

LOCAL VARIANCE IN THE CRIME DROP: A LONGITUDINAL
STUDY OF NEIGHBOURHOODS IN GREATER GLASGOW,
SCOTLAND

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This paper reports on a novel longitudinal study of local variation in the decline of recorded crime in Greater Glasgow, United Kingdom. We deploy group trajectory analysis (exploring spatial autocorrelation with Local Moran's I) and comparison of means to explore the underlying characteristics and trajectories of neighbourhoods over time. The research finds marked distinction in the level of crime and trajectories of different neighbourhood crime groups. Neighbourhood crime trajectories with high or low levels of crime exhibit spatial clustering and significant distinction in their characteristics. There is more limited spatial patterning, though still clear distinction between the characteristics of neighbourhood crime groups that exhibit different crime trajectories. We consider the research and policy implications of these findings.

Keywords: crime drop, neighbourhoods, the ecology of crime, group trajectory analysis

The 1990s heralded a dramatic decline in recorded crime across many developed polities (Aebi and Linde 2010; Tseloni *et al.* 2010). In Scotland, total recorded crime has fallen to its lowest level since 1974 (Scottish Government 2013). That the crime drop has manifest internationally has prompted the search for explanations that transcend national boundaries. A variety of hypotheses have been explored, spanning mechanisms of formal social control, economic and demographic change, social dynamics and opportunity reduction. Yet, outwith the growth of evidence supporting the impact of changes in the quantity and quality of security, limited consensus has been reached and few clear policy recommendations have emerged (Blumstein and Wallman 2006; Farrell *et al.* 2011; Rosenfeld and Messner 2009).

Set against this focus, there has been relatively scant attention paid to the crime drop at the sub-national level. Examining the crime drop at smaller spatial scales holds merit on two key grounds. First, the possibility that crime has fallen unevenly across space raises a question of territorial equity and consequently of the legitimacy of those agencies charged with maintaining law and order. Recent reform of the organizational structure and spatial scale of service delivery in Scotland serve to highlight the importance of these issues. The *Police and Fire Reform (Scotland) Act* (2013) created a single police force for Scotland. The organizational structure of Police Scotland drills down to the same wards used in local authority elections, each with its own policing plan. These reforms to the political and geographical architecture of Police Scotland increase the likelihood of debate about territorial equity.

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Second, while a lack of suitable data has inhibited comparative interrogation of the crime drop at the scale of the nation state, there is far greater availability of data to enable investigation of changing patterns of crime as they manifest at smaller spatial scales. Though research engaging with narrower geographies might fail to capture the ‘bigger picture’, they do afford the potential to identify the local drivers of crime and in so doing inform the design of effective interventions. The international financial crisis of 2007 and the austerity agenda that has ensued has led to increased pressure being placed on public service expenditure. In these terms, it is important to identify the spatial scale at which interventions might most efficiently be deployed. Here, numerous ‘hot spot’ policing experiments (Braga *et al.* 2014) suggest the potential efficacy of interventions deployed at a micro-geographical scale. On the other hand, if the crime drop is not spatially uniform within a polity, communities may raise questions about the legitimacy of targeting police budgets.

It is against this context that our paper sets out to explore local variation in the crime drop via a longitudinal study of neighbourhoods in Greater Glasgow, Scotland, which cumulatively achieved a crime drop of 39.7 per cent over the period 1998/99 to 2012/13. We make several substantive contributions to the international literature exploring the crime drop. First, and uniquely, we assess whether ‘neighbourhoods’ have exhibited distinct trajectories over the crime drop. Second, and relatedly, we explore whether neighbourhoods with distinct crime levels and trajectories exhibit spatial clustering. The policy relevance of evaluating the crime drop at the neighbourhood level rests in its close relation to the territorial scale at which Police Scotland deploy policing plans. If neighbourhood crime levels and trajectories are evidenced to cluster, this would serve to support the development of policing plans. Further, examining whether neighbourhood crime levels and trajectories exhibit spatial clustering, affords the opportunity to engage in debate of the territorial equity of both the spatial distribution of crime and of the crime drop. Third, we assess the characteristics of neighbourhoods exhibiting distinct crime levels and the relative change in these characteristics of neighbourhoods exhibiting distinct trajectories. This analysis holds the potential to inform future research that seeks to interrogate the factors driving the crime drop at the neighbourhood level and to inform the development of crime reduction strategies.

Our paper proceeds as follows. We begin with an overview of the literatures that have sought to advance the spatial interrogation of crime, paying particular attention to issues of scale, theoretical explanation and to the various structural and situational characteristics associated with the spatial distribution of crime. We then detail our research questions, prior to describing the data and methods deployed in this paper. This is followed by a presentation of the results. To close, we discuss our results in light of existing evidence, highlighting their policy relevance, and set a brief agenda for future research.

Space and Crime

There is longstanding recognition of the non-random spatial spread of crime at the intra-urban level. Distinct patterns of crime manifest at differing spatial scales, across neighbourhoods (Skogan 1986; Wikström 1991), streets or blocks (Taylor and Gottfredson 1986) and micro crime places or street segments (Weisburd *et al.* 2004; Groff *et al.* 2010).

Multiple insights emerge from this analysis. Wikström (1991), e.g., examining the spatial distribution of crime in Stockholm (Sweden), found that offences tended to cluster around the city centre and in certain outer city and poorer public housing areas, while the spatial distribution of crime varied by offence type. Perhaps the most striking though not unexpected finding of this body of research, given the over dispersion of crime across urban space, has been that the smaller the spatial unit of analysis interrogated the greater the contrast in the distribution of crime between these units. Sherman *et al.* (1989), e.g., examining Minneapolis (United States) police data, found that 3.3 per cent of local 'places' (defined as street addresses and intersections) generated 50 per cent of crime related calls to the authorities. Similarly, Weisburd *et al.* (2004), examining Seattle (United States) police data between 1989 and 2002, found that 4–5 per cent of streets accounted for 50 per cent of all recorded crime and that between 47 and 52 per cent of street segments had no recorded crime at all. Moreover, not only does crime cluster at a small number of locations, this clustering tends to exhibit significant temporal stability (Weisburd *et al.* 2004; Groff *et al.* 2010). By contrast, less recent attention has focused on crime concentrations and trends at the level of the neighbourhood or census tract, an exception being Griffiths and Chavez (2004) who examined homicide patterns across census tracts in the United States. In overview, given international recognition of the non-random spatial distribution of crime, there is a clear basis to expect neighbourhood variance in the crime drop. Yet, is this an appropriate spatial scale to examine crime concentrations and trends?

Examining the spatial and temporal distribution of crime at the neighbourhood level can be misleading as these areas may consist of multiple micro locations with distinct crime profiles. The selection of an appropriate level of spatial aggregation is centred on a number of considerations. Bursik and Grasmick (1993) caution against the use of administrative geographies where these hold limited resemblance to lived realities, in terms of people's understanding and use of urban space. Consequently, relying on administrative geographies can lead to the distortion or misrepresentation of crime concentrations, impacting on our capacity to determine their cause and to intervene in their remedy. Thus, Sherman *et al.* (1989) advise in allowing concentrations of crime to emerge from the data, rather than as artefacts of existing administrative boundaries. Weisburd *et al.* (2009) recognize the importance of deploying multiple scales of analysis, as this approach can enable identification of the scale at which explanatory variables hold the most potent effect. Finally, there are pragmatic issues to consider. Brantingham *et al.* (2009: 90) recommend that 'data should be collected at the most detailed level possible and aggregated upward to fit the requisites of theory', but that this exercise also requires taking account of the spatial scale at which explanatory variables are captured.

Theoretical examination of the differential spatial patterning of crime is informed by a set of opportunity theories, these being: routine activity theory; rational choice theory and crime pattern theory. Routine activity theory holds that there is 'interdependence between the structure of illegal activities and the organization of everyday sustenance activities', with the likelihood of crime at any specific time and place being a 'function of the convergence of likely offenders and suitable targets in the absence of capable guardians' (Cohen and Felson 1979: 589–90). Rational choice theory, developed by Cornish and Clarke (1986), assumes that the decision to offend is based on a calculation of risk (the likelihood of being caught) and reward (target attractiveness

and accessibility), though this decision-making is bounded by local knowledge, time and resource. It follows that if the risks of offending can be increased, and the potential rewards decreased, then the offender will be deterred from committing an offence. Finally, crime pattern theory (Brantingham 1981; 2008) explores the ways in which offenders and targets are brought together, and therefore crimes distributed, across urban space. Through activity nodes and travel paths, people develop their own activity spaces (Golledge and Stimson 1987) and awareness spaces, which offenders utilize to select their targets (Bernasco and Nieuwbeerta 2005). Activity spaces demonstrate a directional bias or preference (Frank *et al.* 2012), in that offenders commit most of their crimes within a certain direction of their homes, towards major crime attractor locations (such as shopping centres). It has recently been shown that a distance-decay function operates not only from activity nodes within an offender's awareness space but also around the travel paths between those nodes (Reid *et al.* 2014).

The strength of opportunity theories resides in the specification of the situational characteristics of localities (and their institutional drivers) that shape the spatial distribution of crime. For example, the availability of alcohol, measured in terms of neighbourhood outlet density, has been shown to be predictive of violent crime (Livingston *et al.* 2014) and neighbourhoods that have many young adults and drinking establishments are said to encourage criminal acts because of the risk-taking life styles of this social group and, through alcohol-induced vulnerability, because they also yield a ready supply of potential victims (Raleigh and Galster 2012). Positive associations have been found between the incidence of vacant properties, the direct and indirect mechanisms of the housing market, lax formal (police) supervision and the incidence of crime (Bottoms and Wiles 1986; Spelman 1993; Raleigh and Galster 2012). Knowing which neighbourhood characteristics are associated with local crime rates can inform both policing and non-policing interventions.

Where opportunity theories offer less is in the consideration of the forces that shape the motivations (to offend) and vulnerabilities (the absence of capable guardians) of the people who reside in these localities. Here, both economic theory and social disorganization theory afford valuable insight. Economic theory suggests that the motivation for offending holds a relation to the economic returns to criminal activity relative to earnings from legitimate employment (Becker 1968). In these terms, deprivation may act as a significant motivation for offending. Indeed, the relationship between crime and poverty rates has been described as 'robust' and a 'bedrock conclusion' (Hipp and Yates 2011), having been observed at city and local levels (Hipp 2007a; Sampson *et al.* 2002). Nevertheless, the precise functional form of the relationship between poverty and crime remains uncertain (Hipp and Yates 2011).

Social disorganization theory, developed by Shaw and McKay (1942), posits that a lack of effective (informal) social control inhibits direct intervention and lobbying for formal (policing) interventions by neighbourhood residents. Building on this foundation, Sampson *et al.* (1997) have advanced the theory of collective efficacy, which offers that the capacity of a community to exercise effective social control is a function of the level of social cohesion and the extent of shared expectations for control. Collective efficacy depends on a level of working trust and social interaction within the community, but it does not assume the existence of strong social bonds. Residents of neighbourhoods with a high level of collective efficacy are able to act as capable guardians, moderating the crime rate. Collective efficacy appears strongly correlated with: community social

cohesion (Bellair and Browning 2010); residential stability (Sampson and Groves 1989; Hipp 2007b) and home ownership rates (Dietz and Haurin 2003; Lindblad *et al.* 2013). In contrast, a lack of collective efficacy appears strongly correlated with: high levels of neighbourhood heterogeneity; low economic status; family disruption and high residential mobility (Sampson and Groves 1989; Harcourt and Ludwig 2006).

In overview, empirical evidence and theoretical explanation suggest that crime will be unevenly spread across space at the intra-urban level and that this patterning may well exhibit temporal stability. However, does this hold true in an era of falling crime? Addressing this challenge, our research set out to interrogate the following questions:

- Have all neighbourhoods derived equal benefit from the crime drop? Or do groups of neighbourhoods exhibit distinct trajectories over time?
- Is there both a geographical pattern of crime concentration and of neighbourhood crime trajectories?
- What characteristics of neighbourhoods are associated with neighbourhood crime levels? Further, are neighbourhood crime trajectories associated with a relative change in the characteristics of neighbourhoods?

Data and Analytical Strategy

Study area

The study was conducted in Greater Glasgow (Scotland), which comprises the local authorities East Dunbartonshire, East Renfrewshire and City of Glasgow (as defined in April 2013). It is mostly urban, but also includes small towns and semi-rural areas. At the 2011 Census, it had a resident population of 788,845 with Glasgow City making up three quarters of this total (NRS 2015). Glasgow City is one of the most deprived urban areas in the United Kingdom, containing 30 per cent of the most deprived neighbourhoods (worst 15 per cent) in Scotland; East Dunbartonshire and East Renfrewshire are less deprived, containing 1 per cent of the most deprived neighbourhoods (Scottish Government 2012, Table 2.1c). Glasgow City has an unusually large social rented housing sector by UK standards, occupied by 37 per cent of the city's households in 2011 (NRS 2015); the social rented sector is smaller in East Dunbartonshire and East Renfrewshire (12 per cent in both areas). The population of Greater Glasgow is predominantly White (British, Irish or Scottish), though the ethnic minority population has risen to 13.2 per cent (NRS 2015), mainly due to its doubling in Glasgow City over the past decade to 15 per cent (Freeke 2013). Glasgow City has a higher crime rate than the national average with 889 crimes per 10,000 population in 2012/13 compared with 520 for Scotland. Crime rates in the other two local authorities were much lower (283 in East Renfrewshire, 331 in East Dunbartonshire) (Scottish Government 2013: 28).

Spatial unit of analysis

The geographical unit used in this research is the data zone, which is part of the official reporting geography for Census results in Scotland; they are also the unit used

for assembling much official government data, and the lowest spatial level at which deprivation indicators are released by government. The official definition of data zones stipulates the following ([Scottish Executive 2004a: 1](#)):

Data zones meet tight constraints on population thresholds (500–1,000 household residents), they all nest into local authorities and are built up from 2001 Census output areas. The aim was also to build data zones by grouping together output areas with similar social characteristics, for data zones to have a fairly compact shape, and to take account of physical boundaries.

The Greater Glasgow area has 941 data zones (934 of which were included in the analysis after the removal of outliers) within its boundary, thus giving a mean population of 824 persons in each data zone at the 2001 Census (839 at the 2011 Census). Data zones are a quarter of the size of census tracts used in much US spatial (neighbourhood) crime analysis. Data zones hold the potential, therefore, to map closely to the lived realities of people's neighbourhoods, with households grouped together on the basis of spatial proximity, homogeneity of socio-economic status, dwelling type and tenure.

Crime data

Police Scotland provided geo-coded crime data for the period 1998/99–2012/13, including all crimes committed in Greater Glasgow other than crimes of a sexual nature. The date and exact location (comprising a six figure grid reference) of the crime are given, though in a minority of cases where the precise location is unknown the police beat location is given; as police beats are smaller than data zones, the allocation of those crimes to the data zones at the centre of the beat will be correct in the majority of cases. Recorded crimes are those reported incidents assessed by a police officer to constitute a crime, after an initial investigation. Crimes are recorded and categorized according to a national recording standard, which has been in place since 2004. Prior to this, local police authority standards were deployed ([Scottish Government 2014](#)). The crime groups included in this analysis were: non-sexual crimes of violence (Group 1); crimes of dishonesty (Group 3); vandalism, fire raising and malicious mischief (Group 4) and other crimes (Group 5), which include drugs crimes, handling an offensive weapon and crimes against public justice ([Scottish Government 2013: 17](#)). These recorded crime data were plotted using ArcGIS and assigned to each data zone using point in polygon assignment. Recorded crime was aggregated by financial year (1 April–31 March) for each data zone, creating a data set that contained a total count of crimes per annum.

Neighbourhood characteristics

A range of structural and situational variables were selected according to their demonstrated utility in supporting explanation of the presence or absence of crime in urban areas and their availability at the spatial unit of the data zone. Data were drawn from the national censuses of 2001 and 2011, two points as close as possible to the start and end of the study period. Where data were not available for these census years, data for

the closest available year were used.¹ As a proxy for *Deprivation*, two variables were used: a median household income estimate, calculated by commercial analysts [Experian Limited \(2007\)](#) and the proportion of the population who were employment deprived, a measure created for the Scottish Index of Multiple Deprivation, and based on receipt of out of work benefits ([Scottish Executive 2004b](#); [Scottish Government 2012](#)). *Tenure* structure was calculated according to the proportion of households who were owner occupiers; renting from an agent or private landlord or renting from a social landlord. *Household composition* was calculated according to the proportion of households who were one-person households; lone parents with dependent children and families (two adults with one or more children). *Age Structure* was calculated according to the proportion of: young people (aged 16–24) and older people (aged 55+). Finally, as a proxy for the presence of *Situational Crime ‘Attractors’* ([Brantingham and Brantingham 2008](#)), the proportion of small business addresses from a total count of all postal addresses, created from the National statistics postcode directories for November 2004 and November 2010, was used.²

Analysis

The research deployed three phases of analysis to address the research questions.

To address the first question, phase one deployed Latent Class Growth Analysis (LCGA) to enable the identification of groups of data zones that share similar levels and trajectories of crime over time ([Nagin 1999; 2009](#)). The decision to utilize LCGA was founded on its claimed successful application in previous research exploring the levels and trajectories of crime at varied geographical scales ([Griffiths and Chavez 2004](#); [Weisburd et al. 2004; 2009](#)). Using LCGA enables our paper to directly engage with these literatures, strengthening its international contribution. It is important to note, however, that latent class models have been criticized on the basis of their potential to identify spurious groups ([Skardhamar 2010](#)). However, in situations where it is expected that the subject under investigation is likely to be composed of a mixture of distinct groups, [Nagin and Odgers \(2010\)](#) find latent class models useful in distilling plausible groupings. We considered the existence of distinct crime level and trajectory groupings likely in our case study setting on the basis of a preliminary review of the data. Moreover, that international literatures have also found variation in micro-spatial crime trajectories offered further support to deploy LCGA.

The LCGA model estimates the mean for each group based on the assumption that all trajectories in the group are the same. The analysis was conducted using Mplus 7.3 ([Muthén and Muthén 1998–2012](#)) and utilized a negative binomial count model ([Hilbe 2011](#)) on the assumption that this best represents the underlying distribution of crime across data zones in each year. A population offset was included to account for the potential impact of population change in each data zone. The models were run assuming that both linear and quadratic trajectories were possible.

¹Accessed from Scottish Government: Scottish Neighbourhood Statistics, www.sns.gov.uk 13 January 2015 and 15 January 2015 (2001 census data) and National Records Scotland: www.scotlandscensus.gov.uk 8 January 2015—Census.

²Postcode directory data are ©Crown Copyright 2004; 2010 Source: National Statistics/Ordnance Survey; extracts and data derived from them are Crown Copyright and may only be reproduced by permission accessed from UK Data Archive via EDINA, 11 December 2014 and 29 July 2015.

Each observation (data zone) was assigned a probability of belonging to one or more groups.

A good fitting model aims to group together data zones with similar trajectories, with an optimal number of groups. The modelling commenced from the assumption that there was only one group within the data. Then, the number of groups being tested for was incrementally increased until the best fitting model was found. The model with the lowest adjusted Bayesian information criterion was selected. It was then checked to ensure that it also met the additional model fit criteria suggested by Nagin (2005) of an average posterior probability of above 0.7, and an odds correct classification ratio, the odds of a data zone being correctly assigned to a group, of over 5. During the modelling, 2 very high crime data zones and 5 data zones in which the population declined to less than 100 were excluded, as the model failed to converge while these outliers were included.

For the second question, Phase 2 of the analysis deployed Local Indicators of Spatial Association (LISA). GeoDa 1.6.7 software³ (Anselin *et al.* 2006) was used to calculate Local Moran's I. LISA enables the disaggregation of global measures of spatial autocorrelation such as Moran's I that examine the presence of similarity or difference across the data set as a whole (Anselin 1995). Positive spatial autocorrelation occurs when data zones possess similar characteristics (in our case crime levels) to their neighbours. Negative spatial autocorrelation occurs when data zones possess dissimilar characteristics to their neighbours. LISA also has the potential to detect pockets of negative spatial autocorrelation where there is overall positive autocorrelation and vice versa (Andresen 2011).

Recorded crime count data aggregated to the data zone were standardized by mid-year estimate of the resident population using an Empirical Bayes (EB) rate procedure developed by Assunção and Reis (1999) (Moran's I with EB rate in GeoDa software), which corrects for potential large variances caused by a small population denominator. In addition, results from the LCGA analysis specifying the probability each data zone held of being a member of each identified trajectory group were saved as an output from Mplus. These probabilities were then summed together to give the probability of a data zone being in one of four broad categories (detailed in Results section). Analysis was then undertaken of whether neighbouring data zones had similar probabilities (or not) of being in same broad group using the standard Univariate Local Moran's I option in GeoDa software. In order to calculate the LISA statistic a weights file was generated so that data zones that were contiguous (i.e. touching) were treated as neighbours (Queen contiguity—Order 1). A Moran Scatterplot (Anselin *et al.* 2008) was then used to classify data zones exhibiting positive spatial autocorrelation (high crime neighbouring high crime and low crime neighbouring low crime areas) and negative spatial autocorrelation (low crime neighbouring high crime). The statistical significance ($P \leq 0.05$) of these results was assessed using a permutation method in which actual results are compared with data randomly swapped across the study area in order to counter for the multiple testing problem. The results were mapped using cartograms, which converts

³GeoDa 1.8 can be downloaded from <http://spatial.uchicago.edu/software> (accessed 6 March 2017). This analysis also used GeoDa 1.6.7 downloaded from <https://geodacentre.asu.edu/software> (accessed 15 March 2016).

areas to the same size while retaining the underlying spatial structure, enabling a more accurate visual identification of spatial patterning.

For the third set of questions, Phase 3 of the analysis comprised two components. To assess the association between neighbourhood characteristics and neighbourhood crime levels towards the beginning of the study period (T1), the mean and a 95 per cent confidence interval for each neighbourhood variable in every crime trajectory group identified in Phase 1 at T1 was calculated based on the probability of group membership.⁴ The mean and confidence interval for Group 1 was then compared to the mean and confidence interval for Group 2 to see if there was any overlap between confidence intervals and so on until all groups were compared and differences identified. To assess the association between the relative change in neighbourhood characteristics and neighbourhood crime trajectories, the relative change for each variable within each crime group between T1 and T2 was calculated $((T2 - T1/T1) \times 100\%)$. The mean relative change for each group and 95 per cent confidence interval, again based on the probability of group membership, were compared with those of all other groups as before to identify statistically significant differences.

Results

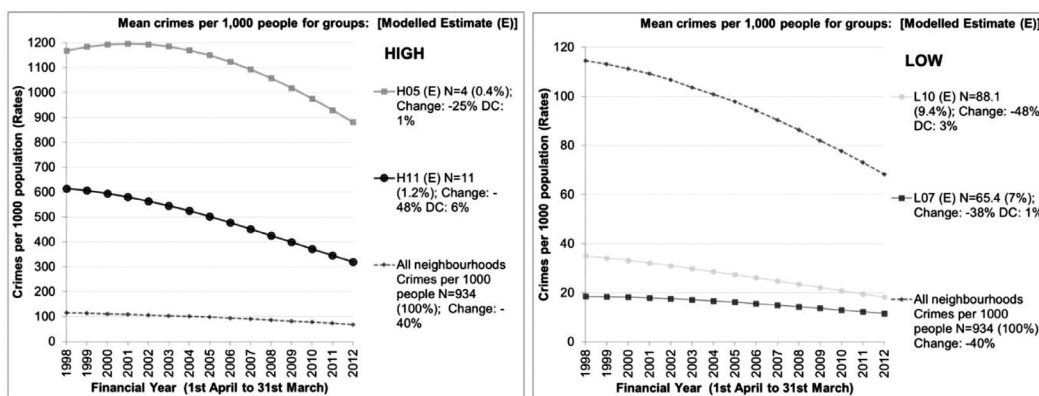
Neighbourhood crime trajectories

The LCGA identified 16 groups of neighbourhoods. The distinctions and similarities between the groups are dominated by a number of key factors. The groups were numbered from 01 to 16 according to their relative change in crime level (or performance) between 1998–99 and 2012–13, where 16 is the group with the largest relative crime drop and 01 is the group with the smallest relative crime drop. The diverse trajectories of these groups are presented in [Figure 1a](#) and [1b](#). The 16 groups exhibit trajectories that are indicative of differing performance at different moments of the study period. In D14, e.g., crime fell at a faster rate at the beginning of the study period. In contrast, crime fell at a faster rate towards the end of the study period in H05. Other groups, such as L10, exhibit linear trajectories.

The 16 groups were allocated into four neighbourhood crime trajectory categories, labelled High (H), Low (L), Drop (D) and Mixed (M), which serve to delineate the major research findings. H contains groups (H11, H05) with a modelled mean crime rate five times higher than the study area mean. L contains groups (L07, L10) with a modelled mean crime rate at least 1/3 lower than the study area mean. D contains groups (D12, D13, D14, D15, D16) that achieved a relative crime drop in excess of 55 per cent, well above the mean drop of 39.7 per cent for the study area as a whole. Further, 95 per cent of all neighbourhoods in these groups experienced a crime drop. Finally, M contains groups (M01, M02, M03, M04, M06, M08, M09,) with diverse mean crime rates and diverse relative change in crime level. Key data pertaining to the four categories of groups are presented in [Table 1](#).

⁴The probability each data zone has of being a member of each trajectory group is calculated by Mplus and saved. These probabilities are used to weight the mean and confidence intervals accordingly; thus, if a data zone has a 0.95 chance of being in group, only a 0.95 proportion of the variable is included in the calculation of the mean for this data zone. The method used for broad groups is reported here, a more complex MPlus software 'built-in' pseudo draw method (Muthén and Muthén 1998–2012) was used to compare individual trajectory groups, results available on request.

a – Trajectories for High (H) and Low (L) neighbourhood crime groups



b – Trajectories for Drop (D) and Mixed (M) neighbourhood crime groups

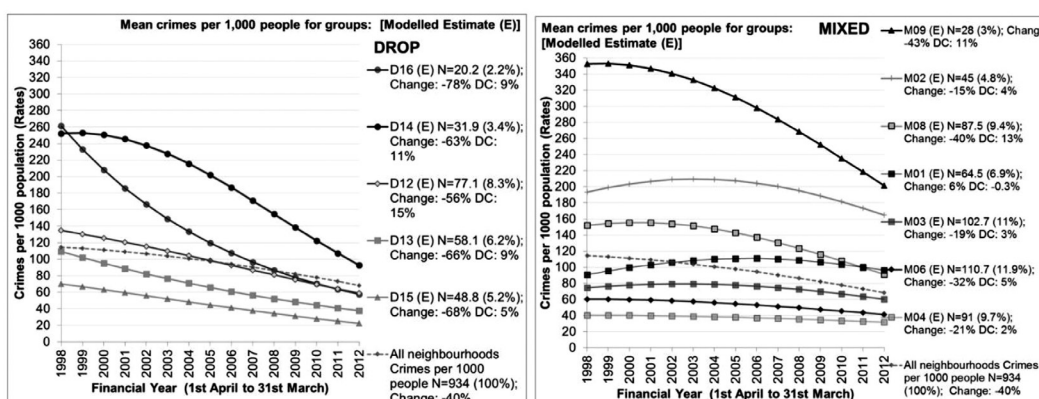


FIG. 1 (a) Trajectories for High (H) and Low (L) neighbourhood crime groups. (b) Trajectories for Drop (D) and Mixed (M) neighbourhood crime groups. N = number in group (expressed as percent of cases in brackets, rounded); Change %: $((\text{Group Mean 2012} - \text{Group Mean 1998}) / \text{Group Mean 1998}) \times 100$, rounded; DC %: drop contribution $(\text{Sum Total Group Count 2012} - \text{Sum Group Count 1998}) / (\text{Sum Count All Areas 2012} - \text{Sum Count All Cases 1998}) \times 100$, rounded.

The categorization of the M groups merits further explanation. Previous research that has deployed LCGA (see, *inter alia*, Weisburd et al. 2004; 2009), despite the critique that latent class models hold the potential to identify spurious groups (Skardhamar 2010), has tended not to expressly consider the actual trajectories of individual neighbourhoods that belong to a particular group. In contrast, we examined the trajectories of individual neighbourhoods within groups (not shown) and found that neighbourhoods ascribed to the M groups exhibited mixed performance, some experienced rising crime while others experienced declining crime. Moreover, at various junctures, the crime levels of M groups were indistinct, leading to an overlap in the probability of an individual neighbourhood being ascribed to one M group or another. It is for these reasons that these groups were placed into the M category. In contrast, the groups in

TABLE 1 *Neighbourhood crime trajectory categories and their contribution to the crime drop*

Group names	Group membership (based on posterior probability of class membership)		Mean crime rate per 1,000 people (model estimates rounded to nearest whole number)		Change in mean crime rates (rounded)		Total crimes in group (counts calculated from model estimates rounded)		Change in total crime		Contribution to Drop	
	Number	%	1998–99	2012–13	Number	%	1998–99	2012–13	Number	%	Number	%
Total	934	100	114	68	-46	-40.4	89,209	53,796	35,413	-39.7	100	
High group	15	1.6	728	432	-296	-40.6	9,694	7,187	2,508	-25.9	7.1	
Low group	153.5	16.4	28	15	-13	-45.3	3,314	1,831	1,483	-44.8	4.2	
Drop group	236.1	25.3	143	52	-92	-63.9	28,704	11,103	17,601	-61.3	49.7	
Mixed group	529.4	56.7	106	77	-29	-27.4	47,496	33,676	13,820	-29.1	39	

the H, L and D categories exhibited markedly different crime levels to each other, and their constituent neighbourhoods exhibited greater consistency in performance. Not only does this afford significant insight into the methodological foundation of international research examining local variance in crime trends, it serves to frame the key insights generated by the research reported here.

Over the study period, recorded total crime fell in Greater Glasgow by –39.7 per cent, whereas the percentage change across the four categories ranged from –25.9 to –61.3 per cent, pointing to stark differences in their relative performance. Further, when the scale or percent of all neighbourhoods comprising the H, L, D and M categories is taken into account, marked differences in their contribution to the crime drop can be discerned. The H category, comprising 1.6 per cent of all neighbourhoods, experienced a crime drop of 25.9 per cent and contributed 7.1 per cent of the overall crime drop (in terms of total number of crimes) in the study area. The L category, comprising 16.4 per cent of all neighbourhoods, experienced a crime drop of 44.8 per cent and contributed 4.2 per cent of the overall crime drop. The D category, comprising 25.3 per cent of all neighbourhoods, experienced a crime drop of 61.3 per cent and contributed 49.7 per cent of the overall crime drop. Finally, the M category, comprising 56.7 per cent of all neighbourhoods, experienced a crime drop of 29.1 per cent and contributed 39 per cent of the overall crime drop.

Geographical distribution of neighbourhoods with different levels and trajectories of crime

At this stage, it is pertinent to consider the spatial patterning of neighbourhoods according to their level of crime over the study period. Figure 2 presents a series of cartograms showing Local Moran's I analysis of actual crime rates across the study area. The cartograms, which capture the H and L neighbourhoods, provide clear visual evidence of positive spatial autocorrelation. Thus, the H neighbourhoods cluster in the centre of the conurbation, while the L neighbourhoods cluster at the periphery of the conurbation. Over the duration of the study period, the clustering of the L neighbourhoods remains stable; however, the clustering of the H neighbourhoods exhibits decline and volatility. This may, in part, be a consequence of the crime drop as particular neighbourhoods fall out of the H category. Alternatively, it may be indicative of the H neighbourhoods becoming more dispersed.

To support the interpretation of the spatial patterning of the performance of neighbourhoods, we present one further cartogram. Figure 3 portrays the spatial patterning of neighbourhoods comprising the D category (only) over the study period. Here, there is some evidence of the D neighbourhoods clustering to the East of the city centre and towards the SouthWest of the study area.

The characteristics of neighbourhood crime trajectory categories

Examining the mean level of the *Tenure, Age Structure, Household Composition, Deprivation* and *Situational* characteristics of neighbourhoods comprising the H, L, D and M categories at T1 (Table 2A), significant distinctions can be discerned. The L neighbourhoods exhibit the highest level of owner occupation, the lowest level of people aged 16–24, the highest level of households with dependent children, the lowest level of

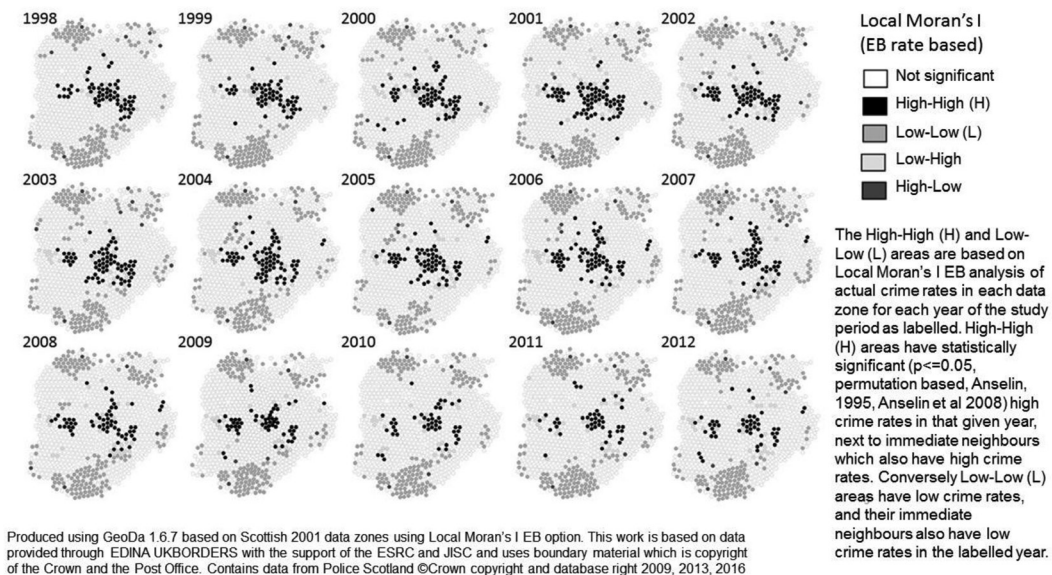


FIG. 2 Cartograms of Local Moran's I analysis showing significant high crime next to high crime areas, low next to low, low-high and high-low areas.

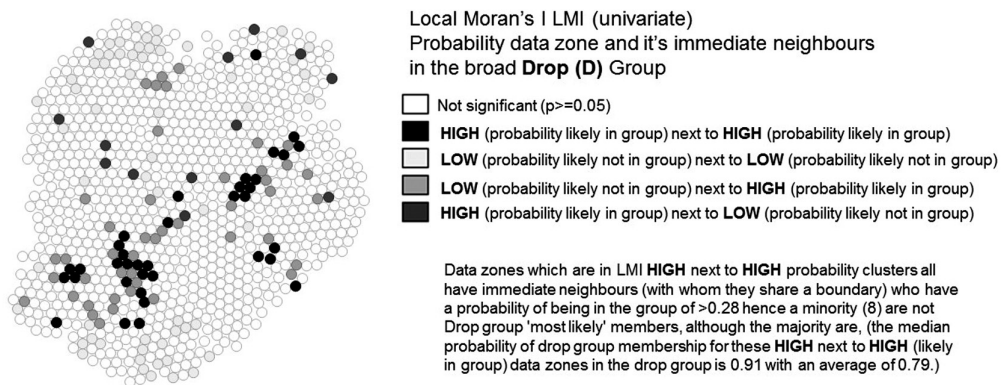


FIG. 3 Clustering of Drop category neighbourhoods.

employment deprivation, the highest median household income and the lowest level of small business addresses. In contrast, the H neighbourhoods exhibit the lowest level of owner occupation, the highest level of people aged 16–24, the lowest level of households with dependent children, the highest level of employment deprivation and the highest level of business addresses. Of particular interest are the similarities and distinctions between the characteristics of the neighbourhoods comprising the D and M categories. Essentially, the characteristics of the D and M neighbourhoods predominantly rest, as would be expected, between those of the H and L neighbourhoods. Although many

TABLE 2 (A) Characteristics at Time 1 for neighbourhood crime trajectory categories. (B) The relative change of crime trajectory category characteristics

(A) Neighbourhood characteristics by level at Time 1				(B) The relative change of crime trajectory category characteristics			
	High (H)	Low (L)	Drop (D)	Mixed (M)			
	Mean (CI)	Mean (CI)	Mean (CI)	Mean (CI)			
Tenure: all households							
% Owner occupiers 2001	37.1 (27.2 to 47)	91.9 (90.3 to 93.6)	57 (53.7 to 60.2)	51.4 (49.2 to 53.6)			
GNO	L; D; M	H; D; M	H; L; M	H; D; L			
% Social rented 2001	46.3 (30.7 to 61.9)	5.5 (3.9 to 7.1)	35.9 (32.4 to 39.3)	41.3 (38.9 to 43.7)			
GNO	L; D; M	H; D; M	H; L	H; L			
% Private let (letting agent or landlord) 2001	17.9 (10.7 to 25.2)	2.3 (1.8 to 2.8)	6.5 (5.4 to 7.7)	5.4 (4.8 to 6.1)			
GNO	L; D; M	H; D; M	H; L	H; L			
Demographics: all people							
% Aged 16–24 2001	21.4 (13.5 to 29.3)	10.5 (10.1 to 10.9)	12.3 (11.6 to 12.9)	12.9 (12.3 to 13.5)			
GNO	L; D; M	H; D; M	H; L	H; L			
% Aged 55 and over 2001	21 (13.8 to 28.2)	24.7 (23.1 to 26.3)	25.3 (24.2 to 26.5)	26.1 (25.2 to 27)			
Demographics: households							
% One person 2001	48.9 (41.9 to 55.9)	21 (19.7 to 22.3)	37.6 (36.1 to 39.2)	38.6 (37.6 to 39.6)			
GNO	L; D; M	H; D; M	H; L	H; L			
% Lone parent with dependent children 2001	9 (4.8 to 13.2)	4 (3.7 to 4.4)	9.4 (8.6 to 10.2)	10.4 (9.8 to 11)			
GNO	L	H; D; M	L; M	D; L			
% Any adults(s) with dependent children 2001	18.9 (11.7 to 26.1)	36.7 (35.2 to 38.2)	28.2 (26.9 to 29.5)	27.7 (26.8 to 28.5)			
GNO	L	H; D; M	L	L			
Employment deprivation and household income							
% Working age adults employment deprived 2002	26.3 (18.4 to 34.3)	6.8 (6.2 to 7.5)	21.4 (20 to 22.9)	23.1 (22.1 to 24.1)			
GNO	L; D	H; D; M	L; H	L			
Median household income £ 2004	19,926 (15,646 to 24,205)	32,053 (30,927 to 33,180)	21,251 (20,179 to 22,323)	19,212 (18,573 to 19,852)			
	L	H; D; M	L	L			
Postcode delivery points: situational crime attractors (or non-attractors)							
% Residential addresses 2004	81.1 (76.3 to 85.8)	98.7 (98.4 to 98.9)	96.8 (96.2 to 97.3)	96.4 (96 to 96.8)			
GNO	L; D; M	D; M	H; L	H; L			
% Small business addresses 2004	18.9 (14.2 to 23.7)	1.3 (1.1 to 1.6)	3.2 (2.7 to 3.8)	3.6 (3.2 to 4)			
	L; D; M	H; D; M	H; L	H; L			
Broad group members pN	15	153.5	236.1	529.4			

TABLE 2. *Continued*

(B) Neighbourhood characteristics relative change	High		Low		Drop		Mixed	
	Mean (CI)		Mean (CI)		Mean (CI)		Mean (CI)	
Tenure: all households								
% Owner occupiers T1:2001 T2:2011	-11.2	(-26 to 3.6)	-1.8	(-2.7 to -0.9)	0.2	(-3.1 to 3.5)	-1.7	(-3.9 to 0.6)
GNO	L		H					
% Social rented T1:2001 T2:2011 (14 cases set as 0 ^a)	-12.7	(-38.8 to 13.5)	42.3	(14.1 to 70.4)	-7.9	(-13.5 to -2.4)	-0.6	(-5.3 to 4.2)
GNO			H		L; H		L	
% Private let (letting agent or landlord)	318.3	(63.4 to 573.3)	230.5	(188.4 to 272.6)	300.3	(251.4 to 349.2)	308	(272.2 to 343.9)
T1:2001 T2:2011 (41 cases set as 0 ^a)			M				L	
GNO								
Demographics: all people								
% aged 16-24 T1:2001 T2:2011 (all overlap)	42.7	(14.4 to 71.1)	10.2	(5.4 to 14.9)	12.8	(9.4 to 16.1)	9.3	(7.1 to 11.5)
% aged 55 and over T1:2001 T2:2011	-11.4	(-29.1 to 6.3)	43.1	(36.3 to 49.8)	4.2	(0.9 to 7.5)	4.7	(2.5 to 6.9)
GNO	L		H; D; M		L		L	
Demographics: households								
% One person T1:2001 T2:2011	0.8	(-6 to 7.6)	21.7	(17.4 to 26)	7.1	(4.9 to 9.3)	8.8	(7.4 to 10.2)
GNO	L		H; D; M		L		L	
% Lone parent with dependent children T1:2001 T2:2011	-23.2	(-40.1 to -6.4)	50.6	(35.8 to 65.5)	4.3	(-1.1 to 9.8)	13.9	(8.4 to 19.3)
GNO	L		H; D; M		L		L	
% Any adults(s) with dependent children T1:2001 T2:2011 (all overlap)	-14.4	(-27.8 to -0.9)	-10.7	(-13 to -8.5)	-8.3	(-10.8 to -5.8)	-7	(-8.7 to -5.3)
Employment deprivation and household income								
% Working age adults employment deprived T1:2002 T2:2011 (all overlap)	-18.3	(-30 to -6.5)	-7.4	(-11.9 to -2.8)	-14.9	(-17.5 to -12.2)	-11.3	(-13 to -9.7)
Median household income T1:2004 T2:2011	24.3	(2.2 to 46.3)	54.3	(50.4 to 58.1)	37.6	(34.6 to 40.6)	37	(34.8 to 39.1)
GNO	L		H; D; M					

TABLE 2. *Continued*

(B) Neighbourhood characteristics relative change	High	Low	Drop	Mixed
	Mean (CI)	Mean (CI)	Mean (CI)	Mean (CI)
Postcode delivery points: situational crime attractors (or non-attractors)				
% Residential addresses T1:2004 T2:2010 (all overlap)	3.3 (0.2 to 6.3)	0.4 (0.3 to 0.6)	0.8 (0.5 to 1)	0.5 (0.4 to 0.7)
% Small business addresses T1:2004 T2:2010 (110 cases set as 0 ^a)	1.7 (-31.3 to 34.7)	-26.3 (-32 to -20.6)	-14.6 (-19 to -10.1)	-7.2 (-11.4 to -3)
GNO		D; M		L
Broad Group Members pN	15	153.5	236.1	529.4

CI, confidence interval; GNO, groups with no overlap.

^aFor data zones where the neighbourhood characteristics variable value was 0 at T1 relative change was set as 0; this impacts on calculating relative change for social rented; private let households and small business address; small numbers for private let households also impact analysis.

of their characteristics are similar, certain key distinctions exist despite a degree of overlap in their confidence intervals. The D category neighbourhoods hold a higher mean level of owner occupation and a higher median household income than do the M category neighbourhoods. In sum, these findings are suggestive of particular *Tenure*, *Age Structure*, *Household Composition*, *Deprivation* and *Situational* characteristics holding influence on the crime level of trajectory categories.

The relative change in the characteristics of neighbourhood crime trajectory categories

Table 2B presents the relative change in the mean levels of the *Tenure*, *Household Composition*, *Deprivation* and *Situational* characteristics of the H, L, D and M categories. In interpreting these data, some caution should be taken given the wide confidence intervals observed and the degree of overlap in change between the groups. That said, a number of key findings emerge. All the categories experienced a significant increase in private rented accommodation, but the lowest increases are found in the L and D categories. Similarly, all the categories experienced an increase in median income, but the highest rises are found in the L category. Of particular interest, once more, are the similarities and distinctions between the change in characteristics of the neighbourhoods comprising the D and M categories. The D neighbourhoods experienced a greater fall in social rented housing, employment deprivation and business addresses in comparison to the M neighbourhoods. Thereafter, more subtle distinctions can be discerned. In overview, however, the D neighbourhoods appear to have made greater movement towards the characteristics associated with the profile of the L neighbourhoods. While these findings are suggestive of the relative change of *Tenure*, *Deprivation* and *Situational* characteristics holding influence on the performance of groups, our analysis does not enable assessment of the causality of these associations.

Discussion

So, how then does this research inform an understanding of local variance in the crime drop? What does the research imply to the question of territorial equity? And, what conclusions can be drawn to guide the search for effective and efficient policy interventions?

Examination of local variance in the crime drop has identified distinct groupings of neighbourhoods and provided clear evidence of both change and stability. Both H and L neighbourhoods achieved benefit from the crime drop, though they remain bound to their initial classification. However, the L neighbourhoods achieved a relatively higher fall in crime indicative of the persistence, if not widening, of territorial inequalities. This reasonably 'stable' pattern of neighbourhood or 'meso' level of inequalities at the extremes of the crime distribution is similar to that discerned by studies of street segments at the 'micro' level (Weisburd *et al.* 2012). Between these extremes, the research identified a distinct D category and a larger and less (internally) distinct M category. The lack of distinction in the performance of the majority of neighbourhood groupings in the mid-range of the crime distribution is in marked contrast to international research that has deployed LCGA. It could be countered that the spatial unit of analysis deployed masked greater clarity in performance that might be observed at a

‘micro’ level, but the spatial unit of analysis deployed was relatively fine-grained and constructed upon homogenous socio-economic population characteristics and distinct physical boundaries. It is plausible, therefore, that our findings simply reflect the fluctuation of crime in the mid-range of the crime distribution (Hope 2015).

The research also found clear stability and change in the spatial patterning of neighbourhoods possessing similar levels of crime; neighbourhoods with a particular level of crime typically nesting within broader areas of a similar crime level. This finding resonates with previous research exploring the spatial variation in crime (see, *inter alia*, Wikström 1991). However, the spatial patterning of H neighbourhoods exhibited dispersion over the study period and D neighbourhoods exhibited limited spatial clustering. These insights might serve to shape policy, given that policing wards are comprised of a set of neighbourhoods (data zones). First, that the H and D categories comprised 12.4 per cent of all neighbourhoods yet contributed 33.1 per cent of the overall crime drop would seem to imply that policing and partner agencies seeking to deliver *efficient* interventions are justified in paying particular attention to neighbourhoods exhibiting high levels of, and distinct drops in, crime. However, the dispersion of H neighbourhoods and the limited clustering of D neighbourhoods represent a challenge to developing such interventions in a *spatially efficient* manner. Policing (and partner) agencies seeking to deliver *effective* interventions should interrogate the causal drivers of long-term crime trajectories, and spatial patterning, of these types of neighbourhood (see Future research section). Thus, understanding the differences between the neighbourhoods comprising the D and M categories, e.g., holds the potential to inform the design and targeting of interventions which might serve to ‘tip’ neighbourhoods into one group or another.

To this end, we now turn to consider whether the level of crime, and performance over the crime drop, of the neighbourhoods in the crime trajectory categories can be understood with reference to the stability of, and change in, their underlying characteristics. Here, we interrogate our findings in relation to research exploring the international crime drop in general and the spatial patterning of crime in particular. These literatures are, of course, related. Examination of the international crime drop has probed the plausibility of explanations centred on the mechanisms of formal social control, economic and demographic change, social dynamics and opportunity reduction (Blumstein and Wallman 2006; Rosenfeld and Messner 2009; Farrell *et al.* 2011). These explanations have been built, in the main, upon opportunity, economic and social disorganization theories vital to the appreciation of the level and spatial patterning of crime.

In undertaking this task, we require to proceed with caution. It is certain that the neighbourhood characteristics included in our analysis fail to capture the influence of a number of factors operating beyond the ecological frame of this investigation. Similarly, it is likely that the research failed to capture some factors responsible for driving the crime drop operating within the ecological frame of this investigation, including both formal social control measures and fine-grained situational factors or ‘crime attractors’. Moreover, the research captured the change in neighbourhood characteristics between the beginning and the end of the study period and not through time. Nevertheless, our analysis does afford a number of key insights to literatures probing the crime drop and the spatial patterning of crime.

The characteristics of the neighbourhoods comprising the H and L categories resonate with a theoretical explanations of crime centred on opportunity, economic and

social disorganization theories. The H groups possess the highest level of ‘crime attractors’ such as business premises, increasing opportunities to commit various crime types (Cohen and Felson 1979; Brantingham and Brantingham 1981; Cornish and Clarke 1986; Brantingham and Brantingham 2008); are the most economically deprived, exerting influence on the motivation to offend (Becker 1968) and possess the highest levels of private renting and people aged 16–24, all factors associated with increased social disorganization (see, *inter alia*, Sampson and Groves 1989; Dietz and Haurin 2003; Hipp 2007b; Bellair and Browning 2010). The L groups, as might be expected, possess the opposite characteristics. It is interesting to note that the D neighbourhoods exhibited characteristics with a closer relation (though marginally so) to the L neighbourhoods (aspects of *Tenure*, *Age Structure*, *Household Composition* and *Deprivation*) than did the M neighbourhoods at the commencement of the study period.

Turning to consider the potential impact of changes in neighbourhood characteristics upon the crime drop, several key insights can be distilled. First, that median incomes grew across all neighbourhood groups, with the highest rises found in the L and D neighbourhoods, offers support to explanations centred on economic change/deprivation, and crime as a function of poverty or low incomes. Second, that the L and D neighbourhoods experienced the smallest rises in private rented accommodation, offers support to explanations centred on residential instability and decreased social cohesion (Dietz and Haurin 2003; Lindblad *et al.* 2013). Third, it is worth noting that the H neighbourhoods had the highest presence of, while the L and D neighbourhoods had the largest reductions in, business premises over time. This finding serves to highlight the importance of situational crime attractors to the spatial patterning of crime. Without further modelling and access to the data upon which this would rest, it is not possible to make an assessment of the causality of the associations identified by our research, nor of the magnitude or direction of their effect. However, that greater relative falls in crime were experienced by the neighbourhoods comprising the L and D categories is suggestive of the characteristics associated with these neighbourhoods serving to accelerate the crime drop.

Future research

The discussion of the findings serves to guide a future research agenda. That H and L neighbourhoods exhibit distinct characteristics and tend to remain stable, bears closer examination, as does the performance of D neighbourhoods. Thus, given that D neighbourhoods possess characteristics in closer alignment to L neighbourhoods, there is merit in focussing attention on the causal mechanisms driving their trajectories. A second, and related route to advance research in this field, would be to collate and deploy additional sets of spatio-temporal sensitive social, economic and environmental variables necessary to enable a causal interrogation of the factors driving the crime drop. Third, recognizing that our findings were derived from an investigation of the overall level of crime and that the volume of crime differs significantly between crime types, it is possible that this approach served to mask factors driving specific crime types. A focus on specific crime types may deliver alternative neighbourhood trajectory groupings. Finally, the shifting spatial clustering of high crime neighbourhoods also merits further investigation.

Conclusion

This paper has addressed an important shortfall in international research investigating the crime drop, by focusing on its local variance. In contrast to existing literatures that have sought to interrogate temporal variation in crime at both macro and micro scales, our research provides substantive advance through analysis of the meso or neighbourhood scale. These data were interrogated through the use of group trajectory analysis (exploring spatial autocorrelation), in an endeavour to engage with existing international literatures exploring crime trajectories at the micro level, and a comparison of means to explore the underlying characteristics of neighbourhood crime trajectory groups and their association with crime drop performance. The group trajectory analysis found marked distinction between H and L crime neighbourhood groups, and a clear set of drop neighbourhood groups. However, this technique proved less successful in distinguishing the performance of the majority of neighbourhoods found in the middle of the crime distribution, raising at least a question of the methodological foundation of research that has claimed to do so at the micro level. Whether judged by crime level or performance, local variance in crime evidences marked temporal and territorial inequality. The H and L neighbourhoods exhibited stability in crime level and spatial clustering, though the former exhibited some volatility in the patterning of its spatial clustering. There was clear distinction in the underlying characteristics of the neighbourhoods comprising the H, L and D categories. While it might be argued that the crime drop benefited all neighbourhood crime trajectory categories and was associated with rising median incomes, the neighbourhoods in the H category retained characteristics long articulated by international ecology of crime literatures as being associated with higher levels of crime. Cumulatively, these findings imply that agencies seeking to deliver *efficient* and equitable interventions should pay particular attention to areas exhibiting higher levels of crime. Moreover, agencies seeking to develop *effective* interventions should interrogate the causal drivers of the long-term crime trajectories of the neighbourhoods comprising the D category.

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