UK-based Terrorists' Antecedent Behaviour: A Spatial and Temporal Analysis

Guy Griffiths, Shane D Johnson* and Kevin Chetty

Acknowledgements

The authors would like to thank the Metropolitan Police Service for providing the data analyzed in this paper.

* Corresponding Author

shane.johnson@ucl.ac.uk UCL Jill Dando Institute of Security and Crime Science University College London 35 Tavistock Square London WC1H 9EZ UK

ABSTRACT

<u>Background and Purpose</u>: Terrorism is a real and present danger. The build-up to an attack includes planning, travel, and reconnaissance which necessarily require the offender to move through their environment. Whilst research has examined patterns of terrorist attack locations, with a few exceptions (e.g. Rossmo & Harries, 2011), it has not examined the spatial behavior of the terrorists themselves. In this paper, we investigate whether the spatial mobility patterns of terrorists resemble those of criminals (and the wider population) and if these change in the run up to their attacks.

<u>Method:</u> Using mobile phone data records for the ringleaders of four different UK-based terrorist plots in the months leading up to their attacks, we examine the frequency with which terrorists visit different locations, how far they travel from key anchor points such as their home, the distance between sequential cell-site hits and how their range of movement varies as the planned time to attack approaches.

<u>Conclusions:</u> Like the wider population (and criminals), the sample of terrorists examined exhibited predictable patterns of spatial behavior. Most movements were close to their home location or safe house, and they visited a relatively small number of locations most of the time. Disaggregating these patterns over time provided mixed evidence regarding the way in which their spatial activity changed as the time to the planned attack approached. The findings are interpreted in terms of how they inform criminological understanding of the spatial behavior of terrorists, and the implications for law enforcement.

KEYWORDS: terrorism, spatial behavior, routine activity space, distance-decay

1. INTRODUCTION

Terrorism occupies a prominent position in a long list of security threats – from climate change to global pandemics to energy shortages – that the world confronts in the twenty-first century. In recent years, it has been Islamist extremism which has represented the major area of concern to the West. Various definitions of terrorism exist, with most emphasizing a reliance on violence in order to further a political goal (Crenshaw, 1992). Yet a terrorist plot is more than just the violent act that is its embodiment, or the motivations of the perpetrators. The practical precursor steps which take place as a plot progresses – training, meetings, securing a safe house, procurement of materials and reconnaissance – take time to plan, and just like everyone else "terrorists operate within the constraints and boundaries of both time and space" (Smith et al., 2008, p.43).

Accordingly, understanding the antecedent behavior of terrorists prior to an intended attack has received increasing attention in recent years. In the context of studies of environmental criminology, this has included studying the steps that must be taken for a terrorist act to occur (Clarke & Newman, 2006). The aim of the current study is to contribute to this literature by examining terrorist patterns of spatial activity during the antecedent phases of the plots with which they were involved. Our intention is to determine whether regularities in their movement exist and whether these resemble those of the wider public or offenders engaged in urban crime. Whilst such patterns have been examined before, much of the research has tended to be anecdotal in nature (Post, Sprizak & Denny 2003), largely due to the difficulties associated with obtaining the necessary data. Where empirical analyses have been conducted (see below), these have tended to be limited to examining the location of terrorists' home and attack locations. In contrast, in

what follows we present an analysis of day-by-day patterns of movements – estimated using data from mobile phone data - for the Emirs (leaders) involved in four UK-based Islamist terrorists' plots in the run up to their attacks. All four plots involved bomb attacks against the UK in the last fifteen years - in three cases, attacks were carried out, while the fourth was disrupted by the police during the final stages of planning. As discussed below, we argue that just like everyone else, terrorists – such as those studied here - are subject to constraints that limit their movement potential, which leads to predictable patterns of activity.

The rest of the paper is organized as follows. In the next section, we discuss movement patterns of the public in general. This is followed by a review of the existing literature on the mobility patterns of urban criminals and terrorists, which informs a set of hypotheses that are tested in subsequent sections. The data and our analytic strategy are then described, along with the results generated. The paper concludes with a discussion of the findings and their implications for policing and criminological understanding.

1.1 Literature review

A natural starting point for this study concerns the spatial activity patterns of the wider population, and those engaged in forms of criminal behavior. A brief discussion of the movement patterns of such actors is useful insofar as it helps to establish what might be expected, and what might represent points of departure in signatures of the spatial behavior of terrorists. Until very recently, establishing what normal patterns of movement are has proved surprisingly difficult to answer, with Gonzalez, Hidalgo & Barabasi (2008, p.779) stating that "our understanding of the basic laws governing human motion remains limited owing to the lack of tools to monitor the time-resolved location of individuals".

As noted by Shoval & Isaacson (2006), research into human spatial behavior has traditionally relied on self-reported data collected using space-time budget diaries. This technique is used in the UK National Travel Survey conducted by the Department of Transport to examine the movement patterns of the public. Analyses of these data (Department for Transport, 2015) reveal regularities in spatial behavior, with there being (for example) a clear pattern of distance-decay, whereby shorter trips are more common than are longer ones (e.g. around 65% of trips are under 7.5kms).

More recent work has also taken advantage of data collected through ubiquitous mobile devices. For example, using mobile phone data, Gonzalez et al. (2008) tracked the movements of 100,000 anonymous individuals over a period of six months. A key finding was that while some trips covered long distances, most were short. Moreover, people's activity patterns were generally predictable, with most making regular trips to the same areas over time. In fact, on average, those sampled were to be found at their two most frequently visited locations about forty-percent of the time (and the four most visited locations around 60% of the time). In a further study, using data from 10 million mobile phone users collected over a 14-week period, Song et al. (2010) found similar results but with a slightly higher degree of predictability, with those sampled visiting their top two locations about 60% of the time (and the four most visited locations 70% of the time). In both studies, other locations were visited but with a diminishing probability. Collectively, these studies suggest that people have routine activity spaces (likely anchored around their home and other nodes of activity); that most of their activity occurs at these locations or nearby; and that the individual segments of their daily trips tend to be short. Simply put, people do not move about randomly.

1.2 Offender Spatial Behavior

Research concerned with terrorist spatial mobility (discussed further below) is relatively limited. In contrast, that concerned with the spatial behavior of offenders engaged in urban crime (e.g. burglary) is much more developed and this will now be discussed as a way of framing what follows. In doing so, following Rossmo and Harries (2011) we make the assumption that an understanding of the spatial behavior of offenders (one form of law breaking at odds with social norms) can inform understanding of that for terrorists (another form of law breaking also at odds with social norms). Obvious objections to this are that while criminal activity might be seen to be rational in nature, terrorist activity, which often involves the risk of death in the pursuit of a perhaps unattainable goal, seems inherently irrational. Moreover, while urban crime is often financially motivated, terrorist activity is generally ideologically-driven. In relation to the first point, it is worth noting that many have argued that urban criminals do not always act rationally (e.g. Wright et al., 2006), and most scholars (Cornish and Clarke, 1986; Bennett and Wright, 1984; Cromwell, Olson and Avary, 1991) that do argue that offender decision making is rational, assume that it is boundedly so. That is, that offenders seek to maximize the benefit of their activity whilst minimizing the effort and risks involved, but do so on the basis of incomplete and often biased information. Moreover, they are assumed to use heuristic styles of thinking (Simon, 1978) rather than carefully evaluating the costs and benefits of action alternatives. This is a far cry from the classic economic model (Becker, 1968) of the rational decision maker invoked by many.

As to the differences in objectives of urban criminals and terrorists, not only does a Darwinist perspective see no contradiction in altruistically risking one's life for the benefit of

one's kin (Dawkins, 2006), terrorism, being goal-driven, is not inherently mindless or irrational (Roach, Ekblom & Flynn, 2005, p.7). Indeed, Ruby (2002, p.15) suggests that "terrorism is perpetrated by rational, lucid people" and there seems no reason why actions in pursuit of these goals shouldn't also be rational (see also Cothern et al., 2008; Townsley et al., 2008).

Considering the movement patterns of offenders, crime pattern theory (e.g. Brantingham and Brantingham, 1993) suggests that just like everyone else, offenders have routine activity spaces that are shaped by the locations of key activity nodes and anchor points (such as their home) and the routes between them. Furthermore, that most of the activities they engage in, including crime, will take place within these spaces, since familiarity reduces uncertainty as to the likely outcome of a given action (e.g. Beavon, Brantingham and Brantingham, 1994). A large and expanding body of empirical research provides support for crime pattern theory, demonstrating (for example) that most crimes are committed near to an offender's current (e.g. Townsley and Sidebottom, 2008; Bernasco and Nieuwbeerta, 2005; Bernasco et al., 2005; Rengert and Wasilchick, 2000; and for a recent review, see Frith, Johnson and Fry, 2017) or previous home locations (Bernasco, 2010), or near to other activity nodes such as their friends' homes (e.g. Wiles and Costello, 2000; Rengert and Wasilchick, 2000). However, it is important to note that the distances offenders travel varies both between offenders and type of crime. For example, relative to their older counterparts, juvenile offenders are generally found to travel shorter distances to engage in crime. That said, changes in the journey to crime do not change linearly with age. That is, the distances travelled to offend initially increase with age, but peak in the offender's early 20's, declining thereafter (Andresen, Frank, & Felson, 2014; Clarke & Eck, 2003). With respect to offense types, Rossmo (2000) reports that crimes which are violent

in nature (e.g. manslaughter and assault) tend to occur closer to the offender's home than do other forms of offending, such as property crime and burglary.

Like the space-time budget studies employed in transport research, studies such as those discussed above are limited to the analysis of data concerned with a limited number of locations. In this case, data recorded by the police concerning offender home (current or previous) and offense locations. More recently, researchers have used dedicated wearable electronic devices to automatically record time-stamped location data to examine offender spatial behavior. For example, using Global Positioning Satellite (GPS) offender monitoring tags, Rossmo et al. (2012) studied the movement patterns of a group of 14 reoffending parolees, convicted for a variety of offenses (including sexual offenses, drug dealing and burglary). Using data for a one-week period, which included days on which offending occurred, they studied the parolee's movement patterns before and after offenses took place. The offenders were a heterogeneous group and hence their precise mobility patterns varied. However, just like the wider public (see above), and in line with crime pattern theory, it was apparent that most visited only a small number of locations each day (typically 2-7 different sites).

1.3 Terrorist Spatial Behavior

During the antecedent phase of a terrorist attack, analyses of available data (Cothren et al., 2008) suggest that terrorists engage in and proceed through a series of stages ranging from recruitment, to planning, to the acquisition or manufacture of tools necessary to carry out their attack(s). During these stages, the risk of detection is a very real possibility, and one they will seek to avoid. In relation to this, Cronin (2009, p.104) argues that terrorism rarely flourishes without the active or passive support of sections of society, since a group

operating in a hostile environment is unlikely to avoid detection for long. Awareness of the environment within which terrorists' act is thus important. Indeed, Kenney (2010, p.923) argues that the 7/7 (London) bombers "drew on their local knowledge and experience to move around...without having their plot exposed" (see also, Sageman, 2004). Consequently, one expectation is that terrorist's patterns of spatial behavior will typically reflect those of the wider public (and offenders). In particular, we expect to observe a routine activity space comprising a relatively limited set of nodes of activity, around which terrorists develop an awareness and in which their presence will not seem out of place (Hypothesis 1).

Just like urban criminals, their home location is likely to feature as an anchor point in this activity space. Also likely to feature are safe houses. To explain, a well-documented feature of terrorist cell behavior is the use of safe houses, with Nance (2008, p.105) noting that "virtually every terrorist group has a series of safe houses used as bomb factories, supply centers, or weapons armories". For example, the 'Al-Qaeda training manual', the possession of which led to the conviction of an associate of the 7/7 ringleader, directs operatives to choose a location for their premises which is adequate for their mission.

Considering empirical research on the spatial behavior of terrorists, Cothren et al. (2008) examined a sample of data - collected through U.S. criminal court trial files and open source materials - to explore the distance travelled by terrorists who conducted attacks on U.S. soil (see also Smith et al., 2008). They found that while one-third of their sample lived very far away (in excess of 800 miles), about one-half lived close to their targets (within 30 miles). Gill et al. (2016) examined the distance travelled by members of the Provisional Irish Republican Army (PIRA) from their home to attack locations and found that most travelled a distance of less than 5 miles. In their study, Rossmo and Harries (2011) analyzed the spatial behavior of terrorist cells in Turkey using police records for which data were available on

both the location of terrorist cell (referred to as safe houses hereafter to avoid confusion with what follows) and attack sites. The groups for whom data were available engaged in multiple attacks (resulting in 1,292 home-attack combinations), and in some cases used multiple safe houses, facilitating the analysis of both the distance travelled from their safe houses to the attack sites, and the distances between the latter. For both types of analysis, there was clear evidence of spatial clustering. In the case of the safe houses, and in line with hypothesis 1, (on average) the two nearest safe houses used by the same group tended to be within two miles of each other. Furthermore, the distance between the nearest safe house and an attack site was around one mile. Taken together, the findings of these studies suggest that - not unlike urban criminals - many terrorists engage in their activities, including the attack itself, at locations near to their routine activity nodes. Consequently, in the current study, we expect that as well as spending most of their time at a relatively small number of discrete locations, most of the spatial activity of the Emirs examined will be observed to occur near to these locations if not at them (Hypothesis 2) and for the distance between sequential movements to be short (Hypothesis 3).

With respect to the locations that form a terrorist's activity space in the prelude to an attack, both Cothren et al. (2008) and Rossmo & Harries (2011) discuss the issue of whether terrorists select an intended attack location first and then develop an activity space around it, or whether their existing activity space determines where an attack takes place. In the studies discussed above, scholars have exploited data such as the terrorist's attack locations and their home or safe house locations, in some cases, having data for multiple safe houses and attack sites. While such data allow for the testing of some hypotheses regarding terrorist spatial behavior, they do not allow for a more nuanced understanding of terrorist spatial behavior and if and how it develops over time. In the current study, we

have access to data for a limited number of terrorists, but have detailed data on their spatial activity over a substantial interval of time. This provides a more complete picture of their movement activity, and allows us to examine if and how their spatial behavior changes (for a similar analysis in relation to urban offenders, see Rossmo et al., 2012). In the event that terrorists select targets first and then develop their activity spaces as part of their preparatory behavior, we may expect their activity spaces to increase over time as the time to attack approaches (Hypothesis 4). In line with this, Cotheren et al. (2008) report that their data suggest that as an attack date draws nearer, those involved tend to home in on the attack location. However, they do not provide empirical analyses to support this assertion. In their study of urban crime, Rossmo et al. (2012) examine changes to offender spatial behavior prior to offending and do find some evidence of this, but only for a small number of those studied. However, it is important to note that their study examined a very different type of offending. With respect to Hypothesis 4, we may also expect to see variation in their activity patterns over time not because of the location of the target, but because of changes in those with whom the Emir's might need to interact.

In the next section, we describe the data analyzed to test hypotheses. We begin by describing the mobile phone data and how it was collected before providing a summary of the sample of data analyzed.

2. METHODOLOGY

2.1 Mobile phone data

One consequence of mobile telephony technology is that service providers record the location, in the form of the nearest cell mast, that each call/text carried by their network is made or received from (Mobile Operators Association, 2006). A cell mast is a fixed structure

housing the electronic equipment necessary to transmit data from one device to another (Cancer UK, n.d.). This recording of mobile phone location data means that the movement of individual customers can be tracked, and this has been exploited by law enforcement as an investigative tool, and researchers as a method of collecting data.

Time-resolved locations of the mobile-phones used by the Emirs of four Islamic terrorist plots were obtained from the Metropolitan police. Mobile phones may, of course, be used by a number of people, or associates. Consequently, prior to analysis, to ensure that the movement patterns inferred from the data were generated by only one individual, it was necessary to interrogate the available data to isolate only those phones that were used by just one individual. Moreover, it is a recognized tactic (Metropolitan Police, n.d.) that terrorists may use several phones in the run up to an attack. This was observed in the current data, and consequently to provide a more complete picture of their activity, data from all mobile phones identified as being used by each subject (but only that subject) were used in what follows.

The accurate attribution of which phones were used by which subjects is thus fundamental to the accuracy of the analyses that follow. Of course, the attribution of mobile phones to actors was also critical to the police investigations, the subsequent court cases and the coroner's inquests, for which the data analyzed here were originally collated. Given the gravity of such cases and evidential standards, the task of attribution was taken very seriously. It was achieved methodically and using a combination of techniques, with all analyses conducted by two or more people. While we cannot detail these processes due to issues of sensitivity, we are confident that the attribution process was conducted as accurately as possible.

Having identified the set of telephones used by each subject, evidential records prepared for use in public court were obtained and analyzed. For the purposes of the research, we extracted the date, time and cell mast location ('cell site') for each call made or received. Cell site locations were geocoded using service provider-generated cell site identification codes and a gazetteer, which provided data with a spatial accuracy equivalent to a full unit postcode, which in the UK cover a small area of approximately 0.14 km². No data regarding the telephone numbers called or other details were extracted.

Table 1 provides a summary of the data available for each plot. The details provided have been anonymized due to the sensitivity of the data and are presented to show the period over which data concerning cell site activity were available, the percentage of hours for which call activity was recorded, and the number of cell site locations at which call activity was logged. It is evident that the coverage varies in each case, both in terms of the period of time over which data were available and the fraction of hours for which call activity was logged. This was due entirely to the nature of the attacks and the associated investigations, and is, of course, a limitation of using secondary data. In their study, Smith et al. (2008, p.51) found that plots last an average of three months from "the first known preparatory activities...to the incident date" and so it is reasonable to assume that the data analyzed here are likely to cover the period of activity during the build-up to each attack (see also Sothern et al., 2008).

INSERT TABLE 1 ABOUT HERE

In their study, Song et al. (2010, p.1019) found that users tend "to place most of their calls in short bursts...followed by long periods with no call activity". Analysis of the

timing of calls for our data suggests that the same was true here. For example, Figure 1 (top panel) shows a "timecode" of all calls logged to the phones used by the Emir involved in Plot A over the period for which data were available (For Plots B-D, see online Supplementary Information (SI) Figures 1-3). Each vertical line indicates the time a call was logged for that plot. The bottom panel of Figure 1 shows the observed distribution of waiting times (the time elapsed between sequential calls) between call logs, aggregated to hourly intervals. It also shows the expected distribution, computed assuming that the timing of calls was random¹. Inspection of the waiting time distributions indicates that the time elapsed between calls was typically shorter (typically 1-2 hours) for the observed distribution than that expected, and that far fewer calls occurred (say) 4-10 hours apart than would be expected, assuming that the timing of calls was independent. Simply put, visual inspection of the data, and a statistical analysis of the waiting time distribution between call logs, suggest that the pattern is 'bursty' or 'clumpy'.

Further inspection of the data indicated that while some of this pattern was likely due to the subjects' rhythms of activity, it was also due to the fact that some calls logged were either missed or failed attempts (calls that lasted zero seconds), which were then repeated (often) a few minutes later in an attempt to make contact. While this issue has not been discussed in previous studies (e.g. Song et al., 2010), to assume that calls are independent might provide a biased picture of the subject's mobility patterns insofar as estimates of the time spent at particular locations might be inflated by failed and missed call

¹ To calculate the expected distribution, we simulate a Bernouli trial for which the likelihood that a call will be made or received within any hourly interval is assumed to be constant (and equal to the total number of hours with calls divided by the number of hourly intervals). Using a Monte Carlo simulation, we generate 999 "trials" and for each compute the waiting time distribution and compare this to that for the observed data. This allows us to compute the mean expected value, confidence intervals and the probability of observing a given value, assuming the null hypothesis (that the timing of calls is independent) is true.

attempts. As a sensitivity test to reduce the potential influence that repeated calls at the same location might have, in what follows, we performed every analysis for each data set in its entirety (as in Song et al., 2010), and for a smaller sample for which each individual mast was counted just once in any single hour-period. The patterns for the two sets of analyses did not differ and so the latter analyses are discussed no further.

INSERT FIGURE 1 ABOUT HERE

At this point, it is important to note that unlike GPS data, 'cell siting' provides only an *approximation* of the user's actual location at the time a call was made or received. While the approach taken here follows an established methodology (Gonzalez et al., 2008; Song et al., 2010) it is necessary to outline its limitations. When a mobile phone is used the call is routed through a cell tower. In previous research, and that reported here, it is assumed that this will be the cell tower closest to the user, since this is the way call routing is intended to work. The location of the user at that time is then estimated with reference to the coverage area (represented as a voronoi lattice) of the cell site mast to which the call is connected. However, masts have different coverage areas, ranging from tens to hundreds of meters in cities, to several kilometers in rural areas (Mobile-phone Base Station Database, n.d.). Additionally, network capacity management processes mean that whilst the nearest mast will normally carry a call, this may not always be the case. Inevitably then, there will be some error in the estimate as to exactly where a caller is located at a particular time² and this must be considered when interpreting the findings of studies which use this

² For a sample of data, the size of this error could be estimated using data regarding the coverage area associated with each cell site mast to which calls were connected. However, in the current case, the cellsite data are 10-15 years old and data on the coverage of each cell site was not available for analysis.

type of data. In the current case, the individuals involved lived in urban areas, where the (higher) density of base stations means that the estimated locations are likely to be more accurate than they would be for (say) rural areas, which reduces the potential error. However, given the uncertainty discussed, it is important recognize that the data analyzed here and in previous studies provide insight into overall rather than *exact* patterns of movement.

It is also important to note that like previous studies (Gonzalez et al., 2008; Song et al. (2010), data were not generated using GPS data or a systematic sampling methodology. Instead, they were captured (only) when subjects happened to make or receive calls. Consequently, the call records obtained do not provide a complete picture of terrorist mobility. There are two consequences to this. First, as shown in Table 1, data are not available for all intervals of the day, or even all hourly intervals. The percentage of coverage was understandably higher during daylight (8am-8pm) than night-time (8pm-8am) hours (26% vs. 13% of hours covered), but these figures are quite low and are less than those reported in Song et al. (2010), who found that for a typical user, location updates were available for about 30% of the hourly Intervals considered. Given the nature of the current study this is perhaps not surprising, but the reader should bear this in mind.

It is also important to note that for plot B, the amount of data recorded reduced drastically halfway through the period. This was because the subject involved generally (but not exclusively) used one particular mobile phone, for which cell site information was unavailable from this point on. The mean number of cell site 'hits' in the earlier period (when the subject typically used a variety phones) was 16 per day, but this reduced to 2.5 during the second half of the period (when one phone was used more consistently). In addition, for plot D, there was a one-month period for which data were unavailable.

More generally, because the data are not captured continuously, and because those involved can use a number of phones, it is important to note that the data can be patchy and fail to provide a complete picture of the movement of those involved. In two of the four cases, however, they capture the subjects' movements during their attacks, suggesting that with the exception of plot B, it is unlikely that there was a systematic bias in the missing data. In what follows, however, we encourage the reader to acknowledge the limitations of the data and to consider them to represent only a proxy for true movement patterns.

2.2 Safe houses and Home locations

In all four plots, the Emirs used a safe house away from their normal home address to conduct preparatory activity. The location of these addresses formed an important part of the prosecution in each case and were used in open court, as well as being reported in the press. Consequently, these addresses and each subject's home address were used in what follows to examine the Emir's movement around these 'anchor' points. For three of the plots, only one home location and one safe house was identified. For Plot A, there were two safe houses, although these were used consecutively rather than concurrently. At any point in time then, for this plot, the Emir would have used exactly one home location and one safe houses.

3. ANALYTIC STRATEGY AND RESULTS

3.1 Predictability of movement

To see if the Emir's appeared to have routine activity spaces (Hypothesis 1), we first considered the number of cell site locations they visited and the frequency with which they

did so over the entire period for which data were available. As well as summarizing their activity patterns, this provides an indication of how predictable their patterns of movement were. To do this, following previous research on the wider population (e.g. Song et al., 2010), we identified each unique cell site mast to which each Emir's calls were logged, and calculated the frequency with which each cell site appeared in the data for that subject. Figure 2 shows an example of the spatial distribution of the cell sites for Plot A (maps for the other plots are shown as online SI Figures 4-6). The point locations are scaled proportionately to indicate the frequency with which they were visited. The lines connecting them provide an idea of the sequence and length of movement, and these too are proportionately scaled to indicate how frequently the subject moved between each pair of nodes.

INSERT FIGURE 2 ABOUT HERE

The maps for all plots, including that shown in Figure 2, suggest a routine activity space. That is, some cell site locations were clearly visited more than others, and while activity took place further afield, most activity was clustered at, around or between the safe house(s) and home locations. To examine such patterns more systematically, following previous research (Gonzalez et al., 2008; Song et. al., 2010), for each plot we computed the cumulative frequency with which an Emir's phone connected with each cell tower. Figure 3 shows the cumulative probability distributions for all four plots. For reference, it also shows the patterns observed in the Song et al. (2010) study, which examined patterns of activity for the wider population.

INSERT FIGURE 3 ABOUT HERE

The patterns shown in Figure 3 suggest that for each Emir, most call activity occurred at or near a small number of cell site locations, providing support for Hypothesis 1. Relative to the sample of people examined in the Song et al. (2010) study, it would appear that the Emirs' activity was a little more dispersed than that observed for the wider public. However, the concentration of activity was not so different to that reported in the Gonzalez et al. (2008) study, and it is important to consider that the sample size considered here is small and that context (geographical or otherwise) may matter.

3.2 Range and pattern of movement

While the above analysis suggests that the Emirs routinely visited particular nodes, it does not provide an indication of their range of movement in geographical terms. In this section, we examine this by considering: 1) the distance between sequential cell site hits; and, 2) the distance between the locations at which calls were made or received and the Emirs' home and safe houses.

Ideally, we would have isolated specific journeys for each Emir and computed the distance travelled for each (for an example of such an analysis for criminals, see Rossmo et al., 2012). However, this was not possible since calls were not made at regular intervals (e.g. every minute) and hence it is not possible to determine the locations (destinations) at which the Emirs' stopped (visited) for a period of time. Instead, we examine the distances between sequential cell site hits (for which the time between calls varied), which we consider here to provide insight into the length of specific segments of each Emir's spatial activity during a given day. When computing these distances, we use the details of the cell

tower to which each call was initially connected and calculate the distance between this location and that of the location at which the next call was made or received. Consequently, in the case that a caller was moving through an area and their calls were diverted from one cell tower to another, our analysis would not generate a series of short distances since only the first location would be included in the analysis.

Figure 4 shows the empirical cumulative distribution function for these distances for each Emir. As noted, it is not possible to isolate specific journeys for each Emir, and so each distance is considered only to provide an indication of their range of movement from one point in time to another. Figure 4 suggests that in most cases, the distances between sequential cell site hits are relatively short (e.g. around 80% are less than 6km). While not directly comparable for a variety of reasons, it is interesting to note that according to findings from the Department for Transport National travel survey (Department for Transport, 2015), for the general public, around 65% of all trips are 7.5km or less - not unlike those observed here. However, it is also apparent that some distances are substantial, in some cases exceeding 200km³. This suggests that while the movement of all Emir's was typically constrained, as expected (Hypothesis 3), there was also clear evidence of variability in their patterns of movement (explored in more detail below).

INSERT FIGURE 4 ABOUT HERE

Considering the Emir's range of movement around their home and safe houses (or anchor points), Figure 5 shows the empirical cumulative distribution functions (ECDF) for

³ For the purposes of comparison, for the general public (DfT, 2015), around 2% of all trips exceed 75km.

the distance of each cell site hit and these two anchor points. In the case of plot A, we compute the distance from the safe house they were using at the time. To enhance differentiation at shorter distances, a logarithmic scale is used for the x-axis in Figure 5. In line with Hypothesis 2, it is evident that most cell site hits are near to one or both anchor points. For example, across all plots, 40% of cell site hits are within 5km of the safe houses, and over 90% are within 20km. Interestingly, where activity was more clustered around one anchor point than the other, this tended to be around the safe house rather than the home location (see also SI Figures 4-6).

INSERT FIGURE 5 ABOUT HERE

3.3 Variation over time

The analyses presented above are for the entire time period and hence may conceal changes in the patterns of movement for each Emir over time. In this section, we examine whether this was the case. One option would have been to examine changes in the mean distance between the cell site locations the Emirs' phones were connected to and their intended attack locations. However, due to the nature of the plots, the attack locations were not discrete and hence this approach would be potentially misleading. For this reason, we conducted two alternative forms of analysis. For the first, for each plot we calculated the mean distance between cell site log locations for the corresponding Emir and their home and safe houses for each week. For the purposes of illustration, Figure 6 shows such a result for plot A (Figures for the remaining plots are shown in the online supplementary information). In this case, the patterns are imperfect but suggest a positive association, whereby the average distance traveled from the safe houses increased over

time. For the second analysis, we counted the number of unique cell site hits recorded per week to provide a different picture of spatial behavior.

INSERT FIGURE 6 ABOUT HERE

Table 2 shows simple Spearman's bivariate correlations for the mean distance between cell site log locations and the Emir's anchor points and the week of activity. The results are mixed. For two Emirs (plots A and C) their estimated range of movement from at least one anchor point increased as the time to the plot they were involved in approached. For the other two (Plots B and D), the patterns were non-significant (see also, SI Figures 7-9).

Considering the number of unique cell site hits per week, the results are again mixed. For three of the Emirs, the number of unique locations they visited appeared to increase nearer to the time of the intended attacks, but this trend was only statistically significant for two of them. For the Emir involved in Plot B, the pattern was reversed, with their pattern of movement appearing to decline nearer to the time of the attack. However, recall that for this plot, the number of observations reduced drastically half way through the interval studied as a result of this Emir largely (but not exclusively) using a single mobile phone for which location data was unavailable. In the case of this analysis, this bias in the data would clearly affect the results obtained and may entirely explain the negative correlation observed. Thus, there is some evidence to support Hypothesis 4, but for the (small) sample of terrorists considered here the precise patterns clearly varied.

INSERT TABLE 2 HERE

4. DISCUSSION

The aim of the current study was to examine the spatial behavior of a sample of UK-based Islamist terrorists. In particular, analyses were conducted to determine whether their patterns of movement resembled those of the wider public and everyday criminals, or whether the extreme nature of their offending leads to very different patterns of spatial behavior. Previous research concerned with the spatial behavior of offenders and terrorists has generally made use of datasets for which the activity of a large number of actors is available, but where few movements are available per offender (for an exception concerned with urban crime, see Rossmo et al., 2012). In contrast, in the current study data were available for only four terrorists meaning that the analyses presented are essentially case studies. However, hundreds of observations were available for each Emir over a non-trivial period of time, providing a rich set of data for a very much understudied population. Also unlike other studies, the data analysed were of mobile phone call logs. Relative to the intelligence reports used in previous work concerned with this population, this enabled us to develop a more precise picture of their spatial activity over time and to examine how this evolved.

In line with research on human movement and crime pattern theory (see above), there was a clear regularity to the spatial behavior of each Emir, which appears to be constrained by geography. First and foremost, most of their activity – estimated using data on the locations at which their calls were made or received - took place at or around a small number of locations. Second, as with the journey to crime literature for urban crime, there was a clear pattern of distance decay such that most of the time, the likelihood that an Emir was to be found at a location was inversely proportional to the distance between that location and their home or safe house locations. Third, just like the trips of members of the

wider public (Department for Transport, 2015), and the sequential locations of burglaries committed by offenders (Johnson, 2014), the movements of the Emirs (from one call log to the next) tended to involve short 'jumps' rather than lengthy journeys, suggesting a predictability to their spatial behavior.

The findings thus provide support for a small but growing body of literature, discussed above, that suggests that the activity patterns of terrorists may not be unlike those of everyday criminals. Such findings have implications for the policing of terrorism. For example, in their study, Rossmo and Harries (2011) discuss the potential utility of geographic prioritization models, which might be used to search for terrorist safe houses, other activity nodes, or future potential target locations. The current findings certainly support the potential value of such an approach for the sample studied, illustrating that most locations at which the Emir's calls were logged, tended to be near to, clustered around, or between two of their anchor points (their safe houses or home locations). A key aspect of such models is that they may help to filter the signal from the noise when a large amount of intelligence is generated for a particular plot. To elaborate, a huge amount of terrorist-related intelligence is produced daily. Yet the processing and exploitation of such data, which in its raw format is useless, lags behind (Lowenthal, 2009). Geographic prioritization approaches may help in this respect.

In addition to looking at patterns of spatial activity, we considered if and how these varied as the time to the planned attack drew nearer. As discussed above, changes in activity patterns were expected as different patterns of movement and activity are likely at different stages of a plot. The obvious value of identifying any "signatures" in changes of terrorist activity prior to a plot is that they may provide a means for prioritising suspects, and when to do so (see also, Rossmo et al., 2012). With respect to this expectation, our

findings were mixed. We found evidence that three of the four Emir's exhibited some evidence of a change in spatial behavior, but the precise nature of this change differed across subjects. Two showed an increase in the number of cell site locations at which their activity was recorded over time, suggesting that they visited more varied locations over time. For one the reverse was true, but it seems reasonable to conclude that in this case this was due to the change in the mobile phones this Emir used part way through the period (which generated substantially fewer cell site logs) for which data were available (see above), as this would likely reduce the unique number of cell site locations at which calls were logged per week, regardless of actual changes to the spatial behavior. For one Emir, the distance between their home location and those at which cell site logs were recorded increased over time, while for another the same trend was observed with respect to their safe house location. Thus, while changes were observed for three Emirs, the pattern was by no means consistent. Moreover, it is important to note that the current findings relate to a small sample of Islamic terrorists, and only to those who operated in the UK. As such, it will be for future research to examine whether such patterns are observed more generally and if so, which patterns are most consistent. Moreover, it is important to consider that there will be other reasons that people might change their spatial behaviour over time (e.g. changing job) and hence adequate caution would need to be applied before basing operational decisions on such patterns. What represents normal variation in spatial variation is also not well understood and hence future research might also seek to examine this in the general population.

The study is, of course, subject to a number of other limitations. The most obvious is that the data analyzed are incomplete. First, as noted above, the movement of the Emirs was captured using cell site logs, which are only registered when a call is made or received.

Data captured using GPS telemetry would provide more complete coverage, but these data were not available at the time of the attacks studied. Moreover, such data can only be captured on GPS enabled phones (which may be avoided by those of interest). Second, the locations of the safe houses examined here were based on police intelligence which may have been incomplete. Consequently, the possibility exists that the Emir's used additional safe houses, but that this was unknown to the police.

In concluding, we note that while terrorists may think globally, empirical research conducted to date suggests that they act locally. Preparations have to occur somewhere and the principle of least effort (Zipf, 1950) suggests that like everyone else, terrorists will not want to invest unnecessary time and resources travelling to and from locations of activity. As such, embedding their activity in familiar environments makes sense. The current research provides novel insight into the spatial behavior of a small sample of actors involved in extreme events and we hope that it will inspire further work.

REFERENCES

Beavon, D.J.K., Brantingham, P.L. and Brantingham, P.J. (1994). The influence of street networks on the patterning of property offenses. *Crime prevention studies* 2, 115-148.

Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of Political Economy*, 76(2), 169-217.

Bennett, T., and Wright, R. (1984). *Burglars on burglary: Prevention and the offender*. Aldershot: Gower Publishing.

Bernasco, W, and Nieuwbeerta, P. (2005). How do residential burglars select target areas? A new approach to the analysis of criminal location choice. *British Journal of Criminology* 45, 296–315.

Bernasco, W. (2010). A sentimental journey to crime: effects of residential history on crime location choice. *Criminology* 48(2), 389-416.

Brantingham, P. I. & Brantingham, P. J. (1993). Nodes Paths and edges: Considerations on the Complexity of Crime and the Physical Environment. *Journal of Environmental Psychology*, 13, 3-28

Cancer UK (n.d.). *Cellular Phone Towers*. Retrieved August 1, 2011 from http://www.cancer.org/cancer/cancercauses/othercarcinogens/athome/cellular-phone-towers).

Clarke, R.V. & Newman, G. R. (2006). *Outsmarting the terrorists*: Westport: Praeger Security International.

Cornish, D. B. & Clarke, R. V. (Eds.) (1986). *Reasoning Criminal - Rational Choice Perspectives* on Offending. Secaucus: Springer-Verlag Cothren, J., Smith, B. L., Roberts, P., & Damphousse, K. R. (2008). Geospatial and temporal patterns of preparatory conduct among American terrorists. *International Journal of Comparative and Applied Criminal Justice*, *32*(1), 23-41.

Crenshaw, M. (1992). How Terrorists Think: What psychology can contribute to understanding terrorism in Howard, L. (Ed.), *Terrorism: Roots, Impacts and Responses.* London, Praeger.

Cromwell, P. F., Olsen, J.N., and Avary, D. (1991). *Breaking and entering: An ethnographic analysis of burglary*. Newbury Park: Sage.

Cronin, A. K. (2009). *How terrorism ends: understanding the decline and demise of terrorist campaigns*. Oxford: Princeton University Press.

Dawkins, R. (2006). The Selfish Gene. Third edition. Oxford: Oxford University Press

Department for Transport (2015). National Travel Survey, Data Table nts0308 - Average number of trips by trip length and main mode: England, since 2002 (with chart), Retrieved 26th October 2016 from https://www.gov.uk/government/statistical-data-sets/nts03modal-comparisons#table-nts0308

Frith, M., Johnson, S.D., and Fry, H. (2017). The role of the street network in offender spatial decision making. *Criminology*, Advanced online access.

Gill, P., Horgan, J., and Corner, E. (2016). Do Terrorists Behave Like Ordinary Criminals? A Distance-to-Crime Approach. *Terrorism and Political Violence*, in press.

Gonzalez, M. C., Hidalgo, C. A. & Barabasi, A. (2008). Understanding individual human mobility patterns. *Nature*, 453, 779-782

Kenney, M. (2010). "Dumb" Yet Deadly: Local Knowledge and Poor Tradecraft amongst Islamist Militants in Britain and Spain. *Studies in Conflict and Terrorism*, 33(10), 911-932 Metropolitan Police (n.d.). 'If you suspect it, report it'. Retrieved August 3rd, 2011 from http://www.met.police.uk/so/at_hotline.htm

Mobile Operators Association (2006). *Mobile-phones and Base Stations - How mobiles work*. Retrieved July 20, 2011 from http://www.mobilemastinfo.com/images/stories/documents/fact_sheets/mobile_phones_ base_station_a.pdf

Ofcom (2011). *Mobile-phone Base Station Database*. Retrieved June 12th – August 17^{th 2011} from http://www.sitefinder.ofcom.org.uk/

Nance, M. W. (2008). Terrorist Recognition Handbook. Boca Raton: CRC Press

Post, J., Sprizak, E. & Denny, L. (2003). The terrorists in their own words: Interviews with 35 incarcerated Middle Eastern terrorists. *Terrorism and Political Violence*, 15(1), 171-184

Rengert, G.F., and Wasilchick, J. (2000). *Suburban burglary: A tale of two suburbs.* Springfield: Charles C. Thomas Publisher.

Roach, J., Ekblom, P. & Flynn, R. (2005). The Conjunction of Terrorist Opportunity: A Framework for Diagnosing and Preventing Acts of Terrorism. *Security Journal*, 18(3), 7-25

Rossmo, D. K., & Harries, K. (2011). The geospatial structure of terrorist cells. *Justice Quarterly*, *28*(2), 221-248.

Rossmo, D. K. (1999). Geographic profiling. CRC press.

Ruby, C. L. (2002). Are Terrorists Mentally Deranged? *Analyses of Social Issues and Public Policy*, 2(1), 15–26

Sageman, M. (2004). *Understanding Terror Networks*. Philadelphia: University of Pennsylvania Press

Shoval, N. & Isaacson, M. (2006). Application of Tracking Technologies to the Study of Pedestrian Spatial Behaviour. *The Professional Geographer*. 58(2), 172–183

Simon, H. (1978). Rationality as Process and Product of Thought. *The American Economic Review*, 68(2), 1-16.

Smith, B. L., Cothren, J., Roberts, P., & Damphousse, K. R. (2008). Geospatial Analysis of Terrorist Activities: The Identification of Spatial and Temporal Patterns of Preparatory Behavior of International and Environmental Terrorists. Retrieved June 26th 2011 from https://www.ncjrs.gov/pdffiles1/nij/grants/222909.pdf

Song, C., Qu, Z., Blumm, N. & Barabasi, A. (2010). Limits of Predictability in Human Mobility. *Science*, 327,1018-1021

Townsley, M., & Sidebottom, A. (2010). All offenders are equal, but some are more equal than others: Variation in journeys to crime between offenders. *Criminology*, *48*(3), 897-917.

Townsley, M., Johnson, S. D., & Ratcliffe, J. H. (2008). Space time dynamics of insurgent activity in Iraq. *Security Journal*, *21*(3), 139-146.

Wiles, P., & Costello, A. (2000). The'road to nowhere': the evidence for travelling criminals. Home Office Research Series 207. London: Research, Development and Statistics Directorate, Home Office.

Wright, R., Brookman, F., & Bennett, T. (2006). The foreground dynamics of street robbery in Britain. *British Journal of Criminology*, *46*(1), 1-15.

Zipf, G. (1950). The principle of least effort. Reading, MA: Addison-Wesley.

Table 1 Period of coverage for each plot from the first hour of cell site activity to the last, the number of cell site 'hits' and the number of unique cell sites at which call activity was logged

	Full days of coverage	Hours (hrs) of coverage*	%hrs with cell	Number of cell	Unique cell
			site activity	site 'hits'	sites visited
Plot A	77	1,838	15	548	90
Plot B	131	3,127	13	1,073	61
Plot C	161	3,842	11	947	131
Plot D	201	4,808	28	3,789	169

*NOTE: For hours of coverage, this is calculated from the first hour of cell site activity to the last and so it is not simply the number of days of

coverage multiplied by 24.

Table 2 Simple Spearman's rank correlations between the mean weekly distance travelled

 between cell site log locations and safe houses and the week of the plot, and Pearson's

 correlations between the number of cell site hits and the week of the plot

	Distance from Home	Distance from Safe	Variability in cell site			
	Location	house	hits			
Plot A	0.05	0.76***	0.42			
Plot B	0.24	0.27	-0.54***			
Plot C	0.59**	0.21	0.48***			
Plot D	-0.14	-0.01	0.75***			
*** p<0.01 **p<0.05 *p<0.10 (two-tailed)						

Figure 1 The timing of calls logged by the Emir for Plot A (Top Panel) and the observed and expected (vertical bars are 95% confidence intervals computed using a Monte Carlo simulation) waiting time distribution between call logs (Bottom Panel)





Figure 2 Spatial patterns of the cell site nodes visited during Plot A (Top panel: complete







Figure 3 Fraction of call logs recorded at the most visited locations





Figure 5 Empirical Cumulative Distribution Functions of the distance (in km) of cell site hits from (home and safe house) anchor points (Plots A (top left)-D (bottom right)).





Figure 6 Mean weekly distances (in km) of cell site log locations from safe houses for Plot A

ONLINE SUPPLIMENTARY INFORMATION (SI)

SI Figure 1 Timing of calls logged by the Emir involved in plot B (Top Panel) and the observed and expected (vertical bars are 95% confidence intervals computed using a Monte Carlo simulation) waiting time distribution between call logs (Bottom Panel)



SI Figure 2 Timing of calls logged by the Emir involved in plot C (Top Panel) and the observed and expected (vertical bars are 95% confidence intervals computed using a Monte Carlo simulation) waiting time distribution between call logs (Bottom Panel)





SI Figure 3 Timing of calls logged by the Emir involved in plot D (Top Panel) and the observed and expected (vertical bars are 95% confidence intervals computed using a Monte Carlo simulation) waiting time distribution between call logs (Bottom Panel)





SI Figure 4: Spatial patterns of the cell site nodes visited during Plot B (Top panel: complete





SI Figure 5: Spatial patterns of the cell site nodes visited during Plot C (Top panel: complete





SI Figure 6: Spatial patterns of the cell site nodes visited during Plot D (Top panel: complete







В





С



SI Figure 9: Mean weekly distances (in km) of cell site log locations from safe houses for Plot

D



NOTE: for this plot, data were unavailable for a one-month interval (weeks 19-22 of the 30week interval). In the figures shown, we exclude this period as the aim of the analysis was simply to examine whether the Emir's spatial behavior changed over time.