

TARGET CHOICE DURING EXTREME EVENTS: A DISCRETE SPATIAL CHOICE MODEL OF THE 2011 LONDON RIOTS*

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KEYWORDS: riots, random utility model, discrete choice, spatial decision making

Riots are extreme events, and much of the early research on rioting suggested that the decision making of rioters was far from rational and could only be understood from the perspective of a collective mind. In the current study, we derive and test a set of expectations regarding rioter spatial decision making developed from theories originally intended to explain patterns of urban crime when law and order prevail—crime pattern and social disorganization theory—and consider theories of collective behavior and contagion. To do this, we use data for all riot-related incidents that occurred in London in August 2011 that were detected by the police. Unlike most studies of victimization, we use a random utility model to examine simultaneously how the features of the destinations selected by rioters, the origins of their journeys, and the characteristics

* The authors acknowledge the financial support of the Engineering and Physical Sciences Research Council (EPSRC) under the grant ENFOLD-ing – Explaining, Modelling, and Forecasting Global Dynamics, reference EP/H02185X/1. The authors also would like to thank the Metropolitan Police Service, particularly Professor Betsy Stanko and Trevor Adams, for providing data. Direct correspondence to Shane D. Johnson, Department of Security and Crime Science, University College London, 35 Tavistock Square, London WC1H 9EZ, United Kingdom (e-mail: shane.johnson@ucl.ac.uk).

of the offenders influence offender spatial decision making. The results demonstrate that rioter target choices were far from random and provide support for all three types of theory, but for crime pattern theory in particular. For example, rioters were more likely to engage in the disorder close to their home location and to select areas that contained routine activity nodes and transport hubs, and they were less likely to cross the Thames River. In terms of contagion, rioters were found to be more likely to target areas that had experienced rioting in the previous 24 hours. From a policy perspective, the findings provide insight into the types of areas that may be most vulnerable during riots and why this is the case, and when particular areas are likely to be at an elevated risk of this type of disorder.

For certain types of civil disorder, such as a protest against a government, the spatial distribution of unrest often can be explained by the locations of key targets, such as nearby government buildings and symbolic public spaces. In the case of rioting, which commonly lacks the central and coherent political motivation of protest, a wide range of different factors may contribute to an individual's decision as to whether to engage in the disorder. Varying motivations also may affect the choice of where individuals choose to offend or the consistency with which different factors influence offender spatial decision making. If this is the case, then the spatial distribution of rioting should be difficult to predict *a priori* or to explain *a posteriori*. Moreover, one might anticipate that theories designed to explain offender decision making for urban crimes committed when law and order prevail would provide little insight into the spatial decision making of those engaged in rioting when they do not.

To examine this issue, we explore the spatial distribution of the riots that occurred in London during August 2011. Between August 6 and 10, 2011, riots occurred at numerous locations across the United Kingdom. Violence initially broke out after a peaceful protest by family, friends, and members of the community of Mark Duggan, who was shot and killed by police officers in Tottenham, North London, on August 4. On August 6, riots broke out in neighboring communities. For five nights, the riots continued, initially throughout the capital and subsequently throughout the country. After the initial disturbances, the unrest on subsequent nights grew in intensity, before large numbers of police were deployed across the capital and other cities, leading to a restoration of order. It is estimated that the final cost of liabilities associated with damages from the riots is in the region of £250 million (Metropolitan Police Service, 2012).

Predominantly, the riots took place in the highly populated areas of London, Birmingham, and Manchester. However, even within these cities, and particularly in London, civil unrest occurred in some areas but not

in others. Some areas within these cities experienced persistent unrest on more than one night, whereas others experienced no unrest at all. We examine the extent to which these patterns might be considered random or whether systematic patterns emerge that would plausibly be explained by existing criminological theory concerned with crime patterns. To do this, we use a discrete spatial choice approach (McFadden, 1974) to compare the characteristics of those locations at which rioters chose to commit offenses with the characteristics of those locations at which they could have engaged in crime but did not. The approach is distinct from prior research on the spatial distribution of civil disorder in that we consider not only where rioters engaged in these activities but also how their decisions to do so were affected by where they live. In addition, we examine whether and how the overall spatial decision making of offenders changed as the civil disorder evolved and eventually came to an end. Given the political salience of riots, testing theories concerned with the dynamics of such events not only advances criminological understanding but also carries considerable policy value.

This article is organized as follows: First, we discuss a theoretical account of offender spatial decision making, taking into account literature including that concerned with collective behavior and environmental criminology. We explain how the London riots of August 2011 present an opportunity to explore the micrologic target choice of offenders during events of civil disorder (Wilkinson, 2009), particularly regarding the question of whether there are any regularities across the population or, conversely, whether targets are chosen with apparent randomness because of the widely varying motives of individuals. We present a description of the analytical strategy adopted, explain why such an approach is appropriate, and then report our findings. Finally, we discuss the implications of the findings for criminological theory.

THEORETICAL ACCOUNTS AND PREVIOUS EMPIRICAL STUDIES

Empirical research concerned with riots has for some time focused on countering theories of irrational and “animal-like” behavior within groups of individuals, such as those posited by Le Bon (1960) and Freud (1957). These theories assert that a collective act of violence can be understood only by considering the behavior of a crowd as being driven by an irrational collective mind with targets more or less selected at random. Since this early work, however, researchers have argued that the process of rioting is driven by a more rational process (e.g., Berk, 1974; Mason, 1984; McPhail, 1991). According to such accounts, individuals decide whether to engage in the

rioting based on the available information and some internal cost–benefit calculation. Even after individuals have decided to engage, they have more control over their actions than is suggested by early accounts of collective violence. For instance, some studies have found evidence that targets are chosen selectively by rioters (Auyero and Moran, 2007; Berk and Aldrich, 1972; Rosenfeld, 1997) and indeed that, by considering those targets, we can learn more about the dynamics involved in a riot process (Martin, McCarthy, and McPhail, 2009). This perspective is the one adopted in this study.

Criminologists have been concerned with the spatial analysis of crime for some time. Indeed, as early as the nineteenth century, Quetelet (1983) examined spatial patterns of crime across the provinces in France, noting that there were regularities in the variation in crime risk across geographic areas (see also Guerry, 1832; Mayhew, 1965). Shaw and McKay's (1969) classic research also examined variation in spatial patterns, but this time analyses were conducted within cities. Since these landmark studies, a large body of research, using methods of increasing sophistication, has emerged, and with respect to patterns of victimization, the research has shown that crime does in fact form spatial clusters (for recent reviews, see Johnson, 2010; Weisburd, Bruinsma, and Bernasco, 2009). Considering attempts at explanation, a variety of theories exist. In this article, we focus on three sets of accounts, each of which offer different perspectives regarding offender spatial decision making: routine activity and crime pattern theory, social disorganization theory, and collective behavior and contagion. Broadly conceived, these different theoretical accounts may be thought of as informing why an offender might become aware of particular opportunities and favor some over others, how the social makeup of an area might influence the likelihood of crime occurring within it, and how offender decision making might be influenced by the current or recent criminal activity of others. We discuss each of these accounts in turn in the next section.

ROUTINE ACTIVITY AND CRIME PATTERN THEORY

Theories of urban crime have long been inspired by ideas from ecology (see Felson, 2006). Many of these theories stem from Cohen and Felson's routine activity theory (1979), which states that the necessary conditions for crime to occur are the convergence in space and time of a motivated offender, a suitable target, and the absence of a capable guardian. According to this theory, the routine activity patterns of people shape the opportunities for this convergence and, hence, for crime to occur. In this way, crime is viewed as a largely parasitic activity, sustained by everyday routines.

Crime pattern theory (CPT; Brantingham and Brantingham, 1993) more specifically examines how activity patterns shape awareness of criminal opportunities and how this may lead to the emergence of spatial concentrations of crime. According to CPT, people create mental maps of their routine activity spaces, which contain several key elements. For example, routine activity nodes represent those places that individuals visit frequently or at which they spend much of their time. These places would include—but are not limited to—a person's home location, his or her place of work, recreation centers/facilities, and so on. Prominent features of the urban environment also are expected to shape the awareness spaces of people. For example, much of the population will be familiar with, and may spend a significant amount of time at, local landmarks, including retail centers, transport hubs such as train stations, and schools (Bernasco and Block, 2009).

Awareness spaces are assumed to develop for these nodes (landmarks) and the areas around them, but also for the pathways that must be traveled to move from one routine activity node to another. In the case of a single offender, it is at the locations that his or her awareness spaces overlap with suitable opportunities for crime that the offender is anticipated to engage in criminal activity. In support of this, and in line with the principle of least effort (Zipf, 1949), studies of the journey to crime (for a recent review, see Townsley and Sidebottom, 2010) indicate that, despite the many and varied opportunities available to them, most offenders commit crime close to their home location. In the case of more general crime patterns, whereas offender awareness spaces will largely be idiosyncratic, there will be some overlap between them, and it is where these overlaps intersect with suitable opportunities for crime that, according to CPT, spatial concentrations of crime are most likely to form.

On the basis of crime pattern theory, we would therefore expect that, *ceteris paribus*, during civil disorder, offenders will be more likely to choose locations to offend that are close to where they reside, which contain schools, public transport hubs, retail centers, and locations that are proximate to the city center. In the case of rioting, of course, we note that retail centers, in particular, may be targeted simply because they contain opportunities for looting. Nevertheless, we expect retail centers to act as crime attractors and that, where they are targeted, the retail centers chosen will be those that are likely to be within an awareness space of an offender.

Instead of being time stable, awareness spaces are likely to change over the life course (see Bernasco, 2010), with some nodes of activity (e.g., school and work) featuring more prominently for one age group than for another. Similarly, as people mature from childhood to adulthood, their mobility and routine activity nodes are likely to change (e.g., Snook et al., 2005; Townsley and Sidebottom, 2010), thereby extending the range of their awareness

spaces. For these reasons, our expectation is that if CPT applies in the case of riots, then younger offenders will be more likely to target areas that contain routine activity nodes that are particularly relevant to them, such as schools, and are more likely to select targets that are closer to their home location, reflecting their more limited awareness spaces.

As discussed, offender awareness of a location is likely to be inversely related to the distance between that location and their routine activity nodes. This theory is supported by ethnographic studies of offender behavior (e.g., Rengert and Wasilchick, 2000) and is illustrated in the pattern of distance decay exhibited in research concerned with the journey to crime. In the case of the latter, distance can be considered a measure of impedance that affects the likelihood of an individual becoming familiar with a particular area. However, factors other than distance can influence awareness in this way. For example, features of the urban environment, such as natural barriers (e.g., rivers) or transport links (e.g., underground stations), may impede or facilitate the ease with which people can travel to, and hence become familiar with, a particular location. In their study, Clare, Fernandez, and Morgan (2009) examined the extent to which features of the physical environment, such as major highways and rivers, act as barriers to an offender's choice of burglary location. They found that the presence of either feature between the home location of an offender and a potential target area decreases the likelihood that the latter will be selected. In the case of London, it is likely that the greatest such barrier and, thus, influence of this kind on the spatial decision making of offenders is the River Thames. The Thames divides London into distinct northern and southern areas, and although bridges connect North and South London, the presence of the Thames can substantially impede movement between the two. Given the size of the river and the scope for natural barriers to shape offender awareness spaces, our expectation is that offenders will be less likely to cross the river to offend.

SOCIAL DISORGANIZATION THEORY

Theories of social disorganization consider how variation in the social fabric of a community might impact levels of crime (Shaw and McKay, 1969; see also Bursik, 1988). In particular, they suggest that relative to other neighborhoods, in those for which there is a sense of community (e.g., Fisse and Braithwaite, 1983), residents are more likely to intervene to prevent crime. For such theories, social cohesion is a necessary precondition for members of neighborhoods to act in this way, or for the neighborhood to possess what Sampson, Raudenbush, and Earls (1997) referred to as *collective efficacy*.

Social cohesion can be influenced by several factors. For example, in neighborhoods with a transient population, there will be relatively fewer

opportunities for the formation of stable social ties (e.g., Coleman, 1988), thereby eroding the potential for cohesive bonds to form. Ethnic diversity also has been discussed as a potential barrier to social cohesion, with non-homogeneous communities failing to share a consensus (e.g., Sampson and Groves, 1989), thereby decreasing the likelihood that they will act collectively.

Deprivation too has been discussed in this context. In particular, rather than having a direct negative effect on crime (as would be argued by advocates of dispositional theories of crime, e.g., Agnew, 1992), Shaw and McKay (1969) argued that, in disadvantaged neighborhoods, communities lack the resources and organizational base of their more affluent counterparts, which limits the extent to which they can exert informal social control to deter crime in the neighborhood.

Social disorganization may influence the likelihood of riots occurring in a neighborhood in many ways. First, cohesive neighborhoods may exert control over their own residents to reduce the likelihood that they will engage in disorder, or form a rioting crowd. Second, signs of cohesion within a neighborhood might affect whether offenders—wherever they live—choose to engage in disorder within that neighborhood. In the second case, social cohesion might be perceived as acting as a social barrier (Bernasco and Nieuwbeerta, 2005) that deters rioters from targeting or coalescing in a neighborhood. On the basis of theories of social disorganization, we would anticipate more riot-related events to occur in those neighborhoods in which social cohesion may be low, in particular in those neighborhoods that have higher population churn rates, greater ethnic diversity, and that are more deprived.

COLLECTIVE BEHAVIOR AND CONTAGION

Recognizing that an individual's spatial decision making might be influenced by the decisions of others, Bernasco (2006) considered the likely impact of co-offending on spatial patterns of crime. However, the current study is somewhat distinct from much of the previous work on offender spatial decision making, including that on co-offending. This is principally because, for rioting, the mutual activity of previously unacquainted offenders can potentially affect the target choices of others. Moreover, compared with influences that are unlikely to change dramatically on a short time scale, such as offender routine activity nodes, in the case of riots, the actions of others may have a much more dynamic impact on offender spatial decision making. For instance, an offender may choose a location to offend based on where offenses are currently taking place or where they occurred in the past. One reason for this is the idea of safety in numbers, whereby the perceived risk of arrest is likely to be lower in those areas where

rioters substantially outnumber law enforcement (Epstein, 2002; Granovetter, 1978).

Some researchers have suggested that a social contagion process was at least partly responsible for the severe escalation and perseverance of observed patterns during the riots in London (e.g., Gross, 2011). Indeed a process of social contagion, possibly facilitated by social networks or conventional media reports, could lead to the presence of more motivated offenders at particular locations. This concept of social contagion between individuals has been used to model many social processes including the spread of innovation (e.g., Rogers, 1995; Walker, 1969), policies (e.g., Elkins and Simmons, 2005; Shipan and Volden, 2008), opinion formation (e.g., Huckfeldt and Sprague, 1995; Schelling, 1978), democratization (e.g., Elkink, 2011; O'Loughlin et al., 1998), and of course, rioting and urban disorder (e.g., Granovetter, 1978; Midlarsky, 1978; Myers, 2000). However, as outlined by Myers (2000), care must be taken in interpreting the concept of contagion to avoid confusion between irrational actors having no choice in getting "swept up" in rioting—as would be the case in contagion of a disease and, of course, the interpretation of riots by Le Bon (1960)—and those that are more willing to engage because of the contagion after weighing up the costs and benefits of doing so, which is the approach we take here.

In the case of riots, a process of social contagion might encourage potential offenders to engage in the disorder more so than they otherwise would. For example, Wortley (2001) argued that situational precipitators, such as environmental cues, events, or influences, can prompt, pressure, permit, or provoke criminal behavior (see also Wortley, 2008). It is possible that visible signs of rioting act as precipitators that encourage potential offenders to engage in the disorder. In this way, a form of contagion might be considered to operate if it is the case that those who live near to, or happen to pass by, riots are encouraged to engage in the disorder. This would assume that witnessing such disorder serves to prompt, pressure, permit, or provoke such behavior. It is important to be clear that such an argument does not assume that offenders cease to act like rational agents but that the decision to engage in a criminal event can be dynamic and may be influenced by more than an individual's internal desires or motivations. In the case that this explanation has a part to play, we would expect that, where there have recently been riots, this should generate an increase in the number of offenders that are willing to engage in the disorder, but for those that participate, their offending would be expected to be local.

An alternative form of a contagion-like process also could operate by attracting offenders to particular areas, regardless of how far they would need to travel to reach them. In this case, particularly if this were the dominant process, the assumption would be that offenders are in a state of

readiness to offend, and that their awareness of riot locations, or where they are planned to take place, merely influences *where* they decide to engage in the disorder. In this case, the distance between where offenders live and offend would be expected to play a more limited role in offender spatial decision making than has been observed for other types of offenses.

In this study, we take the perspective that a motivated offender will make an independent choice of where to offend; however, that choice may depend on where previous outbreaks of disorder have recently occurred—a form of event dependency (see Johnson, 2008). In other words, we test whether unrest at a particular location results in offenders being more likely to choose that particular location, as opposed to other locations—that would otherwise be equally attractive to rioters—where there is no unrest. We would expect, *ceteris paribus*, rioters to be more likely to select a site at which prior offenses have taken place recently. Additionally, in the event that those engaged in riots select targets by engaging in at least a crude form of rational decision making, we would expect to observe a pattern of decay for the distance between their home and offense locations.

HYPOTHESES

Based on the preceding theoretical discussion, we have derived a set of expectations regarding the spatial decision making of rioters. For clarity of presentation, these are summarized in table 1. Each of these hypotheses will be tested subsequently using data for crimes committed during the 2011 London riots that were detected by the police.

ANALYTIC STRATEGY

Studies that examine patterns of crime at the area level usually examine the characteristics of one of two areas of interest—the location from which the offender originated or resides or the location at which the offense occurred. Studies of the former imply that characteristics such as the demographics of an area will in some way contribute to the number of motivated offenders residing in that area at a given time (e.g., Shaw and McKay, 1969). Studies of the latter suggest that characteristics of an area may increase the opportunity for crime, given the presence of motivated offenders (e.g., Bernasco and Luykx, 2003; Brantingham and Brantingham, 1995). However, as Bernasco and Block (2009: 94) pointed out, “the tendency for crime to take place relatively close to where the person committing it lives (indeed sometimes at home) has led many researchers to confuse the origins and the destinations of criminal events.” In part, this limitation has been addressed by studies concerned with the journey to crime (e.g., Block, Galary,

Table 1. Summary of Hypotheses Organized by Theoretical Perspective

Theoretical Perspective	Hypothesis
Crime pattern theory	<ol style="list-style-type: none"> 1. Rioters are more likely to offend in areas that are closest to the area in which they reside. 2. Relative to adult offenders, juvenile offenders are more likely to offend in an area that is closer to the area within which they live. 3. Rioters are more likely to offend in areas that contain a school, and this is particularly the case for juvenile offenders. 4. Rioters are more likely to offend in areas that contain transport links, in this case, underground train stations. 5. Rioters are more likely to offend in areas that contain more retail facilities. 6. Rioters are more likely to offend in areas that are closer to the city center. 7. Rioters are more likely to offend at locations on the same side of the River Thames as their residence.
Social disorganization theory	<ol style="list-style-type: none"> 8. Rioters are more likely to offend in areas with higher population churn rates. 9. Rioters are more likely to offend in areas with greater ethnic diversity. 10. Rioters are more likely to offend in areas with higher levels of deprivation.
Collective behavior and contagion	<ol style="list-style-type: none"> 11. Rioters are more likely to offend in locations that have recently experienced unrest.

and Brice, 2007; Smith, 1976; Wiles and Costello, 2000). However, Bernasco and Nieuwbeerta (2005) and Clare, Fernandez, and Morgan (2009) rightly emphasized that such approaches do not consider the locations that offenders do *not* target, and therefore, the distance to crime is treated as a dependent variable rather than as an explanatory or independent one.

An alternative approach to analysis is the random utility model (McFadden, 1974) or discrete choice approach. In this section, we discuss the approach, starting with a few examples to illustrate the logic of the method, and then we describe the statistical model applied. Regarding theoretical models of utility in criminology, rational choice theory (Cornish and Clarke, 1986) explicitly considers offender decision-making processes at the event level. Accordingly, when considering whether to offend, it is argued that offenders engage in a rudimentary form of cost–benefit calculus, deciding to offend when the benefits of such action are perceived to outweigh the associated effort and risk (jointly, the associated costs). In terms of spatial decision making, it has been suggested that this is a multistage process, with offenders first selecting an area within which to offend and then selecting a specific target (e.g., Bennet and Wright, 1984; Bernasco and Nieuwbeerta, 2005; Cornish and Clarke, 1986). In the case of area selection, individuals

are assumed to choose the option from a set of alternatives that they perceive will provide them with the greatest utility (the net outcome of their cost–benefit calculus).

More detail will be provided in this article about the discrete choice approach, but this method can be used to model such decision making. In particular, it can be used to consider simultaneously the characteristics of the offenders, the origin from which their journey to crime is likely to have started, the destination selected, and the set of alternative destinations that could have been selected but that were not. To date, this approach has been applied to offender target choice for residential burglary (Bernasco and Nieuwbeerta, 2005; Clare, Fernandez, and Morgan, 2009) and street robbery (Bernasco, 2009; Bernasco and Block, 2009; Bernasco, Block, and Ruiter, 2012). In such studies, the distance between an offender's home location and the choice of target is treated as an independent variable and has been found to be a good predictor of the areas in which he or she chooses to offend. More interestingly, however, other variables, such as the presence of schools (Bernasco and Block, 2009), also have been shown to influence offender spatial decision making.

In addition to examining the influence of a particular variable on offenders in general, in some studies, interaction terms are used to estimate whether it is the case that some factors influence the target choices of one group of offenders more than others. For example, Bernasco and Nieuwbeerta (2005) and Clare, Fernandez, and Morgan (2009) found that the effect of distance is more pronounced for younger offenders than it is for adults (those older than 18 years of age), although the results were only statistically significant in the latter study.

According to rational choice theory, offender decision making will be imperfect or bounded both as a consequence of offenders not having access to complete information and as a result of observers of an offender's choices being unable to account fully for the utility calculation that the offender performs. Nevertheless, according to this framework, the utility of one choice is compared with the utility of others, and the one that offers the best perceived utility to a particular offender is the one selected. Of course, the information that is available to the observer is limited, and the information available to the offender is assumed to be idiosyncratic and hence to vary across offenders.

In terms of formal methods for modeling decision making of this kind, the discrete choice approach is a class of model that concerns an individual's choice between a set of two or more discrete alternatives (for an overview, see Train, 2003). To specify our model of discrete choice, we denote j as a member of the set of alternatives from which chooser i selects a single zone. In this case, the set of alternatives is given by the set of U.K. census Lower Super Output Areas (LSOA) that partition Greater London (see the

subsequent discussion). Supposing that offender i is to choose a member of the set of alternatives in which to offend, we assume that he or she will choose the alternative that maximizes their utility. In other words, if the utility for offender i choosing zone j in which to offend is given by U_{ij} , then the offender will choose the zone k such that $U_{ik} > U_{ij}$ for all $j \neq k$.

We model the utility of offender i choosing zone j as:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \quad (1)$$

where V_{ij} is the utility gained by offender i choosing zone j that is associated with some (systematic or) averaged set of preferences over the population, and ε_{ij} is the utility gained from unobserved personal preferences and the idiosyncrasies of each rioter. For our model, we have:

$$V_{ij} = \sum_{m=1}^M \beta_m X_{mij} \quad (2)$$

where M is the number of characteristics associated with the utility that we are to explain, and it corresponds to the total number of independent variables for which data are captured at the area level. In this formulation, X_{mij} is the measured value of attribute m for offender i choosing to offend in zone j , and β_m is a coefficient associated with attribute m —estimated from patterns in the data—in the evaluation of the utility of each available choice. If attribute X_m is estimated to play little or no role in the observed choices, then β_m will approach zero.

Assuming that the error terms that account for the idiosyncrasies over the population are independently and identically distributed according to an extreme value type 1 distribution (Gumbel distribution), one can show that (McFadden, 1974) the probability an offender chooses zone j is given by:

$$\begin{aligned} P(Y_i = j) &= \frac{\exp(V_{ij})}{\sum_{k=1}^J \exp(V_{ik})} \\ &= \frac{\exp(\beta_1 X_{1ij} + \beta_2 X_{2ij} + \cdots + \beta_M X_{Mij})}{\sum_{k=1}^J \exp(\beta_1 X_{1ik} + \beta_2 X_{2ik} + \cdots + \beta_M X_{Mik})} \end{aligned} \quad (3)$$

where J is the number of zones available for the offender to choose between. This is the conditional logit model, and the β_m may be estimated using maximum likelihood estimation. The $\exp(\beta_m)$ are partial coefficients and are hence interpreted as the multiplicative effects of a one-unit increase in a particular attribute of an area on the probability of chooser i selecting that area. Thus, if, for some variable m , $\exp(\beta_m)$ equals 1, this means

that there is no association between that variable and offender spatial decision making. Values above one suggest that the likelihood of an area being chosen is positively associated with the variable considered. All models are estimated using STATA 10 SE (StataCorp, College Station, TX).

DATA

In executing our research design, we are interested in offender decision making at the area level, and our chosen unit of analysis is the U.K. census LSOA. Data exist across the complete set of 4,765 LSOAs in the Greater London area, and each LSOA typically consists of around 1,500 residents.

These areas are somewhat smaller than the units of analysis used in some of the previous research using the discrete choice approach (e.g., Bernasco and Nieuwbeerta, 2005; Clare, Fernandez, and Morgan, 2009) and indeed are smaller than many previous empirical studies of rioting, which often consider spatial distributions of rioting at a national level (Myers, 2000, 2010; Olzak and Shanahan, 1996; Spilerman, 1970, 1971, 1976). Distributions at finer scales of analysis have shown the complexities inherent in the dynamics of riots and often can seem to raise more questions (e.g., Abudu Stark et al., 1974; Bohstedt and Williams, 1988); however, this approach enables us to test the consistency with which targets are chosen during rioting. The advantage of smaller sized units of analysis in the discrete choice approach is that the explanatory variables are more representative of the population and characteristics of each area.¹

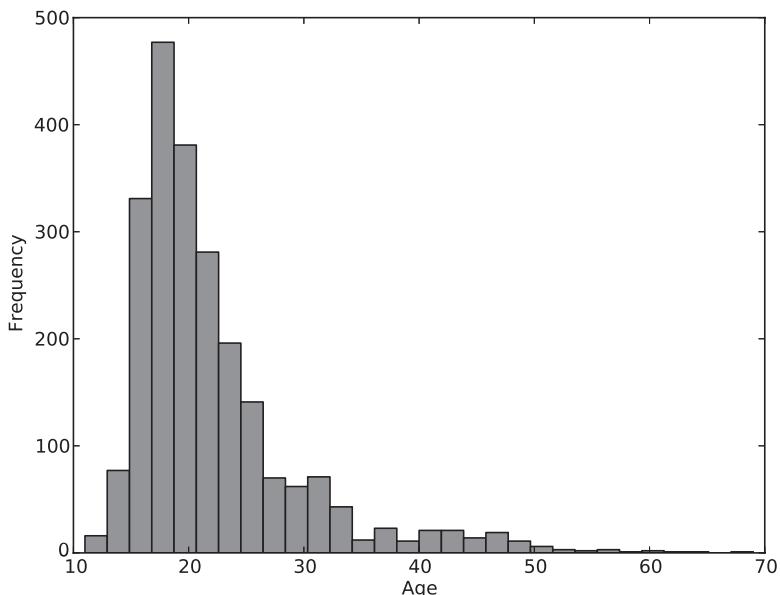
As discussed, factors other than distance are likely to affect offender spatial decision making, and hence, propinquity should be considered as just one explanatory variable alongside others. In the sections that follow, we describe each of the independent variables, identifying their provenance and how they were manipulated, where appropriate. Before doing so, however, we discuss the dependent variable.

POLICE CRIME DATA

The police data consist of all offenses that were detected, and that were identified as having been associated with the riots, by the Metropolitan police for the period August 6–11, 2011. All such offenses occurred within

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1. One issue with using smaller areas is that failing to account for potential spillover effects may lead to errors of inference. Spillover effects occur if an offender chooses a location to offend based on the characteristics of nearby areas rather than on the area itself. To address this issue, the models also were tested with spatially lagged variables. The results were consistent with the model with no spatial lag, and hence, the results were not included in this study.

Figure 1. Histogram Showing the Age Distribution of Offenders During the Riots



Greater London. Each record contained an identifier of the area within which the offense took place, the area in which the offender was recorded as living, the date and time at which the offense was estimated to have occurred, and the age of the offender. No offender appears in the data more than once. Figure 1 shows the age distribution of offenders. A large proportion of the offenders is younger than 20 years of age; however, offenders across the age spectrum are represented, creating the skewed distribution observed—a distribution that is very similar to the typical age–crime curve (e.g., Stolzenberg and D’Alessio, 2008). Of the available data ($N = 3,914$), 2,299 records contained entries for both the residential and the offense location. Only these data were used in the analysis, and table 2 details the daily distribution of recorded riot events.

Table 3 details the types of offenses committed for the 2,299 records used in the analysis. Most crimes were incidents of burglary or theft, which supports the common view that looting was prevalent during the riots, and therefore, it may have influenced the target choice of offenders. Indeed, most crime types identified include those that would commonly be associated with rioting behavior (cf. Abudu Stark, 1974). Because our primary interest lies in identifying the factors that most consistently

Table 2. Number of Detections Analyzed by Day of Unrest

Date	Number of Arrest Records	Number of LSOAs Affected
August 6, 2011	54	20
August 7, 2011	232	42
August 8, 2011	1,477	247
August 9, 2011	446	162
August 10, 2011	90	55
Total	2,299	436

NOTE: The total number of LSOAs affected is the total number of LSOAs that experienced rioting over the 5 days.

Table 3. Distribution of Different Crime Types Over the 5 Days of Rioting ($N = 2,299$)

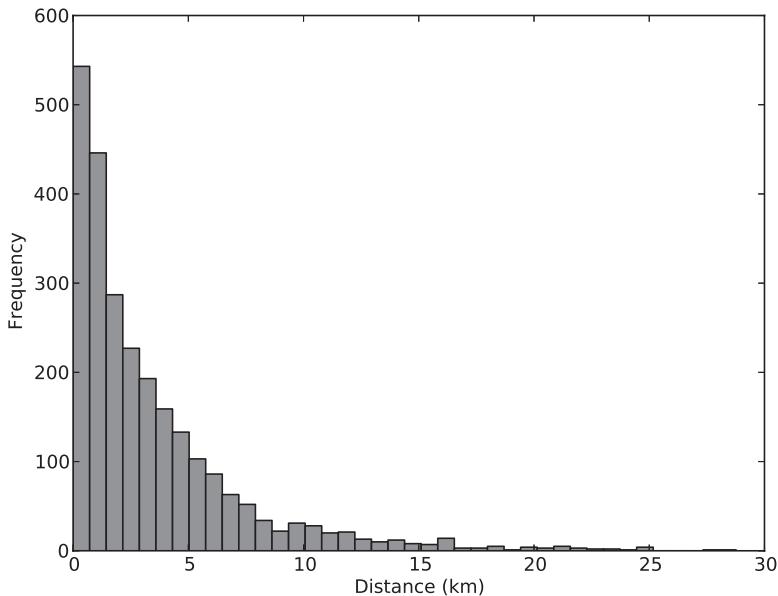
Offense Type	Percentage of Offenses
Burglary	59.1
Theft	11.4
Criminal damage	6.4
Violence against the person	4.5
Robbery	1.7
Other	16.8

influenced offender spatial decision making during the riots, we analyze all the data.²

To implement the discrete choice model, it was necessary to calculate the distance between the LSOA within which each offender was recorded as living and the LSOA in which he or she committed the offense. To do this, in line with previous research of this kind, we computed the Euclidean distance between the LSOA centroids for these origin and destination areas. When an offender committed an offense within the LSOA within which he or she resides, we computed the distance between the more precise locations at which he or she were recorded as living and the locations at which he or she committed the offense. Figure 2 shows the distribution of these journey-to-crime distances. Consistent with previous studies, and in line with the expectations of CPT, we observe a clear pattern of distance decay. Moreover, the scale and central tendency of the distribution of distances traveled is very similar to that for other types of crime (see Rossmo, 2000).

2. In addition to analyzing all incidents together, we conducted analyses separately for those arrests associated with crimes against property (burglary and criminal damage) and for all other offenses. It was not possible to conduct separate analyses for crimes against the person because of the low numbers of offenses involved. The patterns of results (available upon request) were consistent with those reported in the article and hence are discussed no further.

Figure 2. Distance Decay Histogram Showing the Number of Instances Where a Given Distance Was Traveled Between the Residential Location of a Rioter and the Location of the Offense Committed



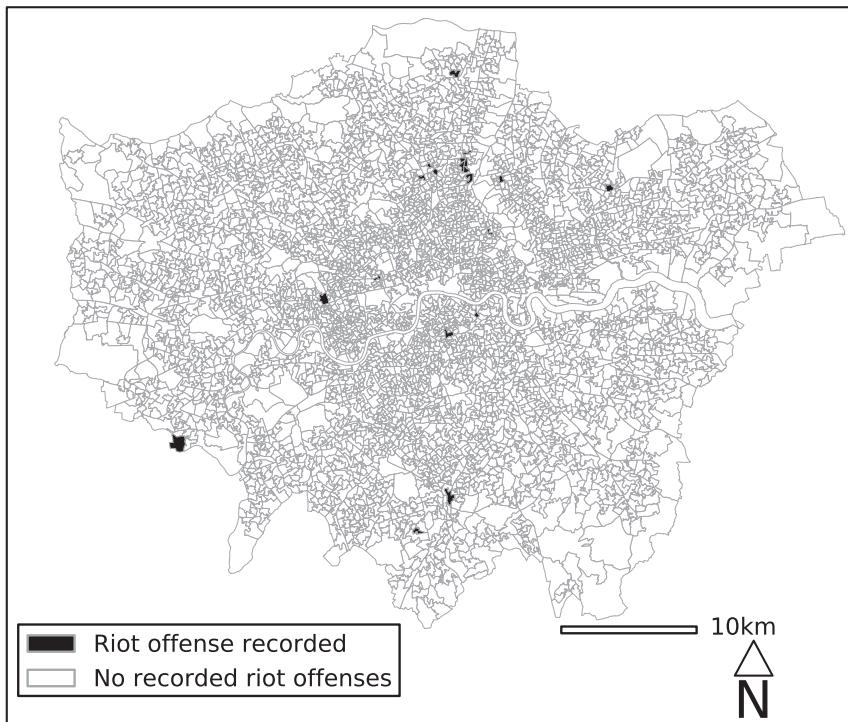
Offenders are more likely to engage in civil unrest at locations that were close to where they reside.

Figure 3 shows a map of Greater London and the LSOA geography. The LSOAs within which offenses occurred on the first day of unrest (August 6) are highlighted. Meanwhile, figure 4 shows the evolution of the spatial distribution of riot events in central London on the second, third, fourth, and fifth days of unrest. A visual inspection of figure 4 suggests that the areas in which rioting occurred varied somewhat from day to day.

CRIME PATTERN THEORY VARIABLES

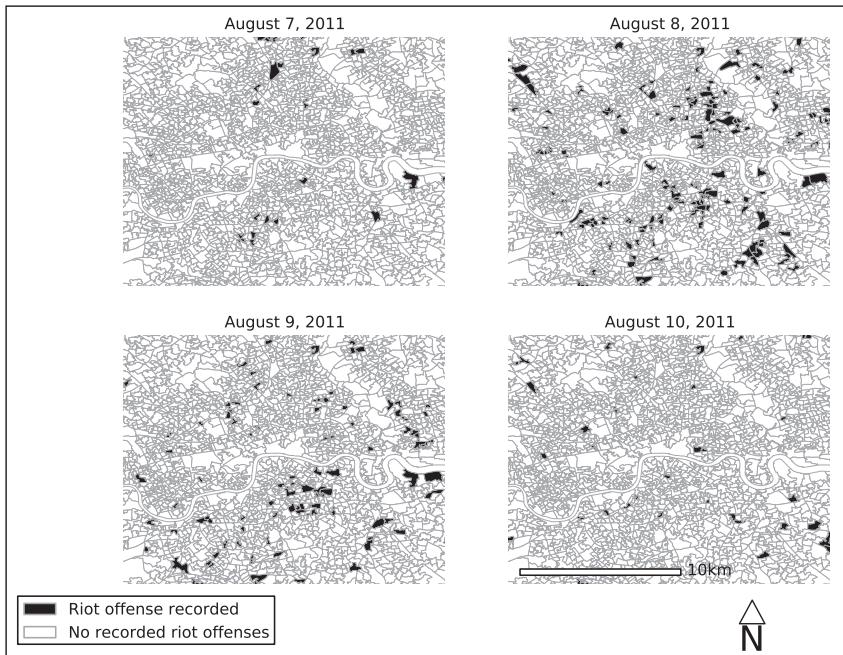
The distance from the city center is calculated as the distance between the centroid of each LSOA and the center of London (measured as a point just south of Trafalgar Square: longitude -0.1277, latitude 51.5073) in kilometers. To determine whether an underground station is located within an LSOA, we use location data of underground stations obtained from Open Street Map (<http://www.openstreetmap.org/>). Operationalized as a binary

**Figure 3. Map of the LSOA Geography of Greater London
(Shaded Regions Indicate the Locations of
Recorded Offenses Associated with the Riots on
the First Day of Rioting)**



indicator, values of 1 indicate that an LSOA contains a station and of 0 that it does not. For retail floor space, we use the Valuation Office Agency floor space data for the year 2004 (see <http://www.planningstatistics.org.uk>) to calculate the total floor space of shops per 250 m² within each LSOA. This scaling is used merely to aid interpretation of the parameter estimates associated with the variable, and it does not affect model estimation, the relative importance of the variables, or their statistical significance. The number of key stage 4 schools (roughly equivalent to secondary schools for those 11–16 years of age) in each LSOA is counted using data from the U.K. Department of Education. Finally, each LSOA was coded as being located north or south of the River Thames so that, for any LSOA pair, it was possible to indicate whether the two areas were located on the same side of the river.

Figure 4. Map of the LSOA Geography Showing the Major Riot Locations in Central London (Shaded Regions Indicate the Locations of Recorded Offenses Associated with the Riots on Each Day of the Disorder)



SOCIAL COHESION VARIABLES

The estimates of population churn rates and ethnic heterogeneity were derived using data from the 2001 U.K. Census. We use the measure of population churn as outlined in Dennett and Stillwell (2008):

$$C_i = \left(\frac{D_i + O_i + W_i}{P_i} \right) \times 100 \quad (4)$$

where D_i is the in-migration to area i , O_i is the out-migration from the area, W_i is the total migrants that relocate from one residence to another while remaining within the same area i , and P_i is the population of area i . To aid interpretation, and for consistency with previous research of this kind (e.g., Bernasco and Nieuwbeerta, 2005), these values are divided by ten so that a one-unit increase in the independent variable represents a ten-unit

change in the churn rate. Again, the data are scaled in this way merely to aid interpretation of the parameter estimates.

To measure the ethnic heterogeneity of an area, we use the index of qualitative variation (see Agresti and Agresti, 1978; Wilcox, 1973), which is calculated as follows:

$$E_j = \left(1 - \sum_{k=1}^n p_{kj}^2 \right) \times 100 \quad (5)$$

where n is the total number of different ethnic groups and p_{kj} is the proportion of individuals belonging to ethnic group k that reside in zone j . E_j is, therefore, the probability that two individuals selected at random from the population of zone j will be of different ethnicities.³

To measure deprivation, we use the Index of Multiple Deprivation (IMD) 2010 obtained from the U.K. Department for Communities and Local Government (McLennan et al., 2011). As with the variable for the churn rate (and for the same reasons), the estimates of ethnic diversity and the IMD were divided by ten.

In addition to the variables discussed, a measure of population density is included in the model. This measure is included to control for the potential effects of this variable, but we do not test a substantive hypothesis regarding the influence of population density in this article. The variable was operationalized using mid-2010 population estimates for LSOAs, obtained from the U.K. Office for National Statistics.

COLLECTIVE BEHAVIOR AND CONTAGION

Finally, to measure the effect that prior offenses at a location have on the spatial decision making of a new potential rioter, for each event level decision, we count the number of detected offenses that were identified by the police as having been associated with the riots that occurred at each LSOA within the previous 24 hours of that decision. Thus, this variable is dynamic, with the count of prior detected offenses for each LSOA potentially varying for every choice modeled. Table 4 summarizes the variables used in our analysis that do not vary over time or by offender.

3. For this purpose, we use the categories for ethnicity as outlined in the 2001 U.K. Census, which are as follows: White British, White Irish, other White, White and Black Caribbean, White and Black African, other mixed, Indian, Pakistani, Bangladeshi, other Asian, Caribbean, African, other Black, Chinese, and other ethnic group.

Table 4. Independent Variables Used to Characterize the 4,765 LSOA in Greater London

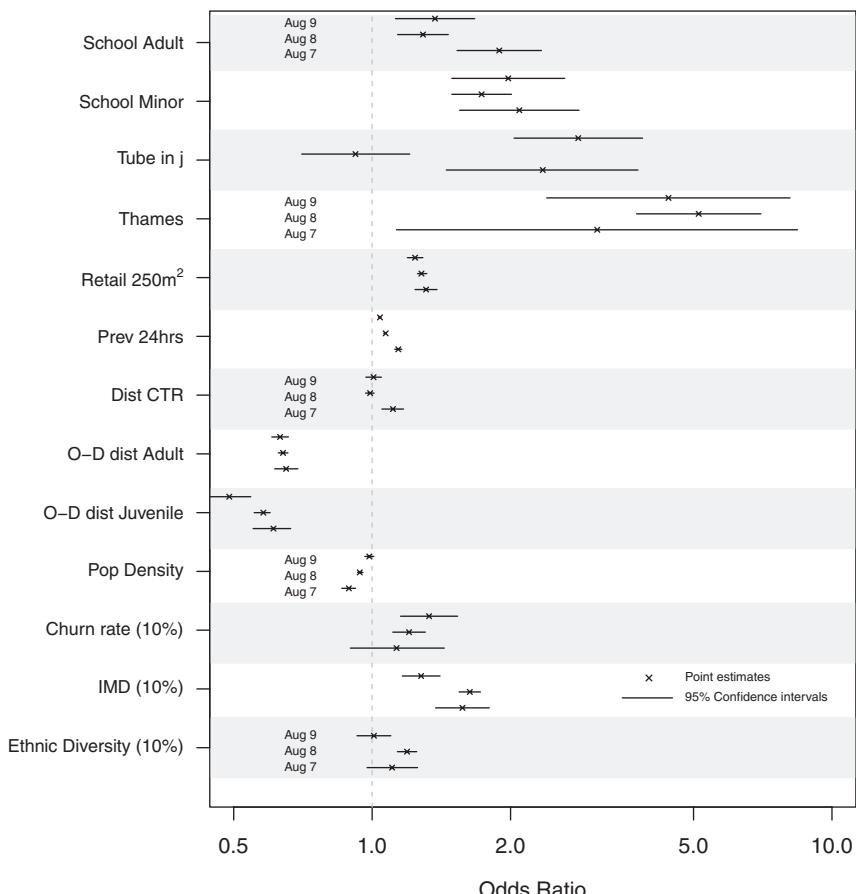
Variable	Description	Mean	Standard Deviation	Minimum	Median	Maximum
School	A count of the number of key stage four schools in the area	.153	.416	0	0	5
Underground station	Binary indicator for whether there is a tube station in an area	.051	.221	0	0	1
Retail floor space	Measured in units of (250 m ²)	.035	.025	0	0	1.169
Distance to the city center	Measured in km	12.454	5.777	.350	12.309	30.167
River Thames	Binary indicator for whether the LSOA is north or south of the river	.373	.484	0	0	1
Churn	Churn rate, as given in equation 4, divided by 10	1.617	.655	1.704	2.381	6.621
Ethnic diversity	Measure of ethnic diversity, as given in equation 5, divided by 10	5.575	2.069	.692	6.072	8.735
Deprivation	Index of multiple deprivation divided by 10	2.524	1.324	.170	2.381	6.621

RESULTS

As discussed, in this section, we examine what seems to have influenced offender spatial decision making and whether and how this changed over the course of the disorder. To do so, we analyze the observed patterns separately for each day of the riots. However, in the presentation of the results, we exclude the analyses for the first and last days of rioting because of the small sample sizes involved (although the parameter estimates for these days were consistent with those for the others). Figure 5 (see also Table A.1) shows the parameter estimates for each of the 3 days of rioting examined, whereas table 5 shows the associated measures of goodness of fit for each model.⁴

4. The results presented are robust to the inclusion of two other variables: a measure of police strength and a measure of police relations in the destination areas. The parameter estimates for these variables are not included in this article as they were measured at a level of geographic resolution that was much larger than the LSOAs. The results also were found to be consistent when the standard errors

Figure 5. Results for Each Variable of the Conditional Logit Model, for Each Day of Unrest



Considering overall model fit, as is observed from table 5, the average McFadden pseudo R^2 squared across all days of rioting is about .34.⁵ Pseudo R^2 values tend to be much lower than the corresponding goodness of fit R^2 values for ordinary regression analysis, and McFadden

were clustered according to the location from which the offenders originated and when the distances used were logged values.

5. Calculated as $R^2 = 1 - \frac{\log(L(\hat{\theta}))}{\log(L(\theta))}$, where $L(\hat{\theta})$ is the likelihood function that is calculated using the best parameter estimates and $L(\theta)$ is the likelihood function without any predictor variables and with intercepts only.

Table 5. Goodness-of-Fit Statistics for Each Run of the Model on Subsequent Days of Rioting

Statistic	August 7	August 8	August 9
Pseudo R^2	.36	.34	.31
Log likelihood	-1,286.64	-8,213.27	-2,611.44
Likelihood ratio X^2	1,424.10	8,624.95	2,331.52
<i>N</i>	232	1,477	446

(1979) stated that values between .2 and .4 represent an excellent fit to the data. Thus, the model seems to explain the observed patterns across the 3 days tested rather well.

We now consider each variable in turn and determine whether the results presented provide evidence in support of or against each of the hypotheses specified. For coherence, the discussion of the results is organized according to the theoretical perspectives identified in the introduction. Figure 5 also is organized in this way; however, for aesthetic reasons, the variables are not displayed in the precise order that they are now discussed.

The results suggest an unequivocal effect of propinquity (hypothesis 1) on offender spatial decision making, with offenders (young or old) being more likely to target areas that were closer to their area of residence. Roughly speaking, the odds of an offender selecting an area reduces by a factor of around .6 for every kilometer an area is located from an offender's area of residence. These findings suggest that the rioting was fairly localized and that in line with CPT, rioters were more likely to target areas that were encompassed by their awareness spaces. This effect was more pronounced for the juvenile offenders (hypothesis 2), a difference that reached statistical significance for August 8 and 9 (all $p < .05$) but not for August 7 ($p > .19$). We suggest that this finding—that the younger offenders tended to travel shorter distances than their older counterparts—reflects the fact that, as discussed in the Introduction, the former are likely to have more limited geographical awareness spaces than the latter.

Considering potential (collective) routine activity nodes, all other things being equal, the odds of an offender selecting an area increases by a factor of between 1.29 and 2.09 for every additional school that is located within it (hypothesis 3). Moreover, as expected, this was particularly the case for juvenile offenders, at least for August 8 and 9 (all $p < .005$), although for August 7, the observed differences were nonsignificant ($p > .65$). Again, the consistency of the findings provides support for CPT and suggests that, as expected, the influence of particular types of routine activity nodes (such as schools) influence the spatial decision making of different age groups of offenders to differing degrees.

Considering the accessibility of an area, or connectivity via the tube network (hypothesis 4), all other things being equal, in line with CPT the presence of a tube station was a statistically significant predictor of whether an area was selected for August 7 and 9. In fact, on those days, the odds of an area being targeted by an offender more than doubled if it contained a tube station. On August 8, the odds (of .92) of an area being targeted were roughly the same despite whether it contained a tube station. This may be explained by the fact that, on August 8, the rioting was so much more widespread than on the other days that the ease of accessibility was less of a concern on this particular day. Additionally, many tube stations were actually closed on the evening of August 8, which would have limited the influence of these nodes of activity on offender spatial decision making.

The effect of retail establishments (hypothesis 5) also was consistent, with the odds of an area being targeted by an offender increasing by a factor of around 1.28 for every additional 250 m² of retail facilities located within it. As for all coefficients, it is important to reiterate that this effect holds after controlling for all other variables. For example, this can be interpreted as suggesting that, given that two areas are located a similar distance from the area within which an offender lives, an offender is more likely to riot in an area that contains higher volumes of retail facilities than in one with relatively lower volumes of retail facilities.

In terms of proximity to the city center (hypothesis 6), the patterns were more ambiguous. On August 7, the odds ratio for this variable was statistically significant, but it was positive, suggesting that rioters were more likely to offend farther away from the city center. On other days, the odds ratio was clearly nonsignificant. One reason for the apparent absence of the influence of this variable might be that, for a city like London, the center may be too crude to represent a routine activity node for all offenders. However, there are no obvious alternatives to use as substitutes, so we do not pursue this issue further. As to the presence of the Thames River (hypothesis 7), the influence of this natural barrier seems to be consistent across all days, with the odds of an offender selecting an area being up to five times higher if that area is on the same side of the river as that within which he or she lived. Again, this is entirely consistent with CPT.

Considering the variables associated with social disorganization, the odds ratios were generally in line with expectation, but the results were mixed. All other things being equal, areas with higher estimated levels of deprivation (hypothesis 10) were more likely to be selected on each day of the riots. To be specific, the odds of an area being selected increases by a factor of between 1.27 and 1.63 for every 10 unit increase in the index of deprivation. With respect to population churn (hypothesis 9), the likelihood of an area being selected increased by a factor of around 1.20 for every 10 unit increase in the churn rate of that area. This effect was

statistically significant on August 8 and 9 but not on August 7. Considering ethnic diversity (hypothesis 8), the odds ratio for this variable was only statistically significant on 1 of the 3 days. In this case, on September 8, the odds of an area being targeted by an offender increased by a factor of 1.19 for every 10 unit increase in ethnic heterogeneity within that area. Given the inconsistency of these findings, we discuss them in a little more detail subsequently.

The variable used to measure contagion (hypothesis 11)—indicating the number of offenses in each area in the previous 24 hours—was significantly associated with target choice during the London riots, as expected. Thus, this suggests that, all other things being equal, offenders were more likely to select an area if offenses had occurred in that area in the previous 24 hours. To illustrate, on September 7, the odds of an area being targeted by an offender increased by a factor of 1.14 for every additional (detected) incident that occurred in that area in the previous 24 hours. An interpretation of the raw odds ratios is slightly complicated in this case because the scale of the independent variable varies from one day to the next. That is, the mean number of incidents that occurred in the previous 24 hours in an area would, in all likelihood, be higher on August 9 than on any other day. Consequently, we would expect the odds ratio to be slightly smaller for this day than for the others, which it is. In terms of the mechanism underlying a process of social contagion, it is clear from the preceding discussion that offenders tended to prefer locations that were close to their home locations and, hence, that rather than attracting offenders from places far away, any influence of social (or other) media most likely encouraged offenders to engage in offending in their own neighborhoods or nearby.

One potential issue with this finding is that the variable used to estimate the role of recent activity on offender spatial decision making may instead have measured unobserved heterogeneity not otherwise captured in the model. That is, it may have served to estimate the influence of time-stable influences that vary spatially that were not explicitly represented by any of the other independent variables. To test this hypothesis, we used an alternative model specification. In this case, just three variables were used. For each possible destination, these were the distance between that area and the LSOA within which the offender lived, the number of offenders who had rioted in that destination in the previous 24 hours, and the number of offenders who had offended in that destination over the entire duration of rioting (minus the number who had offended in it during the previous 24 hours). The third variable was intended to capture unobserved heterogeneity, and hence, in the event that the location of riots in one time period did not affect those in the next, we would not expect our time-lagged variable to explain any unique variance. The results (available upon request) suggested that both variables were statistically significant, in the expected direction. Thus, it would seem that rioters' decisions of where to offend are

not independent and that offenders are more likely to target an area if that area was the location of riots in the previous 24 hours.

With respect to population density, it seems that, whereas the strength of the effect decayed over the course of the 3 days, offenders tended to commit offenses in those areas with lower population density. We do not speculate on what this might indicate, but we note that the significant finding demonstrates the value of including the variable in the model specification.

DISCUSSION

The aim of the current article was to advance understanding of the spatial decision making of rioters and to consider the utility of different theoretical accounts. Models that examine the association between the frequency of events in a set of areas and the characteristics of those areas may identify features that seem to attract offenders, but such analyses usually take no account of the abundance of offenders in or nearby them. This is problematic insofar as an otherwise vulnerable area may be unlikely to be targeted if it is isolated from the population of offenders. Similarly, areas that would otherwise not be particularly vulnerable may be so if there is a high density of offenders living near to them. Studies of the journey to crime suggest the importance of this but consider only how far offenders typically travel to offend and, hence, do not examine how the features of an area influence offender decision making. In the current study, we use the discrete choice approach, as it essentially allows us to exploit the benefits of the two approaches discussed while addressing their limitations.

In accordance with previous research on target selection during rioting, across the 3 days of rioting considered, there is evidence to suggest that offenders selectively choose targets. In addition, our results suggest that, on the whole, those factors that are known to influence offender spatial decision making for everyday urban crime also explain target selection for those engaged in riots. Considering the different theories examined, those factors associated with crime pattern theory—namely, the distance an offender travels between his or her residence and the offending location; whether the Thames is to be crossed; and the presence of schools, retail centers, and transport hubs—all seem to contribute to the spatial decision making of rioters. The consistency of the findings, in terms of both their alignment with the hypotheses articulated in the Introduction and the patterns observed across the days for which data were analyzed, provide further support for crime pattern theory as a model of offender spatial decision making. Importantly, the current findings suggest the value of crime pattern theory in explaining offender target selection in the extreme circumstances associated with riots, for which some scholars have previously argued that rational decision making is abandoned (Le Bon, 1960), thereby suggesting the generality of crime pattern theory as a model of offender decision making.

The results also provide some support for theories of social disorganization as influencing the spatial decision making of rioters. However, in this case, the results were less clear. For instance, while offenders seemed to have a preference for more deprived areas (all other things being equal) on each day of the riots, areas in which residents were from a range of ethnic backgrounds were not (as would be predicted by the theory) consistently those in which incidents occurred. Of course, one issue with interpreting these findings is that the indices used to estimate neighborhood levels of ethnic diversity and rates of population churn were based on data from the 2001 U.K. Census. These data were used as they are the most recent that are available, and in using them, we assume that the demographics (and changes in them) of an area are relatively stable at least on the time scale of a decade or so. However, the reader should take this into account. Moreover, in using such data, we follow the approach of Shaw and McKay (1969) and estimate levels of social disorganization indirectly. This approach is different than using survey samples to measure local social processes (e.g., Sampson and Groves, 1989; Sampson, Raudenbush, and Earls, 1997), and the reader should take account of this too.

In terms of the mechanism through which social disorganization might have a part to play, as discussed, cohesive neighborhoods might exert control over their residents to reduce the likelihood that they would engage in the disorder. Alternatively, signs of social cohesion, or collective action, might act as a barrier to deter rioters from targeting a neighborhood. Such action was reported as helping to stop some of the rioting that took place in the United States during the summer of 1967 (see Corman, 1967), and while not systematic, anecdotal evidence from media coverage of the London 2011 riots suggests that in some neighborhoods at least, residents acted collectively to prevent rioters from targeting their neighborhoods.⁶ In the current study, as our model specification concerns where rioters offend, this type of mechanism is largely examined. Thus, future work might explore the alternative mechanism by considering the neighborhoods in which offenders live, given where they offend.

Considering the temporal dynamics of riots, we tested whether recent activity in an area positively influenced the likelihood that other rioters would select that area to engage in disorder. All other things being equal, our results support this proposition. In the Introduction, we discussed two mechanisms through which recent activity might influence the likelihood of rioters

6. Examples of media coverage that reported examples of collective action on the part of residents can be found at <http://www.independent.co.uk/news/uk/crime/vigilantes-join-16000-police-on-capitals-streets-2334910.html> (accessed November 28, 2012) and <http://www.telegraph.co.uk/news/uknews/crime/8691761/London-riots-residents-fight-back.html#> (accessed November 28, 2012).

targeting a particular area. In the case of the first, the idea is that rioting precipitates further activity, encouraging those nearby to join in. In contrast, according to the second, rioting may attract offenders from other areas, regardless of how far apart they are. Such a process would be expected to operate if the riots were to some extent coordinated, using social media or other means. However, the same dynamics might be observed if the rioters were responding to other information about the locations of riots such as traditional media reports in newspapers, radio, and television. Although we cannot rule out the latter explanation, and recognizing that both processes may have a part to play, the finding that most rioting occurred near to where offenders reside seems to provide more support for the first explanation.

As discussed in the Introduction, this type of effect has been described by some as a contagion-like process, but we are a little cautious of overusing that term because of the connotations associated with it. Nevertheless, we suggest that further investigation into such processes during civil disorder would provide fruitful results. For instance, using a smaller temporal lag than the 24-hour period used in the current study might enhance understanding of the duration over which rioters' spatial decision making is affected by recent events and, hence, inform the deployment of police resources. Further work also might explore the extent to which offenders or groups of them return to the same or nearby areas on consecutive days, or whether those involved vary from one day to the next (for a discussion of such processes, see Johnson, 2008).

Another likely influence on offender spatial decision making that was not included in our analysis was the spatial allocation of police resources. The presence of police officers in an area may have influenced the rioters in several ways. For example, they may have physically prevented rioters from entering areas or engaging in the disorder, or they may have deterred them from targeting a location by shaping their perceptions of the risk of arrest in that area (see Davies et al., 2013). Unfortunately, data regarding police activity were unavailable for analysis, and so we could not estimate the effect of police officer presence, or the number of arrests made in an area during the riots, on offender spatial decision making. In terms of the actual arrests made, however, it is worth noting that the majority took place after the riots, with most resulting from the analysis of CCTV footage (Laville, 2011) rather than from on-the-spot arrests.⁷ Moreover, although it would

7. As of Tuesday, August 9, 2011, 525 people had been arrested in London (Laville, 2011). This number rose to more than 1,000 by August 12—after the conclusion of the riots (<http://www.bbc.co.uk/news/uk-england-london-14501926>)—and rocketed to almost 3,000 by early October 2011 (<http://www.standard.co.uk/news/three-thousand-arrests-made-over-london-riots-offences-6451169.html>).

be advantageous to include such data, it is important to remember that the models reported here explained a large amount of the variance in offender spatial decision making despite such data not being available for analysis.

In summary, using a discrete choice approach, the current study provides further support to suggest that the choices made by rioters are not irrational. Using data concerned with the victims of offenses (e.g., Berk and Aldrich, 1972), previous studies have suggested this to be the case for the types of buildings targeted by looters. The contribution made by this article is to extend this line of enquiry by using data for the offenders involved and by examining the characteristics of the areas within which they offend and those in which they do not. Our findings provide support for the idea that theories developed to explain everyday urban crimes, particularly crime pattern theory, have a role to play in explaining offender decision making, even when law and order is under threat.

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APPENDIX

Table A.1. Odds Ratios (e^β) for the Conditional Logit Model, as Plotted in Figure 5

Variable	August 7			August 8			August 9		
	Lower	Mean	Upper	Lower	Mean	Upper	Lower	Mean	Upper
School adult	1.53	1.89*	2.33	1.14	1.29*	1.46	1.12	1.37*	1.67
School minor	1.55	2.09*	2.82	1.49	1.73*	2.01	1.49	1.98*	2.62
Tube	1.45	2.35*	3.79	.70	.92	1.21	2.04	2.80*	3.87
Thames	1.13	3.01*	8.42	3.76	5.13*	7.01	2.40	4.41*	8.11
Retail 250 m ²	1.24	1.31*	1.38	1.26	1.28*	1.32	1.19	1.24*	1.29
Previous 24 hours	1.12	1.14*	1.16	1.06	1.07*	1.07	1.03	1.04*	1.05
Dist CTR	1.05	1.11*	1.17	.97	.99	1.01	.97	1.01	1.05
O-D dist adult	.61	.65*	.69	.63	.64*	.66	.60	.63*	.66
O-D dist juvenile	.55	.61*	.67	.56	.58*	.60	.44	.49*	.54
Population density	.86	.89*	.92	.93	.94*	.96	.96	.99	1.01
Churn rate	.90	1.13	1.44	1.11	1.20*	1.31	1.15	1.33*	1.53
IMD	1.37	1.57*	1.80	1.55	1.63*	1.72	1.16	1.27*	1.40
Ethnic diversity	.98	1.10	1.26	1.14	1.19*	1.25	.93	1.01	1.10
N		232			1,477			446	

*Statistically significant odds ratio ($p < .05$).