mechanisms behind crimes and offender residence concentrations are distinct [10] and likely to operate at different spatial scales [47]. In this manner, the suitability of highly localized spatial scales, such as micro-places, in studying offender residence concentration, cannot be presumed.

With this in mind, we present a systematic comparison of nested geographic units of analysis to investigate whether 'smaller is better' in terms spatial scale for offender residences. In doing so, we hope to guide future research which seeks to advance understanding into offender residence locations and their role in studying the spatial patterning of crime, answering calls from recent research [4, 5]. First, we provide an overview of existing studies which have explored the use of different geographic units of analysis when studying the spatial distribution of offender residences and (more commonly) crime events. Second, we outline the theoretical reasons why we might expect the appropriate spatial scale for each phenomena (offender residences and crimes) to be distinct. Third, we describe the analytical strategy which is inspired by the methods deployed in a recent study which compared concentration and variance across spatial scales for crime [60]. We do this using ten years of police-recorded data on known offender residences in Birmingham, UK, and three nested geographic scales. Findings are discussed in relation to the theoretical and em-

pirical distinctions between offenders and crimes and the context of the study region. The paper draws to a close with some concluding remarks and proposals for future research.

2   Spatial scales in crime studies

2.1   Origins and development

Although recent years have seen a concerted effort to examine the impact of spatial scale when studying crime and related phenomena, in particular those of micro-level units, interest in the topic is by no means new. In fact, much of these discussions began in relation to offender residences (i.e., where offenders live) rather than the offences (i.e., where crimes occur). The history of these discussions has been traced back to the 19th Century, amidst the first writings on the geography of crime [63, 66]. The earliest investigations into the geographic distribution of criminality were conducted using large, regionwide aggregations in France, with the likes of [49] and [25], but focus quickly turned to more localized spatial scales. This was largely due to the recognition that there was a high degree of variability in where crime occurred and where offenders lived, even within specific urban areas and regions. Henry Mayhew reported as such during his examination of society and crime in 19th Century London [37]. He demonstrated this using 'micro-level' units of analysis, such as specific roads and buildings, albeit often using anecdotal and observational evidence, rather than statistics. Lodging houses in particular were identified as problematic, as they tended to house individuals who were criminally active. It became clear that the regionwide maps generated by Mayhew's predecessors (and often Mayhew himself) might be masking underlying variation occurring at more localized scales.

Soon after, John Glyde conducted a case study of criminal populations in Suffolk, a largely agricultural county in England [23]. Like Mayhew, Glyde provided a novel insight into concentrations of offenders, but did so using multiple levels of aggregation. Within Suffolk, the number of known offenders housed in each local area ('Union') varied considerably. But, even within these areas, Glyde found that each town and village was "not equally favorable or unfavorable" and that "extremes are sometimes met within the same district" (p. 103). In other words, by disaggregating data on offenders down to localized geographies, rather than the large regions, greater variability could be unmasked. Even amidst the earliest mapping of criminality researchers were clearly mindful of the benefits of selecting an appropriately small geographic unit of analysis. It is also noteworthy that Glyde focused on "the localities in which the criminals have resided" (p. 102, emphasis in original), rather than where crimes occurred. In doing so, he observed discrepancies between the two phenomena, noting that many offenders did not reside in the town where the offence took place. This was early evidence to suggest that the factors driving offenders to reside in particular areas differed from those determining where offences were committed.

It would be the Chicago School, some decades later, which would set a benchmark in the study of offenders at 'micro' spatial scales. [54], in collaboration with colleagues, most notably Henry McKay [55], used point-level maps of known offender residence locations in Chicago, alongside area-level aggregations constituting neighborhoods, to demonstrate the non-random distribution of criminality in urban areas. Their studies elaborated upon earlier work by [9] which described and mapped the residential locations of young male offenders, also in Chicago. Both bodies of work were consistent with Mayhew's anecdotal reports and Glyde's descriptive statistics some years earlier, namely, that there was

significant variability in offender residence concentrations, even within the same urban conurbation.

Although much of Shaw and McKay's work is recalled for their theoretical contributions and analysis at neighborhood aggregations, Shaw's maps of residential locations have been credited as the first American study to recognize the value in micro-scale geographies [60]. The Chicago School would go on to inspire a number of works elsewhere. In Britain, a case study by Terence Morris in Croydon examined the spatial distribution of offender residences and crime simultaneously using maps at a resolution which detailed specific streets and buildings in an effort to test the relevance of Shaw's work outside the United States [40]. Later, the spatial patterning of offenders and crimes would be examined in Sheffield, with some maps using pin-point locations much in the style of Shaw's early visualizations [2].

Nevertheless, in the decades following the contributions of the Chicago School, investigations into the spatial patterning of crime and offenders would be few and far between. This has largely been attributed to concerns over the ecological fallacy [52] and a lack of suitable data [66]. In the 1980s, a concerted effort was made to revive interest in offenders with a specific focus on 'meso' units such as communities and neighborhoods, e.g. [51] and [6] in Communities and Crime [50], but in general, focus had shifted towards the concentration of crime, rather than offenders, and in time, towards micro-places, rather than meso units of analysis.

These shifts can, at least in part, be attributed to empirical findings which highlighted a remarkable degree of concentration in crime at fine-grained spatial scales. High-profile case studies in Minneapolis [56], Boston [48] and later elsewhere [17, 59, 65] demonstrated that a disproportionately large volume of crimes and emergency calls for police occurred in particular places. This finding held significance across two key domains. Firstly, evidence that crime is concentrated in specific places, such as commercial stores, residential buildings and street segments, is consistent with theoretical expectations. A key contention of routine activities theory [14] is that crime occurs at locations where motivated offenders and suitable target converge, and where opportunities present themselves, even within the same community [16]. Thus, one would expect variability in crime even within the same neighborhood, depending on the opportunity structure of the streets and buildings nested within it. Secondly, and relatedly, the observed concentration of crime at micro-places supported the drive for 'hotspot' policing interventions as an effective and resource-efficient method for reducing crime [57]. With these policing tactics largely considered to generate favorable outcomes [7] the importance of the micro-place in tackling urban crime was cemented, and the neighborhood unit of analysis fell out of favor.

Recent research examining both concentration and variation across multiple nested spatial scales has further compounded these conclusions. One criticism of the descriptive concentration studies in the 1980s (e.g., [56]) is that they do not include 'traditional' units of analysis, such as neighborhoods or communities. They may, therefore, be overestimating the importance of the micro-geographic units in the explanation of crime. After all, if the micro-places where most crime events happen are clustered in the same neighborhood(s), a neighborhood-based explanation for crime seems plausible. Recognising this shortcoming, later studies were able to demonstrate that both concentration and variation in crime was greater at micro-level places, such as a street segments, compared to larger units of analysis. In the Netherlands, [60] found that not only was crime more concentrated among street segments, but that on average, 62% of total variance in crime was attributable to

street segments, with the remaining variance spread among neighborhoods and districts. Comparable findings have since been reported in the United States [53] and Sweden [21]. Collectively, these findings have formed a concrete evidence-base in support of the micro-level analyses of crime.

2.2   Offenders

While it is clear that environmental criminologists have long been examining the impact of spatial scale for offenders and crime, the recent advances noted above have focused almost exclusively on the latter. During this time, there has been little concerted effort to examine the appropriate geographic resolution to study offender residences. And yet, reasons for reviving interest in offender residences, and conducting examinations into variation and concentration at different spatial scales, are plentiful. Offender residences and crimes are distinct (but related) phenomena. Offenders tend to commit crime relatively close to where they reside, within their behavioral spaces [8], and thus spatially proximate high offender rate areas are a key independent variable when seeking to explain variability in crime concentrations [4]. As such, the factors underpinning where offenders reside is of paramount of interest, even to those occupied with describing and explaining the spatial patterning of crime.

At the same time, there are reasons to suspect that the causal mechanisms driving offender residence and crime concentrations are distinct, operating at different spatial scales [5]. Whereas opportunity theories might be appropriate for explaining street-to-street variability in crime, the factors generating high offender rate areas are thought to manifest at much larger, meso-level aggregations. The most influential causal model for these so-called 'delinquency areas,' social disorganization theory, brought to prominence with [55] work in Chicago, was hypothesised to operate among communities and neighborhoods, rather than streets and intersections. At the core of the process was economic deprivation. Inexpensive housing fostered areas characterised by high residential turnover and population heterogeneity, rendering communities unable to self-regulate and deter delinquent behaviour, especially among its youth [11, 33]. With cheap housing and economic deprivation varying little between spatially-proximate streets, and instead characterizing larger geographic scales, the offender-generating processes of social disorganization were expected to operate at area-level 'zones' and communities.

Studies seeking to disentangle mechanisms by which offenders can be disproportionately 'generated' in certain urban areas via social interaction effects have also conducted analysis at the meso (rather than micro) level. [3] found evidence in the Netherlands to indicate that the propensity of individuals to engage in criminal activity can be influenced by the proportion of known offenders residing in the same neighborhood. For instance, the authors speculated that the risk of becoming a victim of violent crime in a 'tough' neighborhood containing a high number of known criminals might be minimized if individuals themselves engage in violence. The causal mechanism was expected to operate at the neighborhood-level as a "locus of social interaction" between residents (p. 628). [35] found that individuals residing in Glasgow neighborhoods with a high density of prior offenders were more likely to later become active offenders themselves. They too justified the neighborhood as a theoretically appropriate spatial scale to study social interaction effects between offenders nested within the same community.

Rather than offender-generating mechanisms working in isolation, offenders may also select themselves into particular areas, either by choice, or through restrictions like accessibility to suitable housing. Certainly in the wider population, important outcomes of residential selection, such as ethnic segregation, attributable in part to the housing market, are studied using neighborhood units [42, 61]. Similarly, for the offending population, access to housing has been identified as a fundamental determinant of where offenders choose (or are compelled) to reside [67]. Offenders, selecting or forced to search to cheaper housing, return to deprived neighborhoods upon leaving prison [32], and generally speaking, prison releases come and go from the same neighborhoods [12]. Indeed, the first step towards the emergence of socially disorganized communities is self-selection brought about by affordable housing, which as noted, tends to characterize larger areas such as neighborhoods and communities [5, 58].

2.3 Choosing scale

With these discussions in mind, we cannot presume that the merits of fine-grained spatial scales ('where the actions happens') detailed in the crime-strand of literature are directly transferable to offenders. In fact, it is plausible, if not likely, that the causal mechanisms underpinning the spatial patterning of offenders create an urban landscape in which there is a high degree of between-unit heterogeneity in offenders at the neighborhood-level, with the micro-units nested within them remaining fairly homogeneous. Indeed, such a finding would align with expectations that "the location of offender residences is a topic not usually best studied on a truly microlocational level" [5]. The challenge, then, is to examine whether there is empirical evidence to support this claim. In addressing this,we aim to inform future research seeking to describe and explain variation in the spatial patterning of offender residences (see [5]) by providing guidance on the most appropriate geographic unit of analysis.

What follows is the question of which geographic units of analysis will comprise the potential candidates for studying concentration and variation in offender residences. In environmental criminology, authors have tended to discuss micro units in terms of street segments, meso in terms of neighbourhoods or communities, and macro in terms of counties or nations [62]. Crime concentration research, usually conducted within a single urban conurbation, has thus adopted spatial scales which broadly resemble micro and meso-level units of analysis (micro, small meso, large meso).

Studies specifically seeking to quantify variation in crime across different spatial scales have tended to follow in this vein. As noted, the most fine-grained 'micro' units are theoretically consistent with criminal opportunity structures, containing homogeneous environmental characteristics and thus enhancing the explanatory power of models seeking to explain between-unit variations in crime [44]. In practice, micro places tend to be defined as street segments [53,60], but in cities less suited to grid-based street networks, small areal units approximating Output Areas (OA), a micro census block unit in England and Wales, have been used [21, 45].

Here, OA hold particular merit as a theoretically meaningful behavioral setting, not just to study the spatial patterning of crime, but also for offender residences. First, OA are purposefully constructed from household-level data to contain resident populations which are internally homogeneous in terms of housing tenure and dwelling type [36]. So, boundaries are designed in a manner which maximizes between-unit heterogeneity in key

variables thought to determine offender residential concentrations. Boundaries are also designed to reflect physical features 'on the ground' which define activity spaces, such as major roads [13]. Thus, we suspect that OA represent a useful setting to study the manifestation of social disorganization, social interaction and selection, as key determinants of offender residential concentrations.

In addition, OA are designed to be uniform in terms of population size. Containing around 125 households, their residential scale is broadly comparable to street segments, which typically comprise 99 street addresses [64]. This is particularly pertinent given that the factors thought to underpin both the generation and self-selection of offenders within certain urban areas, such as housing accessibility, may characterize areas much larger than a typical OA. In an effort to minimize their scale, OA boundaries may divide otherwise comparable resident populations. Indeed, OA which are spatially proximate tend to contain similar demographic characteristics [19]. This opens prospect for the (larger) units in which OA are nested to hold greater theoretical (and explanatory) value when studying offender residences.

In England, OA form the building blocks of larger, meso-level units, namely, Lower Super Output Areas (LSOA) and Middle Super Output Areas (MSOA). LSOA are commonly used to report neighborhood deprivation statistics [43]. MSOA have been used as the principal scale to report housing prices, amongst other statistics [46], and were recently given locally-recognized names as part of a public consultation [30]. LSOA and MSOA are too designed to be uniform in terms of residential scale, and house approximately 2,000 and 10,000 residents, respectively. Despite their larger size, the manifestation of offender-generating (and selecting) mechanisms at the meso level provides clear reason to suspect that the 'action' in offender residences may well be occurring among such units. Providing empirical evidence to substantiate (or refute) this expectation–and guide future research–represents the key motivation of the study.

2.4   Looking forward

In summary, spatial criminologists appreciate the theoretical and methodological value of fine-grained geographic units as well as their clustering into larger spatial units such as neighborhoods, but systematic investigations of concentration and variation using nested units have only been conducted on police-recorded crime data. No such investigations have been undertaken for offenders, despite there being reason for suspecting that findings may differ, and clear motivations for conducting such analyses. This study is a first step to fill this gap. We use geocoded police-recorded data on known offender residences over a 10-year period in Birmingham, England. Data is aggregated to three nested spatial scales, namely, Output Areas, Lower Super Output Areas, and Middle Super Output Areas. The nested feature of the dataset is comparable to existing studies which have sought to describe and measure variability and concentration in crime [21,53,60]. With some modification given the characteristics of the data, the methods deployed mimic those conducted in The Hague [60], consisting of descriptive statistics, visualizations and a multilevel variance partition to quantify concentration and variability in offender residences over time. In doing so, we advance understanding into the impact of spatial scale when studying offender residences, and in turn, assist in guiding future research.

3   Data and methods

3.1   Police data

This study uses geocoded police-recorded data containing the coordinate location of known offender residences in the city of Birmingham, England, for the 10-year period 2006/07 to 2015/16. Study years run from 1 April to 31 March. Birmingham is the second-largest city in the United Kingdom (UK) with a population of around 1.1 million people. It sits at the centre of the West Midlands region, served by West Midlands Police Force.

3.1.1   Dependent variable

Offender records kept by West Midlands Police included two relevant categories, namely, those identified as a defendant/offender and suspects. A decision was made to the use the category of defendant/offender because these are individuals who have been allocated a clear-up code following a formal charge or caution. Henceforth, these individuals are simply referred to as 'offenders.' It is important to note, however, that the use of charged and/or cautioned as a proxy for offenders in our analysis is based on available data. We do not have access to information regarding the final verdicts of these charges (i.e., in court). Consequently, we would advise some caution when interpreting the results, as we are unable to assess robustness across different definitions of 'offender' (e.g., including only those that were found guilty in court).

Using this individual-level offender data, we use a measure of resident participation in offending based on a set of criteria. Individual offenders are identified in police records by a unique nominal reference which might be duplicated for the legitimate reason that the individual committed (and was linked to) multiple crimes. Thus, a high offender count for any given geographic unit might be an artefact of the same individual(s) being apprehended by the police multiple times, whilst continuing to live in the same place, rather than reflecting the number of active criminals residing there. To address this, duplicate nominal references are only counted more than once if the offender was known to have moved to a new area (defined as an OA) 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 property located in a different OA. 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 OA, the individual would only be counted once in any given year. This was to avoid over-inflation. We recognize that such decisions are up for debate, and sensitivity analysis was conducted to ensure that findings were not dictated by this decision, as detailed later.

Known offender records are included for all crime types. This is justified on a number of grounds. Firstly, offender data inevitably suffers from sparsity, especially when using fine-grained units of analysis such as OA. Not only do crimes have to be reported and recorded by the police, but an offender must be identified. In recent years, the nationwide detection rate during the study period was around 15% [29]. We aggregate offenders irrespective of crime type to avoid having to exclude particular areas or specific crime types due to low counts. Crime types have been aggregated for reasons of sparsity in the equivalent crime literature [60]. Given that this is the first endeavour to examine variability and concentration in offender residences across nested spatial scales, this also sets a baseline from which future research can be compared.

3.1.2 Citywide trend

The number of known offenders residing in Birmingham fell throughout the study period (see Figure 1). The absolute count declined from around 20,000 in 2006/07 to below 8,000 in 2015/16. This is unsurprising given the widespread fall in police-recorded crime during the same 10-year period. As such, the wider context of this study, as has been the case for longitudinal studies of crime concentration in recent years, is a decline in crime [1], and in this case, known offenders.
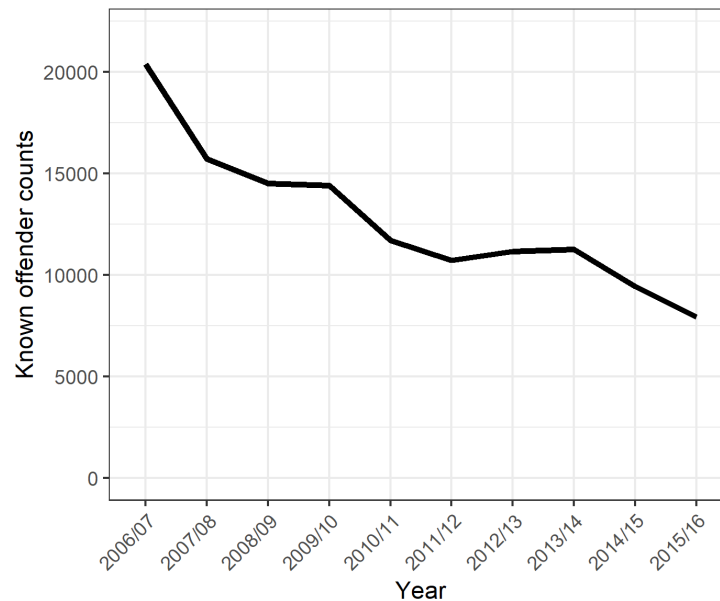

Figure 1: Citywide decline in known offenders in Birmingham.

3.2 Units of analysis

We make use of administratively-defined census units, namely, Output Areas (OA), Lower Super Output Areas (LSOA) and Middle Super Output Areas (MSOA). Birmingham consists of 3223 OA, 639 LSOA and 132 MSOA. The availability of offender residence coordinates permits the aggregation of counts to each scale using the measure of participation described earlier. As noted above, these units are considered theoretical appropriate to study variation in offender residences across urban spaces, and have the necessary statistical characteristics (i.e., nested structure) to mirror established studies in the crime strand of literature.

3.3 Analytical strategy

In alignment with [60], the analytical strategy has two principal stages. First, a series of descriptive statistics are reported which quantify and visualize the degree to which offender

residences concentrate in Birmingham across the three respective spatial scales. Maps visualize the spatial distribution for OA, LSOA and MSOA respectively. We deploy hexograms [26] instead of mapping the original boundaries. These have been shown to maintain the spatial patterning (e.g., clustering) of areal-units whilst ensuring anonymity [34].

Percentage thresholds are reported to describe the proportion of total units (e.g., OA) containing 25% or 50% of total offenders, respectively. These statistics have been widely used in the offence-based literature and comprise the evidence-base for the law of crime concentration [62]. Although these thresholds permit a straightforward comparison to existing findings, the thresholds are arbitrary. To visualize all possible combinations of percentage concentration, Lorenz curves can be plotted for each spatial scale (i.e., OA, LSOA, MSOA). These plot the cumulative proportion of crime against the cumulative proportion of spatial units, and demonstrate the degree of crime concentration across spatial scales in isolation (e.g., [31]). The Gini coefficient is a quantified descriptive statistic of concentration based on the Lorenz curve [20], which permits easier comparisons of concentration over time [53, 60]. To compliment the Lorenz plots and permit longitudinal comparisons, we also report Gini coefficients for each scale and year.

The second stage uses linear mixed models [63] to estimate the variance in offender residences attributable to each nested geographic unit of analysis. This permits the estimation of the proportion of total variance at each level. We deploy a four-level model of years, nested within OA (micro), nested within LSOA (small meso) and MSOA (large meso). In alignment with existing studies (see [60]), we add a fixed effect of time to estimate the citywide trend. The slope of time is allowed to vary across levels to permit the estimation of longitudinal changes in variance at each level. Thus, the model reportedly has t yearly measurements nested within i OA, nested within j LSOA, further nested within k MSOA, as follows in Equation 1.

$$\log(Y_{tijk} + 1) = \beta_{0tijk} + \beta_{1ijk} time_{tijk} \tag{1}$$

Where Y_{tijk} represents the transformed count of offenders at time t, within i^{th} OA, j^{th} LSOA, and k^{th} MSOA. The β_{0tijk} and β_{1ijk} terms are the intercept and slope coefficients for time at each level, respectively, described in more detail as:

$$\beta_{0tijk} = \beta_0 + f_{0k} + v_{0jk} + u_{0ijk} + \epsilon_{0tijk}$$

$$\beta_{1ijk} = \beta_1 + f_{1k} + v_{1jk} + u_{1ijk}$$

In these sub-equations, β_0 is the overall intercept across all units, and β_1 is the overall slope for time. The term f_{0k}, v_{0jk}, and u_{0ijk} represent random effects at the MSOA, LSOA, and OA levels, capturing the variability at each level of aggregation, while ϵ_{0tijk} is the residual error term. Similarly, f_{1k}, v_{1jk}, and u_{1ijk} represent the random slopes for time at the MSOA, LSOA, and OA levels, respectively. To calculate the variance of the random effects at the OA level, for instance, Equation 2 below can be derived:

$$var(u_{0ijk} + u_{1ijk} time_{tijk}) = \sigma_{u0}^2 + 2\sigma_{u01} time_{tijk} + \sigma_{u1}^2 time_{tijk}^2 \tag{2}$$

The variance components σ_{u0}^2, σ_{u01}, and σ_{u1}^2 represent the variance of the random intercept (u_{0ijk}), the covariance between the random intercept and slope (u_{1ijk}), and the variance of the random slope, respectively. The term $time_{tijk}$ is the time variable, which allows the examination of how variance changes over time within OAs.

We deploy this modelling approach on random samples of units from the 'population' of geographic areas comprising Birmingham. This is justified on two grounds which reflect those outlined by [60]. Firstly, one assumption underlying random effects models is that observations have been randomly drawn from a population. Running models using every single unit in Birmingham, which represents our population, would violate this assumption. Secondly, like crime, the geographic patterning of known offender residences is characterised by positive spatial autocorrelation (i.e., spatial clustering). Consequently, it is likely that observations with geographic proximity are dependent on one another and thus have correlated errors, violating another assumption of random effects models. [60] countered these issues by conducting analysis on stratified samples created by randomly drawing 25% of street segments (micro-level) from each neighborhood. The linear mixed models were then deployed on each sample, and mean of these estimates reported, along with the cumulative mean of estimates as a function of the number of samples.

A comparable approach is adopted for this study using offender residence counts in Birmingham, with some modification. Here, we use a step-wise stratified sampling procedure for each spatial scale. First, 25% of LSOA are randomly sampled from within each MSOA, then from these LSOA, a further 25% of OA are drawn from within each LSOA, to comprise a single sample. This procedure was replicated 500 times to create 500 stratified samples for analysis, from which the mean estimates were computed. This step-wise procedure was used because positive spatial correlation was observed at all levels of analysis (OA, LSOA and MSOA), and thus it is insufficient to only account for this at the micro-level. A secondary benefit of this approach is computational efficiency.

Initial analyses on the raw dependent variable (offender residence counts) highlighted issues around the normality of residuals. Diagnostic plots indicated that the residuals in the dependent variable violated the assumption of normality. To rectify this, we used a log(count+1) transformation (see equation 1), resulting in only mild violations of normality. This approach mirrors the methodologies employed in both [53] and [60]. In previous studies, a control variable was added representing the length of street segments, since longer streets inevitably have greater opportunity for crime compared to shorter streets. By contrast, a natural denominator to calculate offender residence concentrations is the residential capacity of spatial units. Given that OA, LSOA and MSOA units are purposefully designed to be uniform by residential population, it is not necessary to include such a control variable (or population-standardized dependent variable) and thus, the log transformed count of offenders was used as the dependent variable.

4 Results

4.1 Descriptive statistics

4.1.1 Offender residence concentration

In alignment with existing research and the evidence-base surrounding the law of crime concentration [62], Table 1 reports the concentration of offender residences at 25% and 50% proportional thresholds, respectively. For instance, Table 1 reports that in the study year 2006/07, 25% of known offenders resided in just 8.7% of OAs in Birmingham. For LSOAs, this figure was 11.4%, and for MSOAs, 12.8%. This suggests that known offender residence concentrations are greater using more fine-grained units. Interestingly, concentrations ap-

pear to increase over time. By the final study year, 25% of known offenders resided in 7% of OAs (down from 8.7%). This is observed across all spatial scales and using both 25% and 50% thresholds. That said, there is clearly still some stability in the concentration of offender residences, even amidst the widespread decline in numbers known to West Midlands Police (see Figure 1).

Unit	2006/07	2007/08	2008/09	2009/10	2010/11	2011/12	2012/13	2013/14	2014/15	2015/16
25% of known offenders live in:										
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
50% of known offenders live in:										
OA	22.31	22.03	22.22	23.12	22.22	21.69	21.5	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	30.3	30.3	30.3	30.3	31.06	30.3	30.3	30.3	30.3	29.55

Table 1: Percentage of spatial units in which 25% and 50% of all known offenders reside, per year ending 31 March.

Figure 2 plots a Lorenz curve for the first study year. The line of perfect equality, resembling a scenario in which offenders are uniformly distributed across Birmingham (e.g., 50% of known offenders reside in 50% of OAs) serves as the reference point. The larger the area between the line of perfect equality and the Lorenz curve, the greater the degree of concentration. As such, Figure 2 demonstrates that known offender residences tend to concentrate more at increasingly fine-grained units.
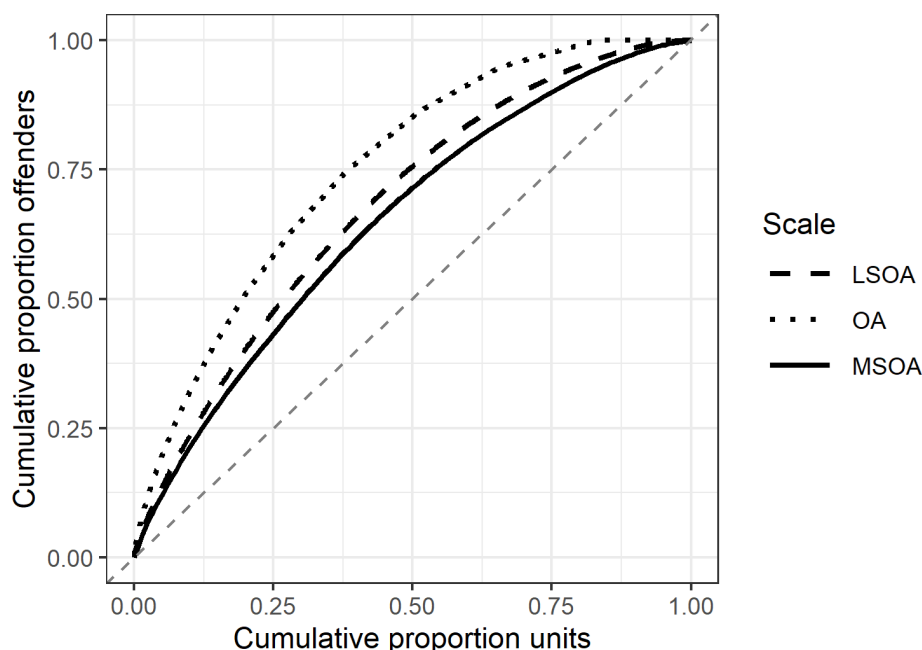

Figure 2: Lorenz curves for each spatial scale for 2006/07. Line of perfect equality included as a reference point.

Figure 3 visualizes the Gini coefficients for each spatial scale across years. As noted, the Gini coefficient simply offers a quantified, singular descriptive statistic of concentration. Here, we observe the slight increase in concentration observed across each unit. For OAs, the Gini coefficient increased from 0.45 in 2006/07 to 0.50 in 2015/17. For LSOA, the equivalent increase was smaller, increasing from 0.34 to 0.36. At the largest spatial scale, MSOA, the increase was only 0.01 (0.29 to 0.30). Not only are offender residences most concentrated at fine-grained (micro) units compared to meso-level aggregations, but longitudinal change in concentrations is also more evident.
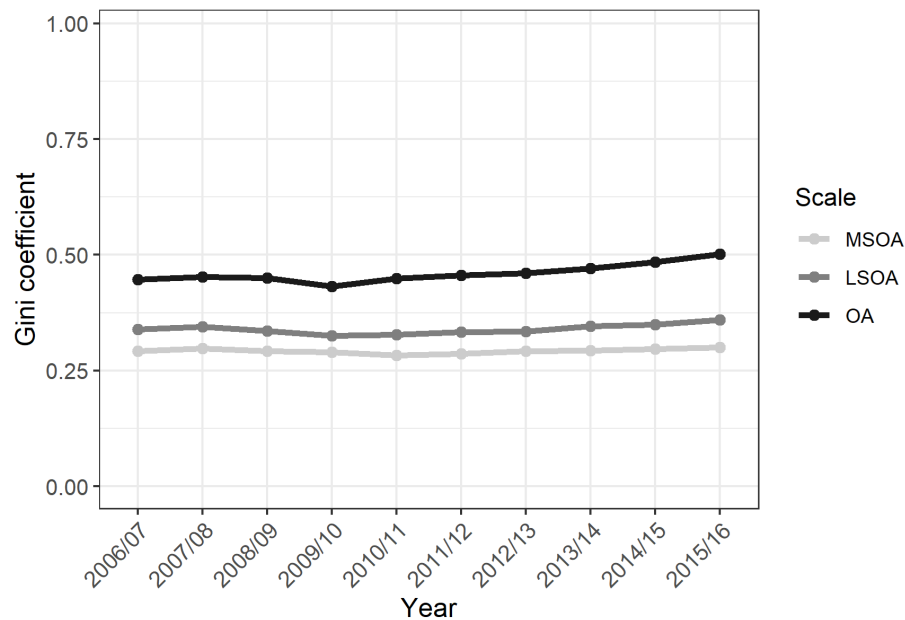

Figure 3: Gini coefficients for each spatial scale throughout the study period.

4.1.2 Spatial pattern of offenders' residence concentration

The spatial distribution of offender residence concentrations in Birmingham using OA, LSOA and MSOA levels of aggregation is visualized in Figure 4. Raw counts are categorized according to the Jenks-Fisher classification [18]. Low-High labels are used rather than raw counts for reasons of privacy.

Using MSOAs, the largest level of aggregation, the spatial clustering of these concentrations emerge. The city centre is distinctly outlined by a bold line and is noticeable due to the minimal presence of known offenders residing in two neighboring MSOAs situated in the middle of the city. We see clusters of known offender residences on the outskirts of the city centre to the north west. Similarly, a number of MSOAs to the north and east of the city centre also have high concentrations of known offender residences. These clusters tend to stand alone, typically encircled by areas with lower—though still comparatively high—counts of such residences.
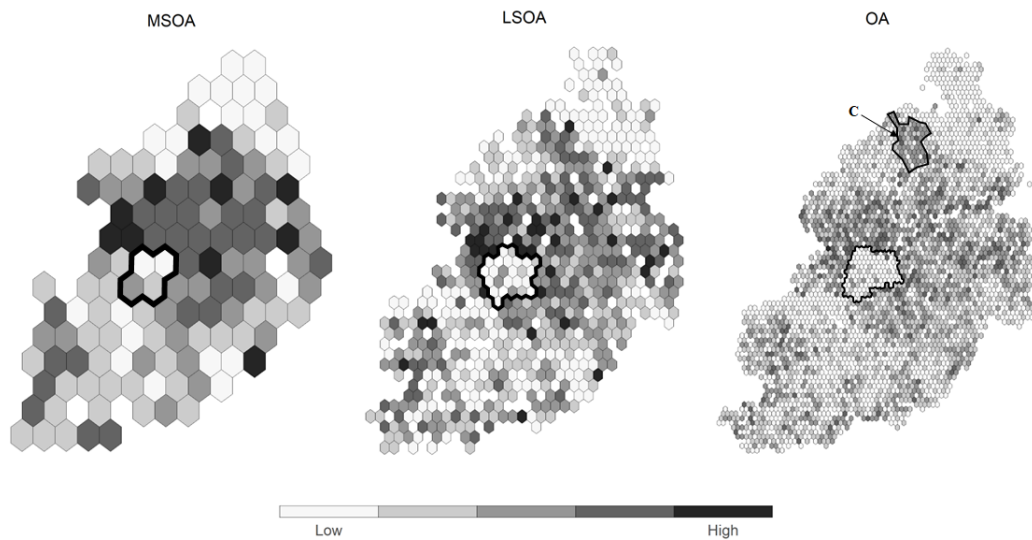
Figure 4: Offender residence concentration counts in 2006/07 using hexograms [26] by spatial scale. Five low to high breaks computed using the Fisher-Jenks algorithm as per [53].

Using LSOAs, the second-largest unit, we can disaggregate these patterns further. The map demonstrates once again that few known offenders reside in the city centre, but the use of this smaller meso unit highlights that even within the city centre, there is some variability. High count LSOAs are evident to the north west of the centre, in alignment with the MSOA map, but a number of high count areas now emerge to the north and north east.

OAs, as the smallest unit, further disaggregate the data. Again, the city centre is largely devoid of known offender residences. Instead, high count areas concentrate around the inner suburbs surrounding the centre. There is a high degree of positive spatial autocorrelation amongst these high offender count areas, with like-for-like counts tending to neighbor one another. One particular concentration of known offender residences in the north of the city, labeled 'C', become apparent using OAs which was not evident using the meso scales of LSOA and MSOA. Although we are clearly getting more detail through the maps at lower aggregations such as OA, the high degree of spatial clustering suggests that meso units might not necessarily contain dissimilar (i.e., heterogeneous) micro units.

4.2   Hierarchical linear models

The descriptive statistics and visualizations reported so far have demonstrated the degree to which offender residences concentrate at each spatial scale. In this way, we have demonstrated that a disproportionately large number of known offenders in Birmingham reside in just a small number of areas within the city. The degree to which this is the case appears to

vary by spatial scale, with smaller aggregations showing the highest concentration. These 'global' measures of concentration also appear relatively stable over time.

That said, these statistics do not consider the nested structure of the units under examination, namely, OA (micro), LSOA (small meso) and MSOA (large meso). Using a linear mixed model, drawing inspiration from [60], we can estimate the degree of variability in these offender residence counts (i.e., between-unit heterogeneity) simultaneously. The figures reported here are the mean estimates of the step-wise stratified sampling procedure, outlined earlier, using a 25% draw from each level.

The variance functions for each spatial scale are visualized in Figure 5. Notably, most variability in offender residences is attributable to the MSOA level, as the largest spatial scale. The quadratic shape of the OA variance function shows a decline, bottoming out around 2011/12, followed by an increase in the final few years. This change occurred amidst a decline in variance for both large (MSOA) and small (LSOA) meso-level units. For MSOA, this appears to be relatively linear, whereas for LSOA this decline begins to flatten out towards the end of the study period.
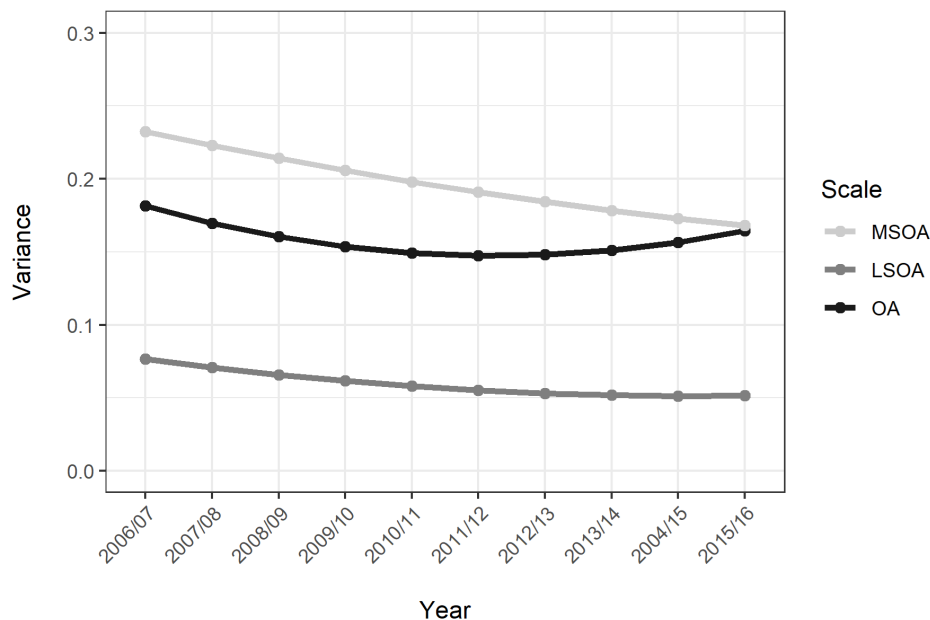

Figure 5: Variance functions for each spatial scale.

Figure 6 visualizes the proportion of total variance in offender residences attributable to each spatial scale. On average, 38% of total variance is attributable to OA, the smallest spatial scale. By contrast, MSOA, the largest spatial scale under examination, accounts for around 48% of total variance on average, and LSOA accounts for 14%. In alignment with the variance functions in Figure 5, the proportional figures suggest that this variability is dynamic. For OA, the proportion increased from 37% to 43% throughout the study period. At the MSOA level, the proportion of total variance peaked at 49% in 2009/10, but overall

it fell to 44% by the final study year. LSOA declined slightly but remained relatively stable during this time.
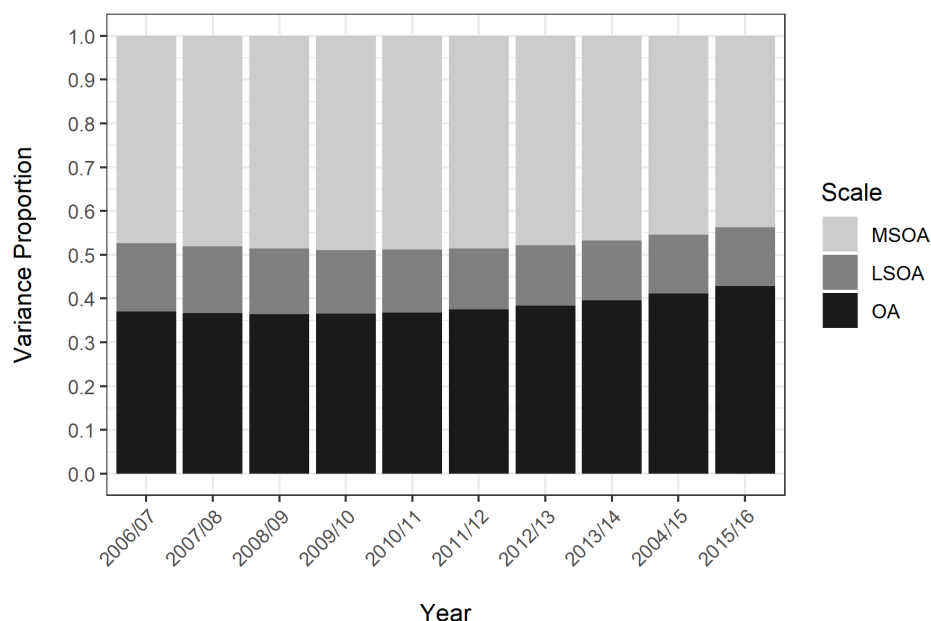

Figure 6: Proportion of total variance attributable to each spatial scale.

These findings from the linear mixed model highlight a number of points for discussion. Most variation in known offender residences appears to be occurring at the largest (meso) spatial scale, rather than at the micro-level. This indicates that there is greater heterogeneity between large, meso-level units compared to smaller, micro-level units, and represents an interesting departure from existing findings using police-recorded crime. We return to this point in the discussion.

4.3   Sensitivity analyses

We generated a number of additional linear mixed models and descriptive statistics to ensure that the variance partition findings were robust. Firstly, the cumulative mean of estimates obtained following each replication (N = 500) were visualized (see Figure A1 in the Supplementary material). This demonstrated that the mean estimates converged and became stable over time, confirming that 500 replications was sufficient, in alignment with [60].

Secondly, we conducted the step-wise stratified sampling technique, whereby LSOAs were first sampled from within each MSOA, followed by OAs from within each LSOA, using different random samples sizes (25%, 30%, 35%, 40%, 45%, 50%). Although larger percentages appeared to marginally decrease the estimated variance attributable to the MSOA, findings are robust to the percentage used for generating the random samples. Equivalent findings using a 50% stratified sample are reported in the Supplementary material (see Fig-

ure A2 and Figure A3), along with cumulative mean of variance estimates upon replication for each percentage sample (see Figure A1).

Thirdly, we investigated alternative operationalizations of the dependent variable. As detailed, we constructed offender counts per unit by counting offenders more than once if the individual was known to have moved to a different OA within the same year. This permits some degree of flexibility. For instance, an offender known to reside within two different OAs in the same year nested within the same MSOA is only counted once in each OA, but twice at the MSOA-level. It is therefore possible that findings around variability could be an artefact of how the dependent variable was constructed.

To assess the sensitivity of findings to the counting criteria, we compared a number of otherwise identical models using different 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 per the previous option, but for MSOA. Re-conducting analyses using these different criteria did not have a significant impact on findings, suggesting that the results are robust to different operationalizations of the dependent variable.

5   Discussion and conclusion

Using descriptive statistics on concentration, offenders appear to be most concentrated at fine-grained spatial scales. The smaller the geographic scale, the greater the degree of concentration. Computing Gini coefficients for each year demonstrates that these concentrations are also relatively stable over time, even amidst a citywide decline in the number of offenders known to police. These descriptive findings largely align with observations made about crime in The Hague [60] and Chicago [53].

That said, by accounting for the nested structure of the data, the linear mixed models demonstrate that the degree of variability (between-unit heterogeneity) is greatest at the largest spatial scale (MSOA), which accounts for around 48% of the total variance in offender residences[1]. By contrast, the smallest spatial scale (OA) accounts for only 38%. This differs with findings for crime, which have tended to attribute most variance to the most fine-grained level of aggregation [21, 53, 60]. In this manner, the micro-level is 'where the action' is happening for crime, but not for known offender residences.

The finding that most between-unit variability occurs at the largest (meso) scale, rather than the micro, is consistent with the distinct theoretical mechanisms underpinning offenders. While crime-based opportunity theories operate among micro-level units such as street segments and addresses, the causal processes said to determine the spatial patterning of offender residences, such as social disorganization, social interaction and self-selection, are thought to manifest among meso-level neighborhood units [3, 35, 55]. Indeed, there is no requirement for the two phenomena to be studied at the same level of aggregation: calls for a re-examination of offender residences in space have been made with the expectation is their spatial patterning is likely best studied at the meso-level, whilst acknowledging the

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[1]The observation that offenders concentrate most at OA level, but have most between-unit variability at MSOA level, is not contradictory. The Lorenz curve and Gini coefficient describe concentration at different levels of aggregation in isolation, whereas the linear mixed models estimate variability whilst accounting for the nested structure of the data.

importance of micro-places when studying crime [5]. Findings from this study certainly offer evidence to substantiate such claims.

That said, the between-unit heterogeneity for OA appears to increase over time, at the expense of MSOA. This is suggestive of a dynamic process by which the variability in offender residences is decreasing at the meso-level whilst increasing at the micro-level (becoming less homogeneous). One potential avenue of investigation which could explain this change lies in the urban development which occurred in Birmingham during the study period. This involved large-scale regeneration projects, subsequently described as "planned gentrification" [41], which may have redistributed offenders to specific areas of the city, increasing concentration and variability at localized scales.

Another potential explanation might originate from the manner in which the citywide fall in the number of offenders occurred (see Figure 1). Descriptive statistics suggest that the decline occurred non-uniformly across the city, with some areas falling quicker than others, and offender count trajectories shifting amongst one another over time (see Table A1 in the Supplementary material). This may have been a result of policing resource allocation or community interventions, amongst other reasons. However, it occurred, this instability is likely to have impacted on the degree of concentration and variance attributable to different spatial scales. Further analysis would be required to unpick the underlying instability. Here, longitudinal clustering methods may prove worthwhile given their established use in identifying local areas which drive citywide trends [1].

The nature of police-recorded offender residence data also opens prospect for individual-level investigations into longitudinal stability. We know that offenders might appear multiple times in police records over the course of a 10-year period. Each time, their residential address is recorded. Of all the unique offenders identified by West Midlands Police during the study period, around 14,000 were known to have moved house to different OA between crimes. Tracking the individual-level residential population flows of these offenders might shed light on how and why concentration and variation at different spatial scales has shifted over time.

While police-recorded data on known offenders opens prospect for new avenues of research, answering recent calls for a revival in environmental criminology [5], its usage comes with caveats. Bias in police-recorded data on crimes has long been acknowledged. For instance, the willingness of victims to report crimes to the police varies according to characteristics such as age, employment, education and ethnicity [27]. Such biases in the volume and consistency of crimes known to the police inevitably trickles down to determine the pool of offenders in police records. Contemporary research in the UK has also demonstrated that police forces may be unjustly targeting particular groups who then become 'usual suspects': individuals from deprived backgrounds, often young men, recycled through the youth justice system as "the deeds of their more affluent counterparts are overlooked" [38]. Policing practices that might lead to arrest, such as stop and search, have also been found to be exercised disproportionality on particular groups, such as ethnic minorities, even when controlling for other factors [39].

As a consequence, offender residence measures constructed from police-recorded data are imperfect. It is likely that certain individuals (e.g., the 'usual suspects,' ethnic minorities) are overrepresented in the data compared to the true offending population. Other groups of active offenders may be underrepresented, such as those from a high socioeconomic background [38]. The spatial patterning of these residential characteristics might plausibly impact on the concentration and between-unit variability in known offenders.

Future research seeking to replicate this study, as has been the case in the crime concentration literature, might consider making use of self-report offender surveys (e.g., [69]) to rectify this shortcoming.

This study has sought to offer the first examination of concentration and variation in the spatial patterning of offender residences at multiple nested spatial scales. It has achieved this by drawing upon methods used in the crime-based literature [60], deploying descriptive (visual) statistics and a multilevel variance partition using 10-years of geocoded police records on known offender residences in Birmingham, England. Larger units clearly hold some merit, empirically and theoretically, when studying offender residences. There is greater between-unit variability at larger, meso-level spatial scales, which appears to be consistent with how offender-generating causal mechanisms are thought to manifest in urban areas. That said, the proportion of variance attributable to smaller, micro-level units has increased over time, at the expense of the meso-level, which is suggestive of a dynamic process. Further analysis is required using longitudinal clustering and individual-level residential population flows to disentangle this change and identify the source of the shift in variance.

Given the variability in offender residences across spatial scales, our findings highlight the necessity for urban policy and crime prevention strategies to be adaptable and targeted, addressing the unique characteristics of each spatial scale and the phenomenon under observation. Our findings, coupled with what we know about crime variability at different spatial scales, demonstrate that policing practices and community engagement initiatives must consider the geography of crimes and offenders as distinct but related phenomenon that might be operating at different spatial scales, and thus merit distinct intervention strategies.

References

[1] ANDRESEN, M. A., CURMAN, A. S., AND LINNING, S. J. The trajectories of crime at places: Understanding the patterns of disaggregated crime types. *Journal of Quantitative Criminology 33* (2017), 427–449.

[2] BALDWIN, J., BOTTOMS, A., AND WALKER, M. A. *The urban criminal: A study in Sheffield*, vol. 159. Taylor & Francis, 1976.

[3] BERNASCO, W., DE GRAAFF, T., ROUWENDAL, J., AND STEENBEEK, W. Social interactions and crime revisited: An investigation using individual offender data in dutch neighborhoods. *Review of Economics and Statistics 99*, 4 (2017), 622–636.

[4] BOTTOMS, A. Crime specifics, offender residences, and social change: developing the criminology of place. *Jerusalem Review of Legal Studies 15*, 1 (2017), 1–11.

[5] BOTTOMS, A. The importance of high offender neighborhoods within environmental criminology. *The Oxford Handbook of Environmental Criminology* (2018), 119.

[6] BOTTOMS, A. E., AND WILES, P. Housing tenure and residential community crime careers in Britain. *Crime and Justice 8* (1986), 101–162.

[7] BRAGA, A., PAPACHRISTOS, A., AND HUREAU, D. Hot spots policing effects on crime. *Campbell Systematic Reviews 8*, 1 (2012), 1–96.

[8] BRANTINGHAM, P. J., AND BRANTINGHAM, P. L. *Patterns in crime.* Macmillan New York, 1984.

[9] BRECKINRIDGE, S. P., AND ABBOTT, E. *The delinquent child and the home.* Survey Associates, Incorporated, 1916.

[10] BRUINSMA, G. J., PAUWELS, L. J., WEERMAN, F. M., AND BERNASCO, W. Social disorganization, social capital, collective efficacy and the spatial distribution of crime and offenders: An empirical test of six neighbourhood models for a Dutch city. *British Journal of Criminology 53*, 5 (2013), 942–963.

[11] BURSIK JR, R. J. Ecological stability and the dynamics of delinquency. *Crime and Justice 8* (1986), 35–66.

[12] CLEAR, T. R. *Imprisoning communities: How mass incarceration makes disadvantaged neighborhoods worse.* Oxford University Press, 2009.

[13] COCKINGS, S., HARFOOT, A., MARTIN, D., AND HORNBY, D. Maintaining existing zoning systems using automated zone-design techniques: methods for creating the 2011 census output geographies for England and Wales. *Environment and Planning A 43*, 10 (2011), 2399–2418.

[14] COHEN, L. E., AND FELSON, M. Social change and crime rate trends: A routine activity approach. *American Sociological Review* (1979), 588–608.

[15] CURMAN, A. S., ANDRESEN, M. A., AND BRANTINGHAM, P. J. Crime and place: A longitudinal examination of street segment patterns in Vancouver, BC. *Journal of Quantitative Criminology 31* (2015), 127–147.

[16] ECK, J. E., GERSH, J. S., AND TAYLOR, C. Finding crime hot spots through repeat address mapping. *Analyzing crime patterns: Frontiers of practice* (2000), 49–64.

[17] FARRELL, G. Preventing repeat victimization. *Crime and Justice 19* (1995), 469–534.

[18] FISHER, W. D. On grouping for maximum homogeneity. *Journal of the American Statistical Association 53*, 284 (1958), 789–798.

[19] GALE, C. G., SINGLETON, A., BATES, A. G., AND LONGLEY, P. A. Creating the 2011 area classification for output areas (2011 OAC). *Journal of Spatial Information Science 12* (2016), 1–27.

[20] GASTWIRTH, J. L. The estimation of the Lorenz curve and Gini index. *The Review of Economics and Statistics* (1972), 306–316.

[21] GERELL, M. Smallest is better? the spatial distribution of arson and the modifiable areal unit problem. *Journal of Quantitative Criminology 33* (2017), 293–318.

[22] GILL, C., WOODITCH, A., AND WEISBURD, D. Testing the "law of crime concentration at place" in a suburban setting: Implications for research and practice. *Journal of Quantitative Criminology 33* (2017), 519–545.

[23] GLYDE, J. Localities of crime in Suffolk. *Journal of the Statistical Society of London 19*, 2 (1856), 102–106.

[24] GROFF, E. R., WEISBURD, D., AND YANG, S.-M. Is it important to examine crime trends at a local "micro" level?: A longitudinal analysis of street to street variability in crime trajectories. *Journal of Quantitative Criminology 26* (2010), 7–32.

[25] GUERRY, A.-M. *Essai sur la statistique morale de la France*. Clearwater, 1833.

[26] HARRIS, R., CHARLTON, M., AND BRUNSDON, C. Mapping the changing residential geography of white British secondary school children in England using visually balanced cartograms and hexograms. *Journal of Maps 14*, 1 (2018), 65–72.

[27] HART, T. C., AND RENNISON, C. M. *Reporting crime to the police, 1992-2000*. US Department of Justice, Office of Justice Programs Washington, DC, 2003.

[28] HIBDON, J., TELEP, C. W., AND GROFF, E. R. The concentration and stability of drug activity in Seattle, Washington using police and emergency medical services data. *Journal of Quantitative Criminology 33* (2017), 497–517.

[29] HOME OFFICE. Crime outcomes in England and Wales: Year ending March 2018. statistical bulletin HOSB 10/18, 2018.

[30] HOUSE OF COMMONS LIBRARY. House of commons library MSOA names. https://visual.parliament.uk/msoanames, 2020.

[31] JOHNSON, S. D. A brief history of the analysis of crime concentration. *European Journal of Applied Mathematics 21*, 4-5 (2010), 349–370.

[32] KIRK, D. S. Where the other 1 percent live: An examination of changes in the spatial concentration of the formerly incarcerated. *RSF: The Russell Sage Foundation Journal of the Social Sciences 5*, 1 (2019), 255–274.

[33] KORNHAUSER, R. R. *Social sources of delinquency: an appraisal of analytic models*. The University of Chicago, 1975.

[34] LANGTON, S. H., AND SOLYMOSI, R. Cartograms, hexograms and regular grids: Minimising misrepresentation in spatial data visualisations. *Environment and Planning B: Urban Analytics and City Science 48*, 2 (2021), 348–357.

[35] LIVINGSTON, M., GALSTER, G., KEARNS, A., AND BANNISTER, J. Criminal neighbourhoods: does the density of prior offenders in an area encourage others to commit crime? *Environment and Planning A 46*, 10 (2014), 2469–2488.

[36] MARTIN, D. Geography for the 2001 census in england and wales. *Population Trends 108*, 7 (2002), 15.

[37] MAYHEW, H. *London labour and the London poor: A cyclopædia of the condition and earnings of those that will work, those that cannot work, and those that will not*, vol. 1. Cass, 1851.

[38] MCARA, L. Youth justice. In *Oxford handbook of criminology*. Oxford University Press, 2017, pp. 938–966.

[39] MEDINA ARIZA, J. J. Police-initiated contacts: young people, ethnicity, and the 'usual suspects'. *Policing and society 24*, 2 (2014), 208–223.

[40] MORRIS, T. *The criminal area: A study in social ecology*. Routledge, 1957.

[41] MURIE, A. Decline and response? lifecycle change and housing estates in Birmingham, England. *Housing Estates in Europe: Poverty, Ethnic Segregation and Policy Challenges* (2018), 121–144.

[42] MUSTERD, S. Social and ethnic segregation in Europe: Levels, causes, and effects. *Journal of urban affairs 27*, 3 (2005), 331–348.

[43] NOBLE, M., WRIGHT, G., SMITH, G., AND DIBBEN, C. Measuring multiple deprivation at the small-area level. *Environment and planning A 38*, 1 (2006), 169–185.

[44] OBERWITTLER, D., AND WIKSTRÖM, P.-O. H. Why small is better: Advancing the study of the role of behavioral contexts in crime causation. In *Putting crime in its place: Units of analysis in geographic criminology*. Springer, 2009, pp. 35–59.

[45] OFFICE OF NATIONAL STATISTICS. National statistics small area geography policy (England and Wales), 2007.

[46] OFFICE OF NATIONAL STATISTICS. Median house prices by middle layer super output area: HPSSA dataset. https://www.ons.gov.uk/peoplepopulationandcommunity/housing/datasets/hpssadataset2medianhousepricebymsoaquarterlyrollingyear, 2020.

[47] OUIMET, M. Aggregation bias in ecological research: How social disorganization and criminal opportunities shape the spatial distribution of juvenile delinquency in Montreal. *Canadian Journal of Criminology 42*, 2 (2000), 135–156.

[48] PIERCE, G., SPAAR, S., AND BRIGGS, L. The character of police work: Implications for the delivery of police service: Final report to the National Institute of Justice. Tech. rep., Northeastern University, College of Criminal Justice, 1988.

[49] QUETELET, A. *Research on the propensity for crime at different ages. Translated by Sawyer F. Test Sylvester*. Anderson Publishing Co, 1831.

[50] REISS, A. J., AND TONRY, M. H. *Communities and crime*. University of Chicago Press, 1986.

[51] REISS JR., A. J. Why are communities important in understanding crime? *Crime and justice 8* (1986), 1–33.

[52] ROBINSON, W. S. Ecological correlations and the behavior of individuals. *International Journal of Epidemiology 38*, 2 (2009), 337–341.

[53] SCHNELL, C., BRAGA, A. A., AND PIZA, E. L. The influence of community areas, neighborhood clusters, and street segments on the spatial variability of violent crime in Chicago. *Journal of Quantitative Criminology 33* (2017), 469–496.

[54] SHAW, C. R. *Delinquency Areas*. University of Chicago Press, 1929.

[55] SHAW, C. R., AND MCKAY, H. D. *Juvenile delinquency and urban areas*. University of Chicago Press, 1942.

[56] SHERMAN, L. W., GARTIN, P. R., AND BUERGER, M. E. Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology 27*, 1 (1989), 27–56.

[57] SHERMAN, L. W., AND WEISBURD, D. General deterrent effects of police patrol in crime "hot spots": A randomized, controlled trial. *Justice quarterly 12*, 4 (1995), 625–648.

[58] SONG, Y., AND QUERCIA, R. G. How are neighbourhood design features valued across different neighbourhood types? *Journal of Housing and the Built Environment 23* (2008), 297–316.

[59] SPELMAN, W. Criminal careers of public places. *Crime and place 4* (1995), 115–144.

[60] STEENBEEK, W., AND WEISBURD, D. Where the action is in crime? an examination of variability of crime across different spatial units in The Hague, 2001–2009. *Journal of Quantitative Criminology 32* (2016), 449–469.

[61] VAN HAM, M., AND MANLEY, D. Social housing allocation, choice and neighbourhood ethnic mix in England. *Journal of Housing and the Built Environment 24* (2009), 407–422.

[62] WEISBURD, D. The law of crime concentration and the criminology of place. *Criminology 53*, 2 (2015), 133–157.

[63] WEISBURD, D., BERNASCO, W., AND BRUINSMA, G. *Putting crime in its place*. Springer, 2008.

[64] WEISBURD, D., BUSHWAY, S., LUM, C., AND YANG, S.-M. Trajectories of crime at places: A longitudinal study of street segments in the city of Seattle. *Criminology 42*, 2 (2004), 283–322.

[65] WEISBURD, D., AND GREEN, L. Policing drug hot spots: The Jersey City drug market analysis experiment. *Justice Quarterly 12*, 4 (1995), 711–735.

[66] WEISBURD, D., GROFF, E. R., AND YANG, S.-M. *The criminology of place: Street segments and our understanding of the crime problem*. Oxford University Press, 2012.

[67] WESTERN, B. *Homeward: Life in the year after prison*. Russell Sage Foundation, 2018.

[68] WHEELER, A. P., WORDEN, R. E., AND MCLEAN, S. J. Replicating group-based trajectory models of crime at micro-places in Albany, NY. *Journal of Quantitative Criminology 32* (2016), 589–612.

[69] WIKSTRÖM, P.-O. H., OBERWITTLER, D., TREIBER, K., AND HARDIE, B. *Breaking rules: The social and situational dynamics of young people's urban crime*. OUP Oxford, 2012.