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Geographic patterns of diffusion in the 2011 London riots☆

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A B S T R A C T

Surprisingly little research has examined the localised diffusion of riots within cities. In this paper, we investigate such patterns during the 2011 London riots, and consider how they changed as police numbers increased. Understanding how offences spread in space and time can provide insights regarding the mechanisms of contagion, and of the risk of events spreading between contiguous areas. Using spatial–temporal grids of varying resolution, and a Monte Carlo simulation, we compare observed patterns with those expected assuming the timing and location of events are independent. In particular, we differentiate between four space–time signatures: "flashpoints" of disorder which appear out of nowhere, "containment" whereby already affected areas experience further events, "escalation" whereby rioting continues in affected areas and spreads to those nearby, and "relocation" whereby the disorder moves from one locality to those adjacent. During the first half of the disorder, fewer counts of relocation diffusion were observed than expected, but patterns of containment, escalation, and flashpoints were all more prominent. For the second half of the disorder, when police capacity increased roughly three-fold, observed patterns did not differ from expectation. Our results show support for theories of spatial contagion, and suggest that there was a degree of coordination amongst rioters. They also show that police activity did not just suppress rioting, but dampened the influence of contagion, without displacement.

Introduction

Outbreaks of rioting and civil disorder, in which groups commit acts of violence against people and property, can be devastating to local communities. The riots that affected London across five days in August 2011 resulted in excess of £200 million of damage to public and private property, over two hundred injuries to police, and two deaths (Riots Communities and Victims Panel, 2011). However, this sustained period of unrest was not equally damaging to all neighbourhoods. Rather, some locations experienced high levels of violence; whilst others, some of which were nearby, experienced few or no events associated with the disorder. Several geographically distinct areas, such as Hackney, Brixton, and Croydon, experienced large-scale violence, looting, and arson; whereas some of the areas in between—including Central London, Shepherd's Bush, and Leyton—experienced comparatively few events. Fig. 1 shows the spatial distribution of the rioting in Greater London over the duration of the disorder.

It has since been shown that the spatial patterns of offences in London are unlikely to be explained by a completely random selection process on the part of rioters: events clustered in space, and did so more than would be expected assuming a simple Poisson process (Baudains, Braithwaite, & Johnson, 2013a). Moreover, research suggests that theories developed to explain offender spatial decision-making for everyday crimes (Brantingham & Brantingham, 1993) explain rioters' target selection and decision-making rather well, with offenders, for example, targeting areas close to their home location, those that were most accessible to them via public transport, and those that were less likely to house cohesive communities (Baudains, Braithwaite, & Johnson, 2013b). Research also suggests that, on the time-scale of days, and at the large area level, areas that experienced disorder on one day were more likely to experience it on the next (Baudains et al., 2013a, 2013b). The precise space–time dynamics of the disorder and how it might have evolved, however, is not currently well

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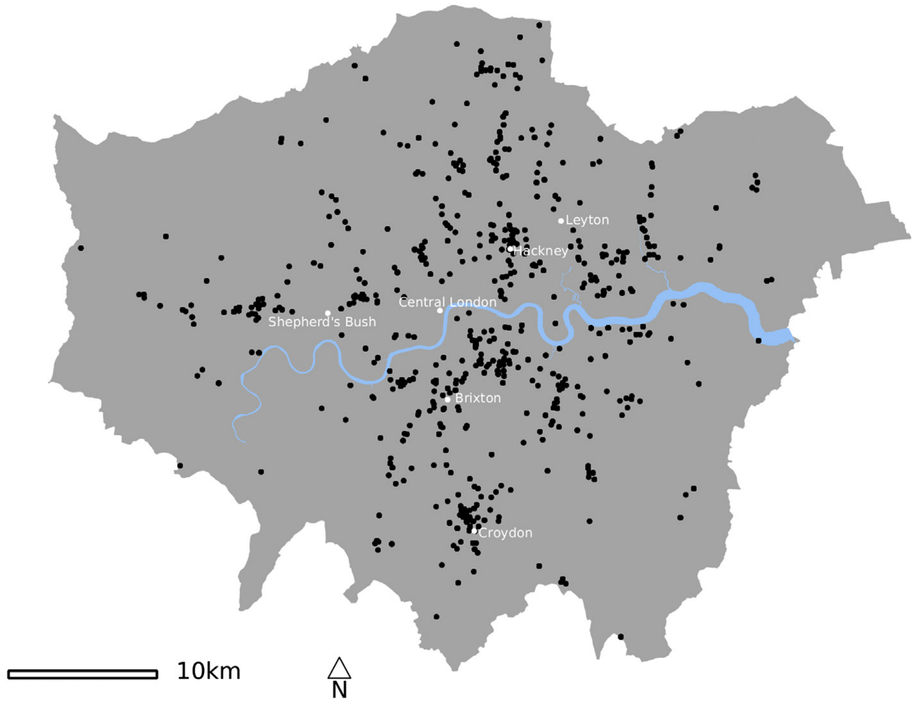

Fig. 1. The spatial distribution of riot-related offences over the duration of disorder in Greater London.

understood, particularly at finer spatial and temporal scales – scales at which the police and others might intervene to suppress the disorder. In fact, few empirical studies have examined localised space–time patterns of offences observed during outbreaks of rioting. Analysis into the diffusion of offences—which can be thought of generally as spatial–temporal emergence, growth and spreading of outbreaks of rioting in space over time—could provide valuable insights into how riots may evolve: insights that would be of value to scholars and the police alike. Several studies have identified space–time clustering in patterns of different types of offences, many of which emphasise the importance of fine-grained data analysis as a means of setting policing priorities (Johnson & Bowers, 2004; Song & Liu, 2013; Wu, Ye, & Webb, 2012). Using a computational approach, in this paper, we characterise the spatial diffusion patterns observed during the 2011 London riots to estimate if and how the disorder spread through space and time, and how such patterns might have changed as the disorder—and the police response to it—continued. In what follows, we articulate expectations as to why and how we would expect the disorder associated with riots to diffuse in space and time before proceeding to test hypotheses.

Social and geographic contagion

Riots involve groups of people at a given location engaging in or threatening acts of violence often for a common purpose. As was the case for the 2011 UK riots, an outbreak of rioting may be followed by other riots, possibly in distinct geographical areas and they can persist over a prolonged period. Riots can spread as a result of a number of processes. For example, large-scale outbreaks of disorder may be consequences of underlying tensions and grievances within a widely distributed population. If news of an initial riot at a given location spreads, then others who share similar grievances, regardless of where they are, may be inspired to behave similarly in an effort to address their grievances. Such a process of social contagion has been offered as one explanation for the severe escalation and perseverance of the patterns of offending observed during the riots in London (Gross, 2011). In particular, news reports and social media have been suggested as a source of encouragement for offenders to engage in disorder at particular locations and at particular times.

Alternatively, geographic contagion may be expected during a riot if an offender's decision to engage in the disorder is influenced by situational precipitators (Wortley, 2008). That is, rioting may prompt, permit, pressure or provoke further offences at a particular location, as bystanders perceive that engaging in the disorder at that location is acceptable, given the circumstances. If it is perceived that the risks of apprehension are lower than they otherwise would be, bystanders may be encouraged to engage in the disorder themselves, leading to further offences nearby (a mechanism explored further in Granovetter (1978) and Epstein (2002), amongst others).

While processes of contagion of both a geographic and non-geographic nature have been discussed in the literature, only a limited number of empirical studies have examined space–time patterns of offending during outbreaks of rioting. In a seminal study of the US race riots in the 1960s, Spilerman (1970) tested for the presence of geographic contagion by examining the extent to which cities were more or less likely to experience riots if those nearby had recently experienced them. Finding no significant effect, he argued that widespread riots might have been stimulated by the sharing of grievances facilitated by national news coverage of injustices on television. Subsequent studies using more precise methods and data have, however, shown that collective violence may diffuse geographically at the spatial scale of cities and on the time scale of days, but have also provided evidence to suggest that contagion is more likely in cities where news outlets such as television provide coverage of disorders occurring elsewhere (Midlarsky, 1978; Myers, 1997, 2000, 2010).

While it can be difficult to disentangle these effects, it is possible to identify particular space–time patterns of events that would be

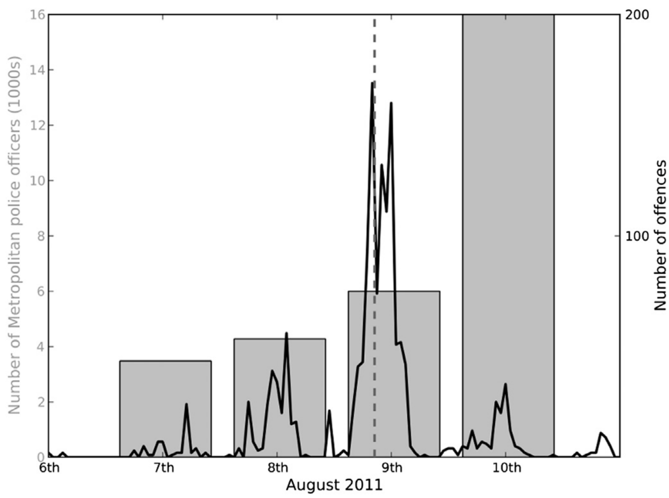

Fig. 2. Police officers and offences. Bar chart of the number of police officers on the streets of London for each night throughout the duration of the disorder, and the number of recorded offences. The dashed vertical line represents the mid-point of the offence data.

anticipated if either or both mechanisms had a part to play. For example, considering patterns of riots within a city, Abudu Stark, Raine, Burbeck, Keith, and Davison (1974) provide one of the few empirical studies of the space–time dynamics of riots at a fine spatial scale, and find evidence to suggest that rioting spread both between contiguous and non-contiguous areas. The former would be expected in the case that the risk of rioting diffuses spatially, the latter where the process is aspatial. Other fine-scale empirical studies have investigated the characteristics of targets during rioting (Berk & Aldrich, 1972; Rosenfeld, 1997); however, few have directly examined localised diffusion and, consequently, the space–time dynamics of civil disorders are not currently well understood. In an effort to address this, in this paper, we explicitly examine the space–time dynamics of the disorder, as exhibited in the diffusion patterns of offences observed during the 2011 London riots, to understand if and what type of contagion processes may have operated. In particular, we evaluate the extent to which the timing and location of offences may be characterised as "flashpoints", whereby outbursts occurring in geographically distinct locations that themselves—or those nearby—had not recently experienced disorder; whether there was evidence of "containment", whereby areas already affected by disorder in one time period were more likely to be affected in the next, but where nearby areas experienced no offences; whether there was evidence of "escalation", whereby rioting continued in already affected areas but also spread to contiguous areas over sequential time periods; and/or if there was evidence of "relocation", whereby the disorder moved from one locality to another over time. In contrast to the previous literature on riots, we examine such patterns at relatively fine spatial and temporal scales to investigate space–time dynamics at the micro level, something that criminologists are increasingly doing for patterns of more everyday crimes (Weisburd, Bruinsma, & Bernasco, 2009).

The interplay between rioters and police

The complex interactions between rioters and police officers provide another mechanism through which disorder may spread or be suppressed. Wilkinson (2009) suggests that this is an area not sufficiently investigated in the previous literature, perhaps largely due to a lack of sufficiently detailed data on law enforcement activities. During the riots in London, the actions of the police came under great scrutiny. In particular, the public and media questioned the course of action taken by police when faced with the disorder (Riots Communities and Victims Panel, 2011). During much of the rioting, it was perceived that, in an effort to limit the spread of events, the police were standing by and containing offenders, without being drawn into the disorder to make arrests, thereby failing to protect some locations from being looted. Even police officers admitted to being unclear as to the best course of action to take (Metropolitan Police Service, 2012).

Police investigations into such criticism have suggested that the uncertainty and prevalence of containment tactics were a consequence of the limited number of police officers available to deal with the unprecedented scale of the disorder. As the riots intensified, extra officers were brought in from other police forces in the UK (see Fig. 2). It is widely claimed that this was the key factor in bringing an end to the prolonged period of disorder. Indeed, Her Majesty's Inspectorate of Constabulary (HMIC, 2011) stated, "while the immediate response to the public disorder in August was hesitant, this transformed into a decisive and effective response in which large number of assets were mobilised to regain control of the streets". Although some have questioned whether the number of officers on the final night of the unrest was, in fact, suboptimal (Davies, Fry, Wilson, & Bishop, 2013), the increase in police numbers would have enabled the police officers present during an outbreak of rioting to be more proactive in stopping on-going disorder: they may have been able to make arrests without the risk of other offenders present dispersing to nearby areas, and thereby spreading the disorder.

The relatively abrupt change in police manpower, and the subsequent arguments that this was the principal reason for the quelling of disorder, provides conditions not unlike a natural experiment, and enables us to evaluate how patterns of offending changed with the police's ability to employ more effective public order tactics. In the present study, we split the time series of offence data in two to see whether this apparent change led to a change in the diffusion patterns of offences.

During the first half of the riots, when police tactics were more constrained, if the on-going rioting provoked or prompted others to engage in the disorder, we would expect the unrest to spread in one of the four ways discussed above. As the range of public order tactics available to the police increased, we would expect to see changes in the diffusion patterns of riot events as the space–time dependency of offences would likely have been disrupted. While some places would still be expected to experience hotspots of activity, we would expect to observe little or less evidence of the spreading of the disorder as time progressed, particularly to nearby localities.

The role of target selection in diffusion

Target selection during rioting has been shown to be non-random (Martin, McCarthy, & McPhail, 2009) and there have been several efforts to understand the features of targets that make them particularly attractive to rioters (Berk & Aldrich, 1972; Rosenfeld, 1997). In particular, a previous paper (Baudains et al., 2013b) explored the environmental factors that contributed to the target choice of rioters during the disorder in London. Areas with a high number of retail facilities, areas that were close to transport links, and areas likely to be prominent in the mental maps of rioters, such as those containing schools, were shown to preferentially influence the choice of target. Environmental features therefore appear to influence the location of events, and it follows that diffusion patterns could also be influenced by such factors.

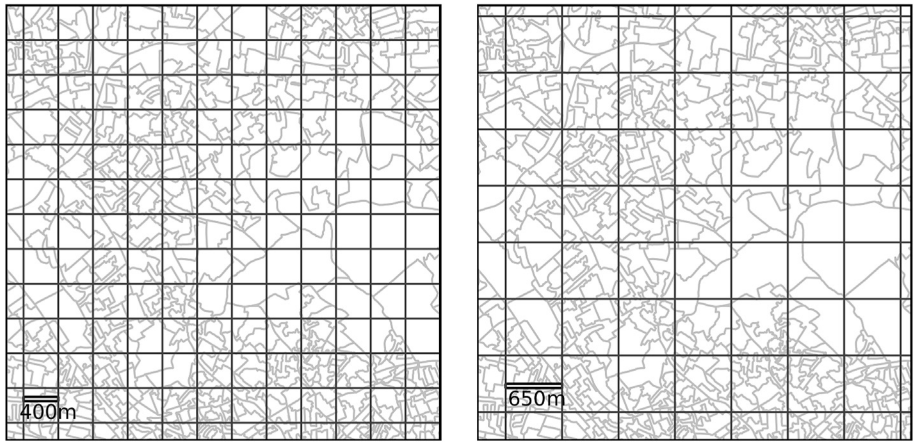

Fig. 3. Spatial grids over a portion of London's Output Area geography. The smallest (400 m) and largest (650 m) spatial grid used in our analysis overlaid on a portion of the Output Area geography of Greater London.

To explain, if the environmental features of places and those that surround them vary substantially (in terms of their attractiveness to offenders), observed instances of containment may be highly likely, as rioting is more likely to continue occurring at particular (attractive) locations, and not to diffuse to nearby (but dissimilar) areas. On the other hand, if rioters' spatial decision-making was less determined by such factors, instances of relocation would be more likely. In this paper, we consequently control for spatial heterogeneity, and focus on the influence that environmental features have on the space–time dependency between events.

Paper outline

In what follows, we examine space–time patterns of disorder during the 2011 London riots to test for evidence consistent with the geographic contagion, spatial contagion, police interplay and target selection hypotheses articulated above. Specifically, we evaluate whether the presence of four types of diffusion were present more or less than would be expected if the timing and location of offences were independent. The four diffusion processes we consider are containment, relocation, escalation and flashpoints, the operationalisation of which is outlined in the next section. As discussed above, strong patterns of containment would suggest either that environmental factors enhanced localised contagion effects and attracted further rioters to a particular area or that strategic police action inhibited the spread of disorder to nearby areas. Relocation would be expected in the case of strong spatial contagion, where police tactics may have displaced the disorder, or where the capacity of the rioters had reached its peak, and where the influence of environmental factors at particular sites was not so strong that other nearby locations offered suitable opportunities. Escalation would be expected in the case of a strong growth mechanism that the police were unable to suppress or contain, and where the influence of environmental features was not a key determinant of rioting sites, meaning that the disorder could spread. Finally, flashpoints would be expected where the rioters engaged in some degree of organisation, selecting sites to target and coordinating the collective activity of at least some rioters. In this case, only a weak geographic contagion effect would be involved in the dynamics of the disorder, with social contagion being the predominant mechanism. In what follows we describe the data analysed and the method used to test hypotheses, before presenting our findings.

Material and methods

Police data

Data regarding the location of riot related offences were obtained from the Metropolitan Police Service and included the location at which offences took place and, where possible, an estimate of the time they occurred. In total, data were obtained for 3914 offences, of which, data regarding the timing and location of offences during the riots were available for 2593 events (see Fig. 1 and Appendix A). For each offence, the centroid of the UK census output area—a geographical region containing approximately 125 households—was used to indicate the location at which the offence occurred. The average area of a UK census output area in Greater London, in which riot offences occurred, is 0.15 km^2.

Analytic approach

Previous authors have investigated the spatial patterns of interdependent events using simple indicators of spatial association. For example, local indicators of spatial association, based on global measures such as Moran's *I* (Moran, 1950), were introduced in Anselin (1995) to examine the extent to which areas with high (or low) rates of events cluster spatially. In Cohen and Tita (1999), changes in these indicators over time were used to estimate how occurrences of homicide might diffuse spatially. More recently, studies of homicides (Ye & Wu, 2011), disease spreading (Hsueh, Lee, & Beltz, 2012), terrorist attacks (LaFree, Dugan, Xie, & Singh, 2012), burglary (Rey, Mack, & Koschinsky, 2011) and civil conflict (Schutte & Weidmann, 2011) have used similar approaches to quantify patterns of spatial diffusion. The latter two studies examined changes in space–time patterns for relatively rare events, and so rather than examining changes in the intensity of risk in space and time (as is the case for Cohen and Tita (1999)), considered changes for those areas in which at least one event occurred. Since we are primarily interested in the occurrence of offences at a particular location in space and time, rather than the relative intensity of events, this is the approach we take in this paper. One reason for this is that, in the case of riots, the number of recorded offences will not directly reflect their intensity or perceived significance. Therefore, we employ a binary approach, and examine patterns associated with when and where one or more riot related offence occurred.

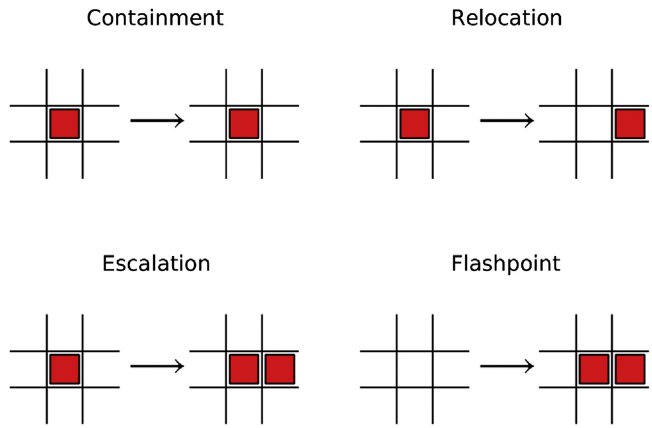

Fig. 4. Geographic patterns of diffusion. An illustration of the simplest examples of each of the diffusion patterns of interest occurring in a spatio-temporal grid.

To operationalise our binary variable, we use a space–time grid of spatial resolution δs and temporal resolution δt. Overlaying this grid over the spatial area of interest (all offences used in the analysis fall within the boundary of Greater London), we map offences into the discrete space–time window within which they occur. One issue associated with using any boundary (spatial or temporal) is that of the modifiable unit problem, whereby even subtle changes to the boundary used can lead to different patterns (Openshaw, 1984). Varying the values of δs and δt allows us to address this problem and to see if, and how, patterns vary over different temporal and spatial scales. Values of s and t were chosen so as not to exceed the precision of the data. For example, as most offences were recorded as occurring to the nearest hour, we use one-hour intervals as the smallest unit of time. Similarly, since the location of each offence is mapped to a UK census output area within Greater London, the smallest spatial resolution chosen was 400 m. Accordingly, the area of each grid is greater than the mean for the area of the output areas and we therefore can be confident that, on average, the offence occurred within the space–time window of the overlaid grid. For the purposes of illustration, the smallest and largest spatial grid used in our analysis is overlaid onto a portion of the Output Area geography of Greater London in Fig. 3.

We interpret the four diffusion patterns of interest—containment, relocation, escalation and flashpoints—by considering how the presence of an offence in a particular space–time cell relates to offences in neighbouring cells. For this purpose, we employ a binary joint count statistic for each space–time unit, indexed by the tuple (s, t), and denoted by $(X, Y)_{(s,t)}$ where $X \in \{0, 1\}$ determines whether at least one offence occurred in the focal space–time window of interest, and $Y \in \{0, 1\}$ determines whether at least one offence occurred in any of the focal area's neighbouring units, which are defined with queen contiguity. Diffusion patterns are defined by considering the change of this joint count for each space–time unit over sequential intervals of time. For example, an instance of containment at spatial unit s and time t is defined as $(1, 0)_{(s,t)} \rightarrow (1, 0)_{(s,t+\delta t)}$, where δt is the temporal resolution of the space–time grid. Thus, containment occurs when offences take place in a focal cell repeatedly without occurring in any neighbouring cells. Similarly, an instance of relocation is defined as $(1, 0)_{(s,t)} \rightarrow (0, 1)_{(s,t+\delta t)}$, so that offences move from one cell to a neighbouring cell, without persisting in the original cell. Escalation occurs when offences persist in the original cell but also occur in neighbouring cells that were previously unaffected, given by $(1, 0)_{(s,t)} \rightarrow (1, 1)_{(s,t+\delta t)}$. Flashpoints are identified if offences are identified within a wider area that had not experienced any events in the previous time step, and is therefore given by $(0, 0)_{(s,t)} \rightarrow (1, 1)_{(s,t+\delta t)}$. The simplest examples of these diffusion patterns are illustrated in Fig. 4.

Statistical inference

Using a similar approach to Schutte and Weidmann (2011), after enumerating the observed patterns of interest, we determine the statistical significance of them by comparing them to what would be expected, assuming a null hypothesis. Previous research indicates that incidents of disorder cluster spatially, and that they also cluster in time (Baudains et al., 2013a), so we account for this in our analysis. Our null hypothesis—assuming that there is no pattern of contagion—is consequently that while events cluster in these two dimensions, their timing and location are independent. To determine statistical significance, we compare the observed patterns with permutations of the data generated under this assumption. A full permutation is virtually impossible, so we use a Monte Carlo simulation to sample 250 permutations from all those possible.

To describe the observed distribution, we construct a space–time grid of spatial resolution δs and temporal resolution δt. We then map the offences to the space–time grid and construct the matrix A, where $A_{st} = 1$ if, and only if, the number of offences in spatial unit s within temporal unit t exceeds zero. We then count the number of observed instances of containment, relocation, escalation and flashpoints, as described above, by considering the values of A_{st}, $A_{s't}$, $A_{s(t+\delta t)}$, $A_{s'(t+\delta t)}$, for all s' in the neighbourhood of the spatial unit s, for all values of s and t.

To generate the expected distribution, assuming the null hypothesis of the space–time independence of events, we construct a bipartite graph denoted by $G = (U, V, E)$, where the sets of vertices U and V can be partitioned so that every edge in E connects one vertex in U with one vertex in V. We define U as the set of spatial units, indexed by s, and V as the set of temporal units, indexed by t, and add an edge (s, t) between s and t if, and only if, $A_{st} = 1$. An example of one such graph is shown in Fig. 5. To generate one permutation of the data, using a uniform random number generator, we select two edges and denote them (s_1, t_1) and (s_2, t_2). We then check to see if the edges (s_1, t_2) and (s_2, t_1) already exist. If they do not, we remove edges (s_1, t_1) and (s_2, t_2), and create edges (s_1, t_2) and (s_2, t_1). We repeat this step N times, where the calculation of N is described below. We then count the instances of containment, relocation, escalation and

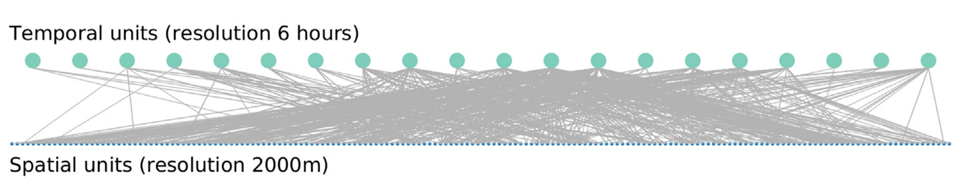

Fig. 5. Network visualisation of the London riot data. The bipartite network G for the London riot data with δt = 6 hours and δs = 2000 m.

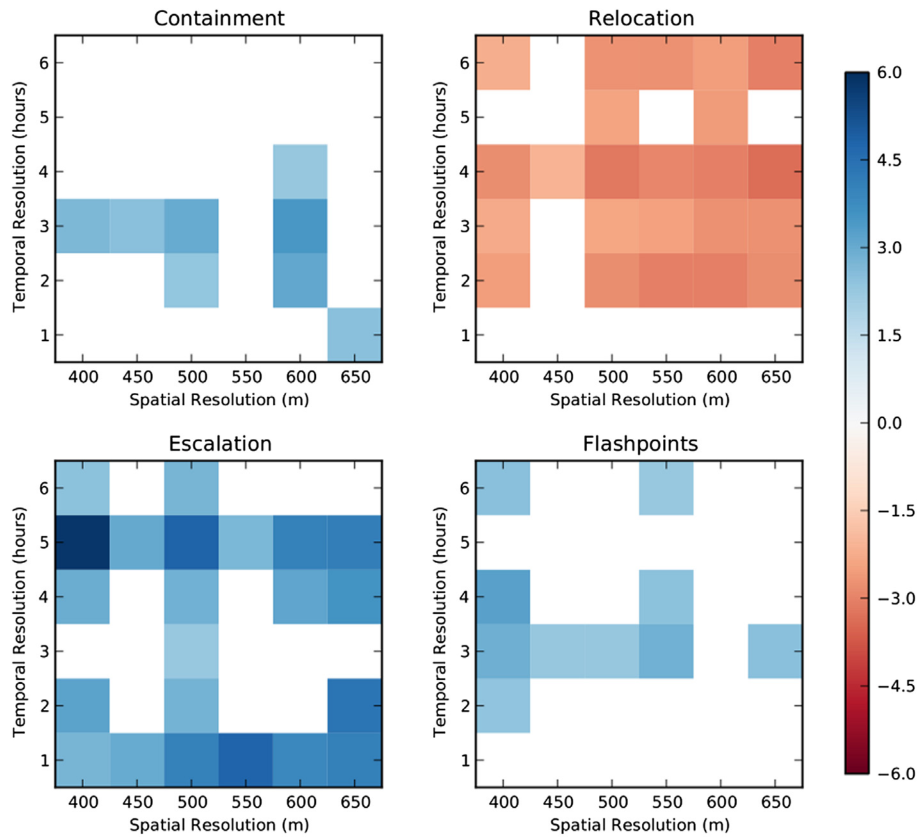

Fig. 6. Results for the first half of the data. *Z*-scores for each observed count outside a 95% two-sided confidence interval of the resulting distribution from the Monte Carlo simulation, for each diffusion pattern for the first half of the data. Spatial–temporal resolutions that do not reach statistical significance are shaded white.

flashpoints for this permutation of the data and compare the results to the observed distributions.

N is the number of times we select two edges at random and rewire them so that they swap end nodes, provided that the new edges created do not already exist. We calculate N by considering the total number of selections required to ensure that every edge is selected at least once. Since edges are selected uniformly randomly each time, and therefore some edges will almost always be selected more than once, this number will vary over different attempts at this procedure. We therefore suppose that this number is given by the random variable X. We then set N to be equal to a value in the distribution of X that is greater than 95% of all of the possible values that X can take. In this way, we have 95% confidence that the procedure described above selects each edge, and therefore ensures that the distribution given by the null hypothesis is sufficiently random, subject to the constraints brought about by preserving the spatial and temporal distributions of offences.

The 95% confidence interval on X is calculated as follows. We first let X_k be the random variable given by the number of selections required in order to select the k-th new edge after $k-1$ distinct edges have already been selected, so that one realisation of X is given by

$$X = \sum_{k=1}^{K} X_k, \tag{1}$$

where K is the total number of edges. The probability of selecting a new edge after $k-1$ distinct edges have been selected is given by

$$p_k = 1 - \frac{k-1}{K}, \tag{2}$$

where K is the total number of edges. It can then be shown that

$$E[X_k] = \frac{1}{p_k}, \quad Var[X_k] = \frac{1-p_k}{p_k^2}. \tag{3}$$

And, therefore, that

$$E[X] = K\sum_{k=1}^{K}\frac{1}{k}, \quad Var[X] < 2K^2. \tag{4}$$

Then, via Chebyshev's inequality, we have

$$Pr\left(X \geq K\sum_{k=1}^{K}\left(\frac{1}{k} + \sqrt{2}cK\right)\right) \leq \frac{1}{c^2}, \tag{5}$$

for all positive real constants c. Setting $c = \sqrt{20}$, we have

$$Pr\left(X \geq K\sum_{k=1}^{K}\left(\frac{1}{k} + \sqrt{40}K\right)\right) \leq 0.05, \tag{6}$$

and, thus for $N = K(\sum_{k=1}^{K}(1/k + \sqrt{40}K))$, the rewiring procedure described above selects every edge with 95% confidence.

We complete this process separately for the two time periods of interest: one for the first half of the data in which we have argued the police were under resourced and unsure of the correct public order tactics to adopt, and one for the second half of the disorder in which there were more police available. The two time periods are split at the median time of all offences contained in the analysis, which is 20:30 on the 8th August 2011. Thus the offence data is split into two equal halves and the results presented in the next section are shown for each of these halves.

Results

Figs. 6 and 7 summarise the results by showing the difference between the observed and expected values (computed using the Monte Carlo simulation) for each of the four patterns explored, for the first and second half of the data, respectively. The *Z*-scores represent the difference between the observed values minus the mean of those expected, divided by the standard deviation of the expected distribution. For the purposes of clarity, these are conditional plots for which cells are shaded only if the observed differences are statistically significant. Statistical significance was also tested using the empirical performance of the Monte-Carlo simulation, as described in North, Curtis, and Sham (2002). The distributions were sufficiently symmetric that these results were consistent with the *Z*-scores reported here.

During the first half of the riots, it is evident that observed counts of escalation were much more prevalent than would be expected, assuming that the timing and location of events were independent. This pattern appears to be relatively insensitive to the space–time resolutions tested. There was also more evidence of containment than would expected, although this was more sensitive to the time window used, being most evident for three-hour intervals. Flashpoints were also observed significantly more than would be expected, particularly for smaller spatial units. In contrast, instances of relocation were observed significantly less frequently than would be expected.

Considering the second half of the disorder, while some of the observed counts exceeded expectation, there were no general patterns. Moreover, given that Fig. 7 summarises a series of significance tests, even on a chance basis we would expect around ($0.05 \times 36 =$) 2 of the comparisons to achieve statistical significance at the 0.05 level. The findings therefore suggest that for the second half of the disorder, the observed distribution did not differ from that expected, given that we know that some locations and times were riskier than others.

Discussion

In this paper, we examined space–time patterns of disorder observed during the 2011 London riots. Our aim was to investigate precisely how these evolved, and the extent to which they were consistent with theories of contagion. To quantify patterns, we compare those observed to those expected, given that some places were known to be more attractive to rioters than others, and that there was a distinct temporal pattern to the disorder.

In line with theories of spatial contagion, during the first half of the riots, it appears to be the case that the disorder tended to persist at locations already affected (containment) and to spread to those nearby (escalation). This provides support for the idea that there were localised effects whereby rioters were attracted to sites where there was on-going disorder. Such an effect could occur either because offenders encountered such activity, which then encouraged them to participate (Wortley, 2008), or because they were mobilised more systematically through social media or other means. In Baudains et al. (2013b), it is shown that most rioters travelled short distances to take part in the events of 2011, and we interpret this as providing support for the former explanation. This

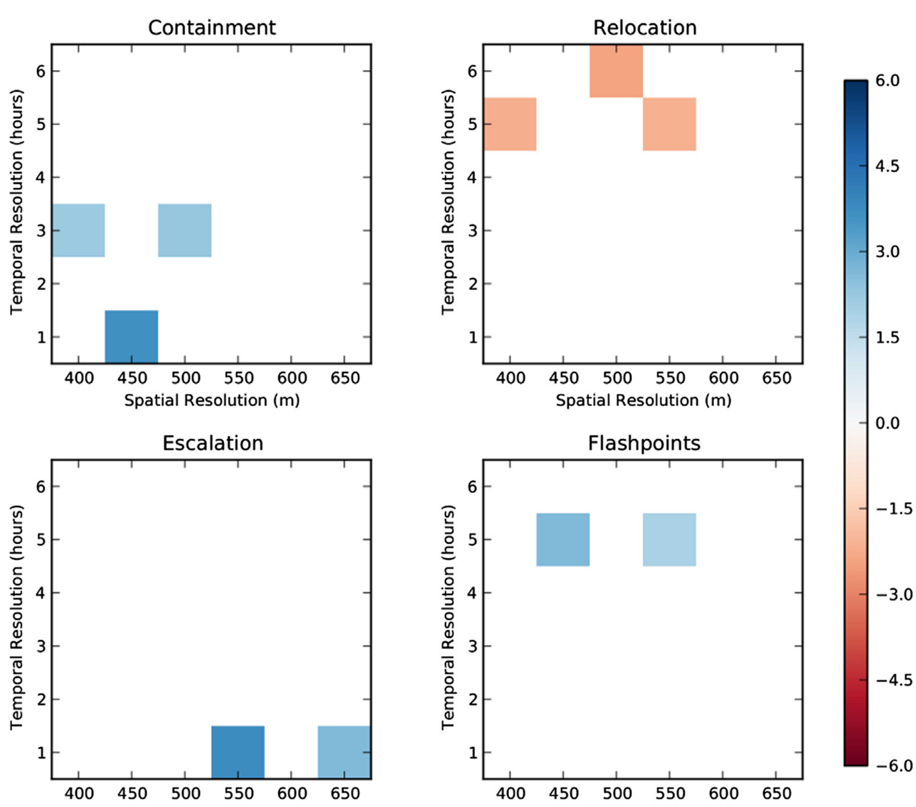

Fig. 7. Results for the second half of the data. *Z*-scores for each observed count outside a 95% two-sided confidence interval of the resulting distribution from the Monte Carlo simulation, for each diffusion pattern for the second half of the data. Spatial–temporal resolutions that do not reach statistical significance are shaded white.

is not to suggest that rioters were not coordinated through social media, but that for the instances of containment and escalation observed at least, propinquity and mechanisms involving less organisation of rioters may provide an explanation for observed patterns.

Regularities observed in the space–time pattern of events during the first half of the disorder thus suggest that the location of some riot sites would have been amenable to prediction through consideration of where incidents had recently occurred. However, during the same period, there was also evidence of flashpoints – events that would be difficult to predict in the same way. While we were unable to measure the role that social media may have played in such incidents directly, these patterns are consistent with the idea that some offender activity was coordinated using such means, and future research may seek to examine such explanations further.

Interestingly, the only space–time signature that we observed (significantly) less often than expected was relocation. A common concern associated with geographically focused police activity is that it will merely displace offending (Bowers, Johnson, Guerette, Summers, & Poynton, 2011). Different riots may have different dynamics, but in the current case, there was no evidence of this, which suggests that police action did not simply move crime around the corner.

Considering the second half of the period studied, during which police numbers and tactics changed, the patterns observed appear to be consistent with what would be expected, assuming that they could be explained by the fact that some places (and times) were more prone to the disorder than were others. That is, during the second half of the disorder, for the relatively small spatial and temporal scales studied here, there is no evidence of space–time diffusion for any of the patterns considered. This suggests that the police not only suppressed the overall level of the disorder, as has been argued by various reports since the riots (e.g. House of Commons (2011)), but also suppressed the role of contagion processes (e.g. escalation and flashpoints) which was a feature during the first half of the disorder.

As with any analysis of real world data, a number of caveats are worthy of discussion. First, as is the case with any study that employs police crime data, not all incidents of disorder would have been recorded by the police, and it is unclear how much disorder went unreported. We hope to have minimized the influence of this issue by using binary indicators (rather than absolute measures of intensity), but the reader should be aware of this potential issue. Second, analyses of the kind reported here are only as good as the precision of the data available for analysis and the data utilised were not perfectly precise in terms of when and where events occurred. To mitigate this issue, we performed a sensitivity analysis by varying the spatial and temporal resolutions at which patterns were explored. Again, such issues are true of most studies of crime and disorder, but should be borne in mind.

To conclude, in this paper we examined if and how the rioting observed during the 2011 London riots spread. We find evidence of spatial and aspatial contagion during the first half of the disorder but none during the second, confirming various reports suggesting that police effectiveness in quelling the diffusion of risk increased as time went on, and police numbers were increased. Further, we find no evidence to suggest that police action might have displaced offending. Questions remain as to whether the use of social media might have been used to coordinate activity during the riots but the methods used here provide valuable insights into just how the disorder evolved in space and time.

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Appendix A. Supplementary material

Supplementary video related to this article can be found online at http://dx.doi.org/10.1016/j.apgeog.2013.09.010.

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