

ROLE OF THE STREET NETWORK IN BURGLARS' SPATIAL DECISION-MAKING*

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Explaining why crime is spatially concentrated has been a central theme of much criminological research. Although various theories focus on neighborhood social processes, environmental criminology asserts that the physical environment plays a central role by shaping people's activity patterns and the opportunities for crime. Here, we test theoretical expectations regarding the role of the road network in shaping the spatial distribution of crime and, in contrast to prior research, disentangle how it might influence offender awareness of criminal opportunities and the supply of ambient guardianship. With a mixed logit (discrete choice) model, we use data regarding (N = 459) residential burglaries (for the first time) to model offender spatial decision-making at the street segment level. Novel graph theory metrics are developed to estimate offender awareness of street segments and to estimate levels of ambient guardianship, distinguishing between local and nonlocal guardianship. As predicted by crime pattern theory, novel metrics concerning offender familiarity and effort were significant predictors of residential burglary location choices. And, in line with Newman's (1972) concept of defensible space, nonlocal (local) pedestrian traffic was found to be associated with an increase (decrease) in burglary risk. Our findings also demonstrate that "taste" preferences vary across offenders, which presents a challenge for future research to explain.

That crime is spatially concentrated now seems incontestable (e.g., Eck and Weisburd, 1995). Explaining why this is so, however, is still a central theme of criminological research and a matter of some debate. Several prevailing theories assert that the environment plays a central role in shaping the distribution of crime by facilitating the convergence in space and time of offenders and suitable targets, in the absence of capable guardians (Cohen and Felson, 1979). One fundamental determinant of this is the road network because it defines how people move through the urban environment. In so doing, it serves

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a “dual function,” determining the opportunities for crime offenders encounter and become aware of (e.g., Beavon, Brantingham, and Brantingham, 1994), and influencing the locations through which ordinary citizens move and provide ambient guardianship. The aim of prior research has been to examine the role of the road network on crime, but it has failed to isolate the influence of these two mechanisms. This is largely because analyses have been conducted to examine only the location of crime events, without reference to the offenders involved. In addition, most researchers have tended to employ crude metrics to describe the network, and their findings have often lacked statistical rigor.

To address these shortcomings, in this article, we make several novel contributions. We use a discrete choice approach (McFadden, 1974), or more accurately an offense location choice approach (Bernasco and Nieuwebeerta, 2005), to estimate empirically how the opportunities that are targeted by burglars differ from those that are not. Our research differs from previous studies of offender spatial decision-making in two important ways. First, in most previous studies, scholars have examined offender location choice at the area level (for the exceptions, see Bernasco, 2010b, and Vandeviver et al., 2015). Here, consistent with contemporary theory (Weisburd, Groff, and Yang, 2012) and the research questions at hand, we do so at the street segment level. Second, we build on previous work (Davies and Johnson, 2015) and introduce to the discrete choice literature a methodological approach that aims to estimate independently how the road network influences offender awareness of crime opportunities, on the one hand, and guardian potential at particular locations, on the other. By following Townsley, Birks, Ruiter, et al. (2015), we also recognize that offenders may vary in the extent to which their spatial decision-making is affected by different factors, and so we employ mixed logit statistical models to estimate parameters and how they vary across offenders. In combination, our approach allows us to examine the dual role that the road network might play in shaping burglar spatial decision-making and the extent to which this varies across offenders.

The remainder of this article is organized as follows. In the next section, theoretical perspectives and research are reviewed to introduce the theoretical model. The second and third sections describe the data and analytic strategy, respectively. The latter includes a discussion of the application of graph theory to quantify the character of the road network, as well as the statistical model employed. The fourth and fifth sections present and discuss the results.

BACKGROUND

OFFENDERS AND THE ROAD NETWORK

The rational choice perspective (Cornish and Clarke, 1986) describes offenders, such as burglars, as nonarbitrary decision-makers who consider (however briefly) the costs and benefits of action alternatives, including the decision of where to offend (Clarke and Felson, 1993). It is suggested that such decision-making will be bounded by imperfect and incomplete information, and that future choices will be informed by the outcome of previous ones (Cornish and Clarke, 1986; see also Bennett and Wright, 1984; Cromwell, Olson, and Avary, 1991; Wright and Decker, 1994). Nevertheless, although choices made may not appear rational to an observer, it is assumed that selections are made that aim to maximize the perceived utility of a decision and minimize the expected costs. In particular, the distance an offender must travel to offend has consistently been shown by researchers to influence offender location choice in both quantitative and ethnographic studies.

For example, offenders have consistently reported (e.g., Brown and Altman, 1981; Rengert and Wasilchick, 1985; Repetto, 1974), and the results of analyses of the journey to crime (Snook, 2004; Wiles and Costello, 2000) have shown, that the likelihood of an offender selecting a location at which to offend is inversely proportional to the distance he or she must travel to reach it. The aim of most studies of the journey to crime has been to examine the Euclidean distance between locations (e.g., Clare, Fernandez, and Morgan, 2009), and even though this provides a good estimate of the likely cost of travel, it is clearly imperfect. The cost of travel is intrinsically linked to the configuration and properties (such as the vehicle speed limit) of the road network as this determines how quick and how easy it is to travel between any two locations. Consequently, in the current study, we expect to find the following:

Hypothesis 1: Street segments that are quicker to travel to (in terms of estimated travel time) from the burglar's home will be more likely to be selected for burglary.

In addition to the fact that the selection of targets near to an offender's home location minimizes the cost of travel, this preference is expected to emerge for other reasons encapsulated by crime pattern theory (e.g., Brantingham and Brantingham, 1993). According to the theory, like everyone else, offenders are assumed to frequent activity nodes routinely, such as their home and workplace. As a consequence of doing so, they develop an awareness of these places and the routes between them. This is not necessary for offending, but it shapes offenders' familiarity and awareness of the criminal opportunities within these spaces. According to crime pattern theory, offenders are believed to prefer such opportunities to alternative targets for two reasons. First, offenders cannot select targets of which they are not aware (Rengert and Wasilchick, 1985). And, second, targeting locations about which something is known reduces uncertainty about the likely outcome of that choice (Beavon, Brantingham, and Brantingham, 1994). As such, we predict the following:

Hypothesis 2: Street segments that are more likely to be familiar to an offender are more likely to be selected for burglary.

In previous studies, scholars have assumed that the distance between a location and an offender's routine activity nodes (e.g., the home) provides a reasonable estimate of that location's familiarity. This assumption is not unreasonable as the findings from qualitative research with burglars have revealed that they are typically most familiar with areas that are closest to their home locations (e.g., Rengert and Wasilchick, 1985). Nevertheless, at the street segment level, an individual's familiarity with locations will be more nuanced than this, and it is likely to be a function of how frequently he or she travels to or through them (Brantingham and Brantingham, 1993; Rengert and Wasilchick, 1985). Although distance will influence this awareness, so too will the configuration of the road network because this affects the likelihood that an individual will travel along a particular street to reach that or other locations (e.g., Beavon, Brantingham, and Brantingham, 1994). Some streets (such as major roads) may feature in many journeys, whereas others less so (cul de sacs and dead ends, for instance). On the whole, streets rarely traveled will be less familiar than those commonly used. Even though it is not possible to determine which streets offenders travel during their routine activities without collecting extensive primary data, it is possible to employ techniques from graph theory to

estimate which routes and, hence, which street segments, they are most likely to use and be familiar with (near to activity nodes such as their home location). To do this, for each offender, we compute a novel idiosyncratic variation of the graph theory metric *betweenness*. Betweenness (which is discussed in more detail later in the article) has been used elsewhere (e.g., Davies and Johnson, 2015) to estimate overall movement potential through the road network. Our idiosyncratic variant is intended to estimate how likely each offender is to use particular street segments and, hence, to develop an awareness of them. Consequently, for hypothesis 2, we specifically predict that offenders are most likely to commit offenses on those street segments with high idiosyncratic betweenness values.

GUARDIANSHIP AND THE ROAD NETWORK

The configuration of the road network also influences the movement of people going about their everyday activities (e.g., Hillier, 2007; Penn, 2003)—people who (in the case of residential burglary) have the potential to provide ambient guardianship (Cromwell, Olson, and Avary, 1991; Felson, 1994) or to regulate behavior (Miethe and Meier, 1994). Nevertheless, the potential role of passers-by is more complex than simply a function of their presence or absence.

To explain, consider two theories of urban design. In the case of the first, Jacobs (1961) suggested that guardianship is provided by everyone not engaged in criminal activity who is present on a street. She suggested that their presence provides “eyes on the street” and that this “natural surveillance” has the potential to deter crime.

Yet, according to Newman’s (1972) *defensible space* perspective (see also Coleman, 1985), whether the ambient population deters crime depends on exactly who is present and where they are. According to this perspective, territoriality, which is communicated by environmental cues regarding who (such as residents) is likely to be responsible for and expected to use (or pass through) a space, plays a key role. Where it exists, for example, through the segregation of public and private spaces, it “may make a stranger more obvious and residents more watchful” (Newman, 1980: 142). In contrast, on streets where territoriality is lacking, the attendant guardianship (potential) is expected to be diminished as there will be ambiguity as to who is responsible for that space.

Although both perspectives champion similar concepts, they principally differ in terms of how they predict the movement of nonlocals along a street to influence crime risk. For the former, anyone, including nonlocals, can provide additional guardianship and this should deter crime. In contrast, according to the latter, on streets where there are large flows of nonlocals, anonymity will be increased and this will be detrimental to the informal guardianship provided by those who are local and live on or nearby that street, or might otherwise feel responsible for it.

The findings of quantitative research intended to test these two theories are somewhat mixed and can be divided into two branches. The first, which includes area-level (White, 1990) and more recently street-level studies (Armitage, 2007; Beavon, Brantingham, and Brantingham, 1994; Johnson and Bowers, 2010; Rengert and Wasilchick, 2000), generally find that locations that are expected to have greater through movement are more likely to experience crime. In most of these studies, researchers have used simple ordinal or categorical variables (e.g., the number of other roads a street directly intersects, or major versus minor road categorizations) as proxies for traffic levels (Beavon, Brantingham,

and Brantingham, 1994; Johnson and Bowers, 2010; White, 1990), but in recent studies, researchers (Davies and Johnson, 2015) have used more sophisticated metrics (see the Graph Theory section) and have come to the same conclusions.

The second branch of research involves metrics computed with the space syntax methodology. Researchers who have used this approach have employed a form of graph theory, but generally, they have found opposing findings to those discussed earlier (e.g., Hillier, 2004; Shu, 2000). That is, consistent with Jacob's (1961) ideas, at locations that are expected to possess greater volumes of passers-by, less crime is observed. That said, in some studies, research teams have employed the space syntax methodology and have reported different results. For example, Hillier and Sahbaz (2009) found that streets that were characterized as being likely used for more localized movements tended to experience less crime (see also Nubani and Wineman, 2005). Moreover, many studies that use the space syntax methodology have been weaker in terms of the statistical methods applied (for an extended discussion, see Summers and Johnson, 2016), often having relied on descriptive statistics (Shu, 2000) or having failed to account for (any) other predictor variables known to influence crime (Hillier, 2004; Hillier and Sahbaz, 2009).

It must also be noted that no previous research of this kind has been designed to account for where offenders reside, and so the influence of offender decision-making has been conflated in these studies. The aim of qualitative research (e.g., Cromwell, Olson, and Avery, 1991; Wright and Decker, 1994) is to provide more insight from the offender's perspective. Qualitative research suggests that most (but not all) offenders avoid targeting locations where they are likely to be seen by neighbors or others (Bennett and Wright, 1984). Nevertheless, in such studies, researchers have not, as far as we are aware, examined how the configuration of the road network affects offender perceptions of this type of guardianship. On the basis of the preceding text, we consider the following hypotheses (detailed descriptions of the variables derived to test hypotheses are provided later in the article). First, in support of the "eyes on the street" perspective where all passer-by guardianship is beneficial:

Hypothesis 3: Street segments for which the potential for the through-movement of *any* passers-by (estimated with a metric of overall *pedestrian betweenness*) is higher are less likely to be selected for burglary.

Second, motivated by both Jacob's "eyes on the street" and Newman's "defensible space" perspectives, where local passer-by guardianship is expected to be beneficial:

Hypothesis 4: Street segments for which the potential for the through-movement of *local* passers-by (estimated with a metric of *local betweenness*) is higher are less likely to be selected for burglary.

Third, as suggested by the defensible space but not by the "eyes on the street" perspective:

Hypothesis 5: Street segments for which the potential for the through-movement of *nonlocal* passers-by (estimated with a metric of *nonlocal betweenness*) is higher are more likely to be selected for burglary.

Although these ideas best apply to pedestrian movement, it is also important to consider vehicular movements. In their study of offender decision-making, Bennett and Wright (1984) showed convicted burglars video recordings of 36 different homes and then asked them to indicate which they would target and why. Among the factors offenders identified as influencing their choices was the type of road, with busy roads being avoided as “the offender might be seen by drivers of passing cars” (p. 64). Thus:

Hypothesis 6: Street segments for which the potential for the through-movement of vehicular passers-by (estimated with a metric of overall *vehicular betweenness*) is higher are less likely to be selected for a burglary.

OTHER FACTORS

Although our focus in this article concerns the role of the road network on criminal location choice, other factors will clearly influence offender decision-making and need to be accounted for. First, according to social disorganization (Shaw and McKay, 1942) and related theories (e.g., Morenoff, Sampson, and Raudenbush, 2001; Sampson and Groves, 1989; Sampson, Raudenbush, and Earls, 1997), the extent to which residents can exert informal social control to deter crime is influenced by how closely knit their neighborhood is. Less cohesive neighborhoods lack communal ties either because (for example) they are transient or because residents do not share common values. According to this theory, in such communities, residents may not feel responsible for their neighborhood and so will be less willing to act collectively as guardians against crime. In previous studies of the kind described here (e.g., Bernasco and Nieuwbeerta, 2005; Clare, Fernandez, and Morgan, 2009), levels of social disorganization have been estimated by researchers using census data that characterize the (lack of) stability, or heterogeneity, of neighborhoods with variables such as population turnover, ethnic diversity (e.g., Miethe and Meier, 1994), and socioeconomic diversity (Johnson and Summers, 2015). In the current study, we control for these factors in the analyses that follow.

Offense location choices are also likely influenced by the type of targets available. For example, as suggested elsewhere (Maguire and Bennett, 1982; Rengert and Wasilchick, 1985), burglars are financially motivated and are therefore likely to prefer more affluent dwellings where greater proceeds are expected. Conversely, it is also likely that more affluent dwellings will have better security measures and are therefore likely to be more difficult to break into. As such, and following the approach taken in previous studies (e.g., Bernasco and Nieuwbeerta, 2005), the affluence of each possible target location is accounted for in the analyses presented.

Finally, it is important to note that even if an offender chooses targets randomly, roads with more homes are more likely to be selected. To account for this, the number of dwellings on a street segment is also included as a control variable.

VARIATION

A final point that emerges from the results published in the qualitative literature (e.g., Bennett and Wright, 1984; Cromwell, Olson, and Avary, 1991; Nee and Meenaghan, 2006; Rengert and Wasilchick, 2000; Wright and Decker, 1994) and in recent quantitative studies (Bouhana, Johnson, and Porter, 2016; Townsley and Sidebottom, 2010) is that although certain features often seem to influence offender decision-making, there

is also clear variation across offenders in those factors. For example, in their interviews with burglars, Bennett and Wright (1984) found that the presence of passers-by deterred approximately one half of their sample either unconditionally or under some conditions, whereas the remaining half reported being undeterred by the presence of others. In their study, Wright and Decker (1994) found that neighborhood watch schemes deterred some offenders, who perceived an increased risk of being reported to the police in such neighborhoods, whereas others were unconcerned by their presence. Such differences it seems emerge as a result of variation in offender experience and of the development of cognitive scripts or templates that have proven successful in the past (Nee and Meenaghan, 2006; Wright and Decker, 1994). Given individual differences in offender experience, such scripts (and offender preferences) can be expected to vary across offenders.

Variation is also to be expected as a result of individual differences in offender characteristics. For instance, motivated by the fact that juveniles are less likely to have access to motorized transportation, and typically have more limited activity spaces, when compared with their older counterparts, the results of several qualitative (e.g., Baldwin and Bottoms, 1976; Repetto, 1974) and quantitative studies (e.g., Bernasco and Nieuwbeerta, 2005; Johnson and Summers, 2015; Townsley and Sidebottom, 2010) have shown that younger offenders generally travel shorter distances to offend than do adults. Similarly, as Wright and Decker (1994) noted, how the characteristics of particular neighborhoods are perceived is relative and “must be viewed from the perspective of offenders” (p. 94) who may perceive the same opportunities differently. Put simply, offenders may vary in terms of what factors influence their location choices.

With the exception of examining systematic variation in location choice for a limited number of categorical variables (e.g., adult versus juvenile offenders), the aim of previous studies of offender location choice (but see, Townsley, Birks, Bernasco, et al., 2015) has been to employ a modeling strategy that essentially assumes homogeneity in the (revealed) preferences of offenders. As the outcomes of both theory and prior empirical research suggest that (additional) variation is to be expected, it is important to examine this. Nevertheless, given the current state of theoretical development and empirical investigation, with a few exceptions (such as the age of the offender), there are no strong *a priori* expectations regarding patterns of variation, other than that they should exist. For this reason, at this stage of the research endeavor, assessing the extent to which heterogeneity exists and for which variables is important and may yield important insights to guide future inquiry. Consequently, like Townsley, Birks, Ruiter, et al. (2015), we employ a mixed-logit model to test hypotheses that allows us to not only examine whether particular preferences exist but also estimate how consistent such preferences are across a sample of offenders (without being limited to testing for variation for one or two categorical variables).

DATA

STUDY AREA

Analyses were conducted for all street segments in the towns of High Wycombe and nearby Beaconsfield and Marlow in Buckinghamshire (U.K.). The study area was defined by identifying the “built-up areas” of the three towns and by applying a 1-km buffer around them (for a map of the study area, see appendix A in the online supporting

information¹). The resulting study area covers a geography of approximately 150 km² and includes 81,682 dwellings situated on 5,286 street segments.

CRIME DATA

Data were provided by Thames Valley Police (TVP) for all residential burglaries recorded and officially cleared for the 10-year period 04/01/2004 to 03/31/2014. These data included each offender's home and offense locations. Where possible, the locations were geocoded with Ordnance Survey² (OS) property data; otherwise TVP-geocoded coordinates were used (~10 percent of locations). As with all previous discrete choice studies, offenses that occurred outside, or that were committed by individuals living outside, the study area were excluded by the researchers from the analysis. Although some studies were conducted omitting offenses that involve co-offending (e.g., Bernasco and Block, 2009), this would lead to the attrition of 70 offenses (of 459). Instead, and by following the design of other studies (e.g., Bernasco, Block, and Ruiter, 2013), for each offense that involved co-offending, one individual was randomly selected as the "single offender" and his or her data were included in the analysis.³ The resulting data set contained 459 residential burglaries committed by 207 offenders. As a result, we obtain a clearance rate of approximately 10 percent of all offenses reported to the police, which is higher than reported in many studies of this kind (e.g., Bernasco and Nieuwbeerta, 2005; Clare, Fernandez, and Morgan, 2009) and produces a similar sample size to that used in previous research (e.g., Bernasco and Nieuwbeerta, 2005). On average, offenders each committed 2.2 burglaries (standard deviation = 5.5, range 1–59). To be a little more precise, of the 207 offenders, 54 committed two or more residential burglaries (accounting for 306 burglaries) and 5 committed more than 10 offenses.⁴

When we considered where burglaries occurred, most street segments (91 percent, $N = 4,827$) had no burglaries on them. Of those that did, the median count was 1 (range = 1–5), but 15 (.3 percent) street segments, which had large numbers of homes on them (on average 92.7 homes compared with 14.2 for segments on which no burglaries occurred), had 5 burglaries and accounted for 75 offenses (16 percent of all burglaries) over the 10-year period. Thus, crime was concentrated at the street segment level. This is to be expected given the outcomes reported in the literature on crime and place (see Weisburd, 2015). Moreover, such clustering is typical of all studies of crime location choice.

STREET AND PATH NETWORKS

Data for the road and path networks were provided by the OS and included geometry information, along with a description of their nature (e.g., "motorway") and any routing

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1. Additional supporting information can be found in the listing for this article in the Wiley Online Library at <http://onlinelibrary.wiley.com/doi/10.1111/crim.2017.55.issue-2/issuetoc>.
 2. The OS is Great Britain's national mapping agency responsible for the official mapping of the country (<https://www.ordnancesurvey.co.uk/about/overview/what-we-do.html>).
 3. A sensitivity analysis confirmed that alternative (random) selections produced the same pattern of results.
 4. As a sensitivity test, the statistical models that follow were conducted with the prolific residential burglars (those who committed more than 10 offenses) excluded. The results of those analyses (available by request) revealed the same pattern of results as those reported later in this article and are hence discussed no further.

Table 1. Road Network Features and Other Information Included in the Pedestrian and Vehicular Movement and Choice Set Networks

Features and Other Information	Pedestrian Network	Vehicular Network	Choice-Set Network
Road and path features included/excluded	All except: Motorways Slip roads	All except: Alleyways Paths Pedestrianized streets	All except: Alleyways Motorways Paths Slip roads Segments with no dwellings
Routing information included	None	One way directionality	N/A
Speed limit ^a (modeled travel speed ^b) (mph)	N/A (3)	Built-up area: Motorway: 70 (70) Divided highway: 40 (36) Local street: 20 (19) All others: 30 (30) Nonbuilt-up area: Motorway: 70 (70) Dual carriageway: 70 (68) Local street: 30 (30) All others: 60 (48)	N/A

ABBREVIATION: N/A = not applicable.

^aSpeed limits for each type of road are estimated with official speed limit guidance (DfT, 2013b).

^bAverage travel speeds are derived from vehicular (Atkins, 2010; DfT, 2014) or pedestrian travel research (LaPlante and Kaeser, 2007).

information (e.g., one-way road). Prior to analysis, these data needed preprocessing. For example, graph theory metrics are susceptible to edge effects because their derivation (discussed later in this article) involves the modeling of movement throughout the wider street network. As a consequence, street segments closer to the boundary of a study area will tend to have artificially lower estimates of movement potential as some street segments to which they are connected (and the routes in which they will feature) will be beyond the study area boundary and, hence, not included in the calculations. To avoid this, we used a temporary 7-km buffer in the calculations. Features that can distort the calculation of the metrics were also cleaned. For example, divided features such as motorways were collapsed to a single edge to reflect the lived reality of such roads, and traffic islands were collapsed to a single edge (see also Davies and Johnson, 2015).

The cleaned networks were then converted into a form suitable for graph theory analyses (discussed later in this article). For example, split links, which can occur when streets have different names at either end but have no junction in between, were merged. The network was then partitioned into three networks to enable estimation of pedestrian and vehicular movement potential (discussed later in this article), and to form the choice-set. These networks differ by the features and traffic rules incorporated (see table 1). To elaborate, the vehicular network includes only vehicle-accessible roads (and, hence, excludes alleyways, paths, and pedestrianized streets), and in the calculations that follow, one-way directionality (where it applies) and variable travel speeds are incorporated into the analyses. The pedestrian network includes only roads and paths that can plausibly be used by pedestrians (and so this network excludes motorways and slip roads). For this network, in what follows, a constant travel speed is assumed for all pedestrian journeys (discussed

later in this article). Finally, the choice-set includes only roads and paths from which residential properties can plausibly be accessed (i.e., it excludes alleyways, motorways, paths, and slip roads) and where at least one property exists.

OTHER DATA

Property data, provided by the OS, were associated with street segments by assigning each home to the nearest applicable feature in each network. To elaborate, a property may be assigned to a pedestrianized street segment in the pedestrian network (as that is where the property is likely to be accessed on foot) but assigned to a different street in the vehicular network. The reason for the latter is that vehicles cannot be driven on pedestrianized streets. When assigning homes to the vehicular network, we thus assumed that vehicle journeys from such homes would begin on the nearest applicable road and consequently assigned homes to these.

Affluence was calculated with residential property sales data from the U.K. Land Registry for all sales between 04/01/04 and 03/31/14 with their prices adjusted (using the U.K. Land Registry's House Price Index) to April 2009 prices. These data were geocoded by matching the addresses with those from the OS property data. Streets segments were assigned the mean house price where at the shortest radii (incrementing by 25 m for 25–1,000 m), there were at least five houses sold. The use of alternative criteria, such as the average price of all houses sold within 500 m or 1 km, produced the same results and are hence discussed no further.

The collection of estimates of social disorganization through systematic social observation was beyond the scope of the current study. Consequently, we follow the approach taken in previous studies of offender location choice (e.g., Bernasco and Nieuwbeerta, 2005) and use indirect measures, or proxies, derived from the 2011 U.K. census. Data were obtained for three variables (ethnic-heterogeneity, socioeconomic heterogeneity, and population turnover) for U.K. census output areas. Output areas contain around 150 homes and are the smallest unit of analysis for which data are available. For consistency, all three indices were operationalized with the index of qualitative variation (Agresti and Agresti, 1978). This can be interpreted as the probability that two people randomly selected from the same area came from different (ethnic or socioeconomic) groups or lived in same output areas the previous year. Street segments were then assigned social disorganization values based on the mean values of the output area(s) within which they were located.

ROAD NETWORK MEASURES

Before describing the statistical method employed, we discuss our approach to quantifying guardianship potential and offender awareness of the road network. The graph theory approach is first discussed, and then a detailed description of how the actual metrics were computed is provided.

GRAPH THEORY

In previous studies, estimates of movement potential along street segments have been used by researchers as proxy measures of ambient guardianship *and* people's collective awareness of locations. A major limitation of much of the previous research (for

exceptions, see Davies and Johnson, 2015; Hillier and Sahbaz, 2009) has been the use of area-level metrics or ordinal variables by the research team (see earlier discussion). Space syntax measures offer an alternative, but pure graph theory (from which the space syntax measures are derived) metrics are preferred here as these metrics may be adapted and applied in novel ways (discussed later in this article).

First, in regard to nomenclature, graphs can be derived to represent road networks in two ways: with either street segments or intersections as the unit of analysis (see, Davies and Johnson, 2015). As used by researchers in previous studies (e.g., Porta, Crucitti, and Latora, 2006), we employ the former, commonly referred to as a “dual representation.” In this case, street segments (any section of road between two intersections) are represented as vertices (at the midpoint of the segment) and intersections are represented as the connections between them. The resulting mixed graphs, which include one- and two-way roads, are defined as $G = (V, E, A)$, which consist of vertices $V = \{v_1, \dots, v_m\}$, undirected edges $E = \{e_1, \dots, e_n\}$, and directed arcs $A = \{a_1, \dots, a_s\}$, where edges and arcs (also called “links” or e for “generic links”) connect vertices. These links can also be weighted where $w(e)$ represents the cost of traversal. In this article, this is the time required to traverse a link that is calculated by considering the metric length of the link, and the speed of travel typical for that link (discussed later in this article). A path existing between i and j is represented by $i \sim j$, and the associated travel time (between the two street segments’ midpoints) is denoted by d_{ij} . If the path is from and to the same street segment, then d_{ij} is calculated as being equal to the mean travel time between two random points on the same street segment.⁵

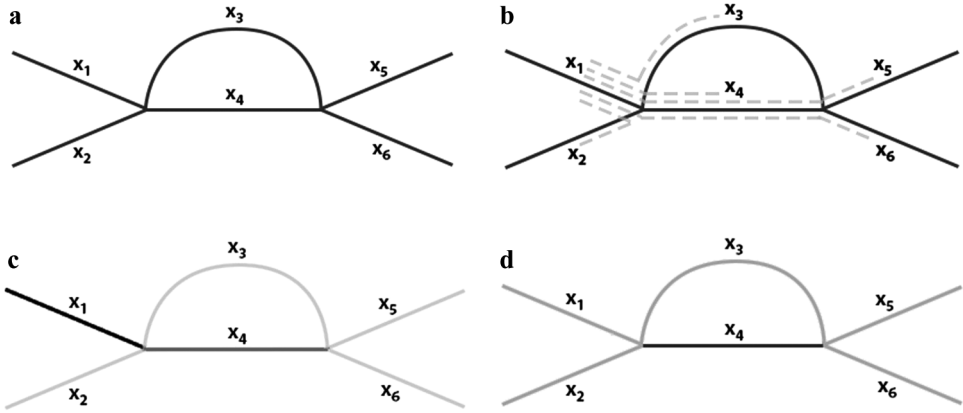
Graph theory metrics can be thought of as providing a way of analyzing and quantifying how a network can be traversed. A key metric is “betweenness” (Freeman, 1977), which has been discussed in detail elsewhere (e.g., Crucitti, Latora, and Porta, 2006; Davies and Johnson, 2015) and has been shown (e.g., Hillier and Iida, 2005; Turner, 2007) and used by researchers (Davies and Johnson, 2015) to estimate traffic and passer-by guardianship. Classically, this is defined as:

$$B_e = \sum_{i,j \in V, i \sim j} \frac{\sigma_{ij}(e)}{\sigma_{ij}} \quad (1)$$

where σ_{ij} represents the number of shortest paths between nodes i and j and $\sigma_{ij}(e)$ represents those that pass through segment e . To illustrate the calculation of betweenness (referred to as *overall betweenness* hereafter) and to specify how our estimate of *idiosyncratic betweenness* is derived, consider figure 1, which illustrates different path structures by using the basic network shown in part a. Here, metrically shortest paths are initially created from the first vertex (x_1) to all others (figure 1b). The degree of overlap of these shortest routes (for x_1) is shown in figure 1c, and it can be observed that for vertex x_1 , the vertex most likely to be traversed (apart from itself) is vertex x_4 . All other vertices feature in only one shortest path through the network that originates from vertex x_1 . As will be discussed, individual estimates such as that shown in figure 1c are not usually used in isolation, but they are aggregated to derive an estimate of overall betweenness (e.g., see also Davies and Johnson, 2015). Nevertheless, as described later in this article, we use

5. For street segment of length L , this is $L / 3$.

Figure 1. Steps in the Calculation of Idiosyncratic (B and C) and Overall (D) Betweenness Metrics



NOTE: In the example shown, idiosyncratic betweenness (b-c) is calculated for vertex x_1 .

them here as an index of *idiosyncratic betweenness* to estimate how familiar an offender residing on any vertex (i) is likely to be with all other vertices (j) in the road network. This produces a matrix (i, j) of idiosyncratic betweenness values.

Before discussing the measure of idiosyncratic betweenness further, let us clarify how the estimate of overall betweenness is derived. To produce this (see also Davies and Johnson, 2015), the earlier process is repeated for all other vertices (in our example, vertices $x_2, x_3 \dots x_6$) in the network. The degree of overlap for the routes from and to every vertex (the aggregation of the steps shown in figure 1b and c for all vertices) is then computed and represents the betweenness value derived with equation (1) and shown in figure 1d. As illustrated in figure 1d, in our example, the vertex x_4 features in most of the shortest paths between vertices in the network and consequently has the highest overall betweenness value. In this extreme example, the other vertices only feature in those shortest paths for which they are the origin or destination, and so they have uniformly low overall betweenness values (unlike the measure of idiosyncratic betweenness). The overall betweenness value for an edge (B_e) may thus be thought of as estimating how likely (or frequently) it is that a street segment is traversed during everyday urban activity in the network (see also Hiller and Iida, 2005). In contrast to idiosyncratic betweenness, this overall index of betweenness provides an indication of overall movement potential for each street segment, and we use it to estimate the likely awareness and presence of passers-by at each location. As such, each street segment has a single overall betweenness value for this index (rather than a matrix of values).

Nevertheless, equation (1) (used in studies such as Davies and Johnson, 2015) comprises the restrictive assumption that an equal number of journeys will originate and terminate at all vertices in the network (street segments). In reality, certain segments (e.g., those with high-density residential properties) will act as origins/destinations for more journeys (Leung et al., 2011). To account for this, vertex weighting is applied where routes are multiplied by w_i (the origin's weight) and w_j (the destination's weight) and divided by $\sum w_k$ (the total weights of all destinations possible from i). Through this approach, we

effectively assume that the number of journeys that start at node i will be proportionate to some factor such as, and as we use in this study, the number of residential properties located on that street segment, and that these journeys will be distributed to other nodes according to some factor (here, the proportion of residential properties at node j):⁶

$$W_e = \sum_{i,j \in V, i \sim j} \frac{\sigma_{ij}(e) w_i w_j}{\sigma_{ij} \sum_k w_k} \quad (2)$$

When considering pedestrian and vehicular journeys, it may be unrealistic to estimate movement potential by including long journeys in the calculation of betweenness. Therefore, and as used by researchers in previous studies (e.g., Davies and Johnson, 2015), trips can be restricted so that only destinations within a specified range ($d_{ij} \leq r$) are considered likely destinations:

$$W_e^r = \sum_{i,j \in V, d_{ij} \leq r} \frac{\sigma_{ij}(e) w_i w_j}{\sigma_{ij} \sum_k w_k} \quad (3)$$

In what follows, it is this measure (equation (3)) of overall betweenness that we used to estimate movement potential for pedestrians (to test hypothesis 3) and vehicles (to test hypothesis 6). With respect to pedestrian movement, trips through the road network can also be divided into those sections of a journey that might be thought of as being more a part of a person's "local area"—and hence that he or she might feel more responsible for—and those that are not. For example, for pedestrian journeys that originate from a person's home, only the first part of the trip may be part of the road network that they perceive as "local." To examine this, we introduce two further variants of overall betweenness. "Local betweenness," which is used to estimate movement potential for local passers-by (to test hypothesis 4), we calculated with a threshold l , where $d_{ie} \leq l$, that is, where the travel time between the origin and focal vertex is less than or equal to some threshold l . Conversely, "nonlocal betweenness," which is used to estimate movement potential for nonlocal passers-by (to test hypothesis 5), we computed for those trips where $d_{ie} > l$. The formulas for local (L) and nonlocal (N) betweenness are respectively:

$$L_e^{rl} = \sum_{i,j \in V, d_{ij} \leq r, d_{ie} \leq l} \frac{\sigma_{ij}(e) w_i w_j}{\sigma_{ij} \sum_k w_k} \quad (4)$$

$$N_e^{rl} = \sum_{i,j \in V, d_{ij} \leq r, d_{ie} > l} \frac{\sigma_{ij}(e) w_i w_j}{\sigma_{ij} \sum_k w_k} \quad (5)$$

Even though betweenness has been used by researchers to estimate macro-level movement through networks (e.g., Davies and Johnson, 2015), and hence collective awareness spaces, its application to micro-level (offender) movement is novel. In previous studies,

6. Intuitively, routes that start and end on street segments with more (less) homes on them will receive a higher (lower) weighting.

researchers have used proximity to the offender’s home location as a proxy for “awareness.” Although not entirely unreasonable, this confounds movement potential and the attendant “awareness” with the “effort” required to reach a location. It is also a crude estimate of both constructs.

Our alternative estimate, *idiosyncratic* betweenness, which was described in general terms earlier, is specified more formally in equation 6. Unlike the overall estimate of betweenness, this is computed for each offender from his or her known activity nodes (Y ; which in this study is their home location), and hence, no origin weighting is applied in this case:

$$P_e^x = \sum_{j \in V, y \in Y, x \sim j} \frac{\sigma_{yj}(e) w_j}{\sigma_{yj} \sum_k w_k} \quad (6)$$

To allow us to differentiate between offender awareness (potential) and the effort (time) required to travel to a particular location, in addition to computing idiosyncratic betweenness values for each offender, we estimate the effort required to reach locations in the network (to test hypothesis 1). This is derived from the graph theory metric “closeness centrality” (Freeman, 1977):

$$C_e = \sum_{j \in V, e \sim j} [d_{ej}]^{-1} \quad (7)$$

For each edge, closeness (C) is simply the inverse of the sum of the shortest travel times to all other vertices. Again, an *idiosyncratic* variant is calculated. Nonetheless, rather than adapting closeness, “idiosyncratic farness” is used for interpretability and represents the travel time between the focal vertex and the offender’s vertices. This is calculated as follows (i.e., by not inverting the sum of the distances as performed in closeness calculations):

$$F_e^y = \sum_{y \in Y, e \sim y} d_{ey} \quad (8)$$

This can be interpreted as the level of effort (in estimated minutes traveling) required to reach a street segment (from the offender’s home location) where segments with higher scores require more effort (time) than do those with lower ones. By definition, idiosyncratic farness will always be greater than, or equal to, the Euclidian travel time between two locations (see appendix B in the online supporting information).

GRAPH THEORY METRICS

To calculate the graph theory metrics, the shortest paths were created between all pairs of vertices. The cost of traversal was estimated by calculating the time required to travel along each link based on acceptable travel speeds. This is to be preferred for vehicular movements, for which the speed limit varies across street segments, as it may better approximate route choices (Leung et al., 2011). For pedestrian movement, this will be equivalent to metric distance as walking speed is assumed constant [3 miles per hour in this case; Department for Transport (DfT), 2013a]. Alternatives to this route choice logic, such as minimizing angular change at intersections, which is often used by research teams

Figure 2. “Local” and “Nonlocal” Betweenness for an Individual Living at Location x



in space syntax studies (e.g., Hillier and Iida, 2005), were also tested but made little difference to the results and so are discussed no further.

Measures of betweenness were then calculated as described earlier. The radii (r) for pedestrian movements was set at 20 minutes of traveling time (approximately one mile) based on the median pedestrian journey times recorded in the 2013 DfT travel survey (DfT, 2013a). This also roughly equates to the distance within which most households in the United Kingdom should find their local services, such as supermarkets (DfT, 2011). As a result of the configuration of the road network, what is “local” for pedestrians is likely to vary across people and places. To examine local and nonlocal betweenness for pedestrians, l was set to half of the maximum journey length (10 minutes). Figure 2 shows an example of what an individual living at location “x” would consider as local (black),

Table 2. Summary Statistics of the Independent Variables Used in the Choice-Set (Excluding Links with No Homes on Them)

Type of Variable	Resolution of Variable	Variable	Total	Mean	SD	Min	Max
Alternative Specific	Segment Level	Number of segments	5,286	—	—	—	—
		Number of burglaries per segment	459	.1	.4	.0	5.0
		Number of dwellings per segment	81,682	15.5	18.9	1.0	307.0
		Affluence (£100,000s)	—	3.5	2.8	.6	2.7
		Betweenness (pedestrian)	—	11.1	13.3	.0	100.0
		Local betweenness (pedestrian)	—	10.9	12.8	.0	100.0
		Nonlocal betweenness (pedestrian)	—	10.1	12.6	.0	100.0
		Betweenness (vehicular)	—	3.2	7.5	.0	100.0
	Output Area Level	Number of output areas	510	—	—	—	—
		Number of segments	5,286	10.7	5.7	1.0	48.0
		Ethnic heterogeneity (%)	—	25.9	19.2	.0	66.8
		Residential turnover (%)	—	21.3	11.5	3.3	83.7
		Socioeconomic heterogeneity (%)	—	68.1	5.8	47.4	79.7
Individual Alternative Specific	Segment Level	Idiosyncratic farness (10min)	—	4.6	2.0	.0	10.5
		Idiosyncratic betweenness	—	.5	4.0	.0	100.0

NOTE: The column “Total” indicates the overall sample size for a particular variable.

ABBREVIATION: SD = standard deviation.

nonlocal but within the pedestrian radii (medium gray), and outside the pedestrian radii (light gray).⁷ Based on the DfT survey, the radii for vehicular journeys were set to 25 minutes of traveling time. Unlike pedestrian journeys, this equates to different geographical distances across the network as a result of variation in the speed limits associated with different types of roads.

Idiosyncratic betweenness was calculated similarly to overall betweenness but included only those shortest paths that originated from the offender’s home vertex. Idiosyncratic farness (road network travel time) was calculated with the average of the pedestrian and vehicular traversal times associated with the shortest paths. The weightings applied were calculated with the number of properties on each (destination) link. Finally, as betweenness has no innate scale, the values were normalized to the range 0–100. Descriptive statistics for the independent variables are presented in table 2. In the table, alternative-specific variables are those that vary for each street segment but are identical for each offender. For example, the level of affluence for each street segment will vary across street segments but not across offenders. In contrast, individual-alternative specific variables are those that vary by street segment (or output area) and for each offender. For example, the idiosyncratic farness of a specific street segment will vary depending on the offender’s home location because it will be measured relative to where he or she lives. Spatial variation in the vehicular and pedestrian (overall) betweenness metrics is illustrated in

7. Sensitivity tests were performed to examine the choice of radii used. Generally consistent results (available by request) were found for “local” distances ranging from 2.5 to 15 minutes, although the effects reported diminish for greater distances.

figure 3. Street segments with darker shading have higher overall betweenness values and are expected to have greater vehicular or pedestrian movement potential, respectively.

ANALYTICAL STRATEGY

Studies of crime event locations are typically aimed at identifying those factors (e.g., indicators of social disorganization or movement potential on the road network) that are associated with where crimes occur. They generally achieve this aim, however, without reference to where offenders live. This is problematic because the results of research concerned with the journey to crime indicate that offenders typically commit offenses near to their home locations. The aim of studies of the journey to crime is also problematic because the research teams ignore the characteristics of the locations in which offenders choose to commit crime. Widely established in other fields, the discrete choice framework (McFadden, 1974) was first used in the field of criminology by Bernasco and Nieuwbeerta (2005) to overcome these shortcomings. It allows the simultaneous analysis of how characteristics of offenders (e.g., where they live) and the areas from which they can select to offend influence criminal location choice. For example, Bernasco and Nieuwbeerta (2005) reported that burglars were found to be more likely to target areas that were closer to their home location and that had more ethnic diversity, more single-family homes, and more homes. The use of this framework has now become well established in the criminological literature, although the units of analysis considered are typically large areal units (for an overview of studies, see appendix C in the online supporting information).

Discussed in detail elsewhere (e.g., Bernasco and Nieuwbeerta, 2005), the framework is straightforward and regards a decision-maker (the offender) who chooses from a choice-set (street segments in the current study) the alternative that he or she expects to derive the most utility from (Train, 2009). When following notation from Bernasco (2010b) and Train (2009), this can be formally expressed as follows. A decision maker, n , faces a choice from J alternatives. The utility, U , the decision maker derives from alternative j is:

$$U_{nj}, j = 1, 2, 3, \dots, J. \quad (9)$$

Although the utility derived from each alternative is only known by the decision-maker, he or she will choose alternative i if it provides the greatest utility:

$$U_{ni} > U_{nj} \forall j \neq i. \quad (10)$$

By observing the attributes of the alternatives, a_{ni} , and of the decision-maker, d_n , a function can be specified regarding the decision-maker's utility:

$$V_{ni} = V(a_{ni}, d_n) \forall i \quad (11)$$

Nonetheless, not all factors affecting utility will be observed:

$$V_{ni} \neq U_{ni} \quad (12)$$

Figure 3. Normalized Vehicular (Top) and Pedestrian (Bottom) Overall Betweenness Scores on Their Respective Networks



Utility is thus expressed as V_{ni} plus an error term, ε_{ni} , which is treated as random and represents idiosyncrasies and unobserved factors:

$$U_{ni} = V_{ni} + \varepsilon_{ni} \quad (13)$$

Consequently, the probability that decision-maker n chooses alternative i is the probability that the utility from i is greater than the utility from all other alternatives:

$$P_{ni} = \Pr(U_{ni} > U_{nj} \forall j \neq i) \quad (14)$$

$$P_{ni} = \Pr(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj} \forall j \neq i) \quad (15)$$

If the unobserved utility components, ε_{ni} , are independently and identically distributed with a Gumbel Type I extreme value distribution, the basic conditional logit (CL) model is derived (McFadden, 1974) with the assumption that the vector of parameters (x_{ni}) is linear:

$$V_{ni} = \beta' x_{ni} \quad (16)$$

The odds of decision-maker n choosing alternative i is then estimated by:

$$P_{ni} = \frac{e^{\beta' x_{ni}}}{\sum_{j=1}^J e^{\beta' x_{nj}}} \quad (17)$$

where β' is a vector of parameters to be estimated and e^{β} is the multiplicative effect of a one-unit increase in an alternative's attribute on the odds of selection.

Nevertheless, even though the previously applied choice models (see appendix C in the online supporting information), such as the CL, are suitable for many types of decisions, several assumptions, such as the independence of irrelevant alternatives (IIAs), should be met for their appropriate application. The IIA states that alternatives are independent if the utility from one choice depends only on that alternative's utility function (Ben-Akiva and Lerman, 1985). To put it another way, if alternative A is preferred to alternative B , the introduction or removal of alternative C should not change this preference. Although this seems logical, it ignores the possibility that some locations are similar and therefore substitutive and not independent. In fact, the two crime location choice studies that comprised models obviating this assumption (Bernasco, 2010b; Bernasco, Block, and Ruiter, 2013) found evidence of violations.

To relax this and other assumptions, other models should be considered. Although various alternative models exist, one that has only recently been used in criminological enquiry (Townsend, Birks, Ruiter, et al., 2015) but has been heavily lauded by researchers in the wider literature (Hensher and Greene, 2003) is the mixed logit (ML) model (McFadden and Train, 2000). As a detailed technical discussion of the use of the ML model in offender location studies is provided by Townsend, Birks, Ruiter, et al. (2015), and because we follow their approach, we limit the current discussion to the basic principles and advantages of the approach. In addition to relaxing the IIA assumption, in contrast to the CL, the ML model assumes a probability density function for the coefficients, $f(\beta|\theta)$, where θ represents the mean and the standard deviation of the β s. By allowing coefficients to vary across decision makers, taste variation can be estimated across offenders.

The ML model also addresses problems associated with modeling repeated choices by the same offender. That is, traditional CL models assume unobserved factors that affect a person's choice are independent on each choice occasion, which will lead to biased standard errors. Although other models partially account for repeated choices by computing "robust standard errors" (White, 1982), with ML models, this is addressed more directly by explicitly modeling choice occasions for serial offenders.

The application of the discrete choice framework requires the specification of the decision-makers, the choice-set, and the choice criterion. In studies of crime location choice, the decision-makers are clearly offenders, and the criteria are those factors hypothesized to influence targeting decisions. In the case of residential burglary, although offenders theoretically choose from every dwelling, the results of studies reveal that offenders follow a spatially structured decision process (e.g., Brown and Altman, 1981). Consequently, the choice-set employed by research teams in previous studies has typically been a spatially aggregated grouping, such as census tracts. Nevertheless, persuasive arguments do exist for the use of finer spatial granularity (Andresen and Malleon, 2011; Weisburd et al., 2004).

For example, people do not navigate from one large area to another; they navigate along the road network. As such, a spatial resolution at this scale (e.g., street segment) should better capture the spatial logic of offender decision-making (Johnson and Bowers, 2010). Also, as constructs such as (the potential for) guardianship and awareness spaces can be more precisely measured at this level, street segments are a natural unit for studying crime (Weisburd, Groff, and Yang, 2012). These smaller spatial units are also methodologically justified as even if an offender's mental map is more generalized than is specified, local variations would be unobserved if aggregated before measurement (Bernasco, 2010b).

MODEL SPECIFICATION

Unlike other logit models, ML cannot be solved analytically (Train, 2009) but must be estimated with either maximum simulated likelihood (MSL) or hierarchical Bayes (HB). Nevertheless, given acknowledged problems associated with large choice-sets and MSL (Hensher and Greene, 2003), as in Townsley, Birks, Ruiter, et al. (2015), the results for models estimated with HB are reported here (see also Train, 2009). We note, however, that analyses were also conducted with equivalent MSL models that use the "mixlogit" (Hole, 2007a, 2007b) routine in Stata (StataCorp, College Station, TX). We used various numbers of Halton draws (all of which converged), with and without correlated coefficients. These analyses generated the same pattern of results as for the HB models and so are discussed no further.

To apply the ML model to offense location choice requires the identification of those variables for which taste variation is expected, alongside the specification of their assumed distributions (all are treated as random variables). As in Townsley, Birks, Bernasco, et al. (2015), all variables were entered nonfixed so that their effects could vary among burglars and are modeled with normal distributions—the default choice of prior probability distribution in the absence of compelling evidence to suggest otherwise. To identify and account for patterns of tastes where the preferences for some variables are associated with the preference for others, all coefficients were entered to allow correlation with each other.

To compute HB models, parameter values were initially estimated from the prior probability distribution and then simulated draws were taken from the posterior parameter distribution, from which coefficient values were reestimated. Through this analysis, we found model parameters (the mean and the variance) to be stable beyond 50,000 (retained) draws, and hence all models were estimated with 100,000 (retained) draws, with the first 25,000 draws discarded and used as a “burn-in” to minimize any effect of the prior probability distributions (Train and Sonnier, 2005). Because subsequent draws from the posterior distributions are necessarily dependent on the previous draws, any autocorrelation is mitigated through thinning, whereby only every 10th draw is retained and the parameters calculated from this sample (Train and Sonnier, 2005). All models were computed with the “bayesmixedlogit” routine (Baker, 2013) in Stata.⁸ Equivalent conditional logit models were also estimated to assess the performance of the mixed logit. As noted, for all analyses, the unit of analysis is the street segment.

RESULTS

For parsimony, table 3 shows the results for the key variables of interest, along with the model fits from the ML models. Estimates for the full models can be found in appendices D and E in the online supporting information. The former replicates table 3 but includes all variables, whereas the latter displays the results for the unscaled form of the variables. In table 3, for completeness, models for each variable are tested independently before being combined. The top panel of table 3 shows the point estimates for the mean (recall that for the ML model a distribution of coefficients is computed for each independent variable) multiplicative odds ratio (OR) of a target street segment being selected after a one-unit increase in the relevant independent variable. In terms of this “one-unit increase,” to make results easier to interpret, some variables’ units are scaled (as indicated). The standard errors shown are approximated with the delta method (Buis, 2014), and they indicate the statistical significance of the mean estimates.

The bottom panel of table 3 shows the standard deviations (SDs) for the between-offender estimates of the ORs. These provide an estimate of the extent to which taste variation exists across offenders for a particular variable. In this part of the table, the numbers in parentheses are *t* statistics, which indicate whether any observed variation across offenders is statistically significant. Although the SDs shown in table 3 give a good indication of preference variability, figure 4 illustrates their estimated distributions (from model 3) more precisely. In what follows, the overall model fits, the point estimates, and the taste variation are discussed in turn.

OVERALL MODEL FITS

In following Townsley, Birks, Ruiter, et al. (2015), model fits were assessed with the intuitive root likelihood (RLH) statistic, which ranges between 0 and 1, and for which a

8. To assess multicollinearity among the independent variables, variance inflation factors (VIFs) and condition indexes were computed where values greater than 5–10 and 30–100, respectively, suggest moderate-to-severe multicollinearity (Belsley, Kuh, and Welsch, 1980; Cohen et al., 2003). The largest VIF score of 4.4 and condition index of 29.6 indicate no major problems as there is only weak (to moderate) evidence of multicollinearity.

Table 3. Mixed Logit Models of Residential Burglar Location Preferences (Estimated Average Odds-Ratios Are Shown in the Top Panel, Whereas Their Standard Deviations Are Shown in the Bottom Panel)

Average Odds Ratios							
Variable		1a	1b	1c	2a	2b	3
Offender Variables	Idiosyncratic Farness – 10 min	.30** (.04)		.34** (.04)			.31** (.04)
	Idiosyncratic Betweenness – 10%		3.53** (1.70)	2.59** (.94)			2.51** (.86)
Guardianship Variables	Pedestrian (overall)				1.01 (.05)		
	Betweenness – 10%						
	Local Pedestrian (overall)					.68** (.06)	.67** (.07)
	Betweenness – 10%						
	Nonlocal Pedestrian (overall)					1.22** (.09)	1.15** (.06)
	Betweenness –10%						
	Vehicular (overall)				.64** (.08)	.64** (.08)	.66** (.10)
	Betweenness – 10%						
Standard Deviations of the Average Odds Ratios							
Variable		1a	1b	1c	2a	2b	3
Offender Variables	Idiosyncratic Farness – 10 min	.51** (4.18)		.48** (4.33)			.53** (4.46)
	Idiosyncratic Betweenness – 10%		6.83** (2.66)	6.02* (2.28)			5.37 (2.06)
Guardianship Variables	Pedestrian (overall)				.46** (5.53)		
	Betweenness – 10%						
	Local Pedestrian (overall)					.40** (4.69)	.46** (4.36)
	Betweenness – 10%						
	Nonlocal Pedestrian (overall)					.64** (5.44)	.69** (5.02)
	Betweenness –10%						
	Vehicular (overall)				.64** (4.29)	.44** (3.96)	.61** (3.55)
	Betweenness – 10%						
Mixed Logit RLH ($\times 10^{-4}$) ^a		16.7	10.5	22.0	7.3	10.1	28.4

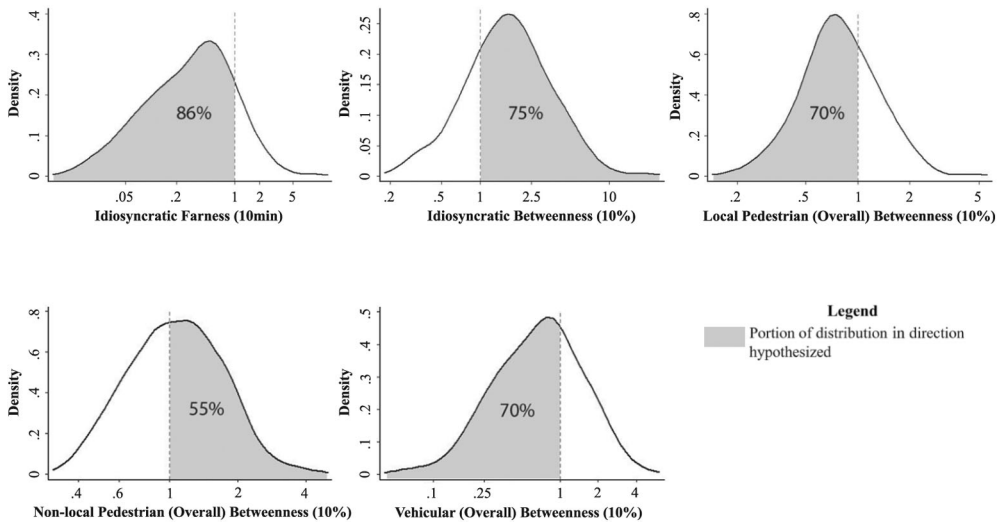
NOTES: In the top panel, the figures in parentheses are the standard errors of the average odds ratios. In the bottom panel, the figures in parentheses are *t* statistics for the between-offender standard deviations. Five other control variables (ethnic heterogeneity, residential mobility, socioeconomic heterogeneity, affluence, and the number of dwellings) were also included in each model, but for conciseness are not shown (a complete table of results is provided in appendix D in the online supporting information).

^aThe null model RLH is 1.9×10^{-4} , and the conditional logit RLH values ($\times 10^{-4}$) are 5.1, 4.2, 5.4, 4.0, 4.2, and 7.4, respectively.

* $p < .05$; ** $p < .01$ (two-tailed).

value of 1 indicates a perfect model (the estimated probabilities of the observed choices are 100 percent). This value can also be compared with the RLH for other models such as the equivalent conditional logit and null models. In the case of the latter, this is equal to $1/\text{number of alternatives}$ (1.9×10^{-4}), and an RLH value less than this indicates that a fitted model performs worse than chance. As shown in table 3, the RLH for the fitted ML models is between 7.3 and 28.4 ($\times 10^{-4}$) and that for the CL models is between 4.0 and 7.4 ($\times 10^{-4}$). This indicates both sets of models fit the data significantly better than do their respective null models, and that the ML models fit the data better than do the CL

Figure 4. Estimated Distributions of the Main Variables' Odds Ratios on the Likelihood of That Target Being Selected



NOTE: Odds ratios computed for a one-unit increase in the respective variable. Distributions presented for the sampled population for Model 3 (ML).

models. In terms of the final model (3), the RLH statistics indicates that the ML model fits the data around $4\times$ better when compared with the equivalent CL model and around $15\times$ better when compared with the null model.

POINT ESTIMATES

When we consider the offender variables first, the estimates of offender awareness (idiosyncratic betweenness) and the travel time (idiosyncratic farness) required to reach offense locations were both significant predictors of location choice when entered independently (figure 1a and b), when entered together (figure 1c), and when the effects from other offender variables were accounted for in the final model (3). In terms of the results for the final model, the findings suggest that for every 10 minutes a street segment is from an offender's home location, the odds of it being selected (all else equal) decreases on average by .31. In contrast, for every 10 percent increase in "idiosyncratic betweenness," the odds of a street segment being selected increases (on average) by 2.51. Hypotheses 1 and 2 are thus both supported in that locations that are easier to reach ("idiosyncratic farness") and are likely more familiar ("idiosyncratic betweenness") to an offender are more likely to be selected. It should be noted that both of these variables were calculated by combining scores calculated from the pedestrian and vehicular networks (e.g., pedestrian idiosyncratic farness and vehicular idiosyncratic farness); nonetheless, there were no significant differences when these were disaggregated.

In terms of passers-by guardianship, model 2a shows that when pedestrian (overall) betweenness—estimated in the aggregate—is entered alone, it is not a significant predictor of crime location choice. Yet, when disaggregated into local and nonlocal movement (model 2b), both were significant. In this case, greater nonlocal (overall) betweenness

was associated with a street segment being more likely to be selected, whereas greater local (overall) betweenness was associated with a street segment being less likely to be selected, as predicted. This pattern of results persists when these variables were entered into model 3 (which also accounts for the offender variables). These results are in line with hypotheses 4 and 5, although hypothesis 3 regarding an increase in likelihood of burglary associated with any passers-by (overall pedestrian betweenness) was not supported (even when entered into the final model). For vehicular betweenness, the point estimate was also statistically significant and suggests that, all else equal, segments that are expected to contain greater levels of vehicular traffic were less likely to be chosen. This finding supports hypothesis 6.

Although entered predominantly as control variables and not shown in table 3 (see appendices D and E in the online supporting information), it is worth noting that two social disorganization variables (residential mobility and socioeconomic heterogeneity) were both statistically significant and positively associated with a location being selected for a burglary, as expected. A third (affluence) was also statistically significant and negatively associated with a location being selected for burglary. In contrast, ethnic heterogeneity was not statistically significant, nor was the number of dwellings.

TASTE VARIATION

For most findings so far discussed, the phrase “on average” is a necessary clause as all SDs associated with the coefficient estimates were statistically significant. When we take each of the main findings in turn, the standard deviations for the offender variables “idiosyncratic betweenness” and “idiosyncratic farness” suggest that the effects of familiarity and accessibility (measured in terms of the time required to travel to a location) vary across offenders. As illustrated in figure 4, the final model suggests that of the sampled offenders, 75 percent seemed to prefer targets located on street segments that were estimated to be more familiar to them, whereas 86 percent seemed to prefer closer targets.

In the case of the standard deviations for the pedestrian passer-by guardianship variables, approximately 70 percent of offenders seemed to prefer segments with fewer numbers of locals, whereas 55 percent seemed to prefer segments with greater numbers of nonlocals. There was also significant taste variation in the vehicular passer-by guardianship variable such that an estimated 70 percent of offenders seemed to prefer segments with lower levels of vehicular traffic. All other (control) variables also exhibited taste variation (see also appendix D in the online supporting information).

OTHER FINDINGS

Calculated from the estimated covariance matrix (not shown), table 4 provides point estimates for the correlations (between coefficients) matrix. This then provides an indication of whether offenders who had a preference for one factor also tended to have a preference for another. Four covariances were statistically significant ($p < .05$). The local betweenness coefficient was highly negatively correlated ($-.90$) with the coefficient for nonlocal betweenness—offenders who preferred street segments with higher expected levels of nonlocal passers-by tended not to prefer those with higher numbers of local passers-by (street segments can have high levels of both). Residential mobility was highly positively correlated with the number of dwellings (.87), suggesting that offenders who preferred to target street segments with larger numbers of residential dwellings also

Table 4. Correlation Matrix of the Coefficients

Variable	1	2	3	4	5	6	7	8	9	10
1. Idiosyncratic Farness (10 min)	1.00	-.17	-.12	.16	-.26	.13	.40*	-.27	-.08	.22
2. Idiosyncratic Betweenness (10%)		1.00	.05	-.03	.06	-.05	-.14	.10	.04	-.01
3. Local Pedestrian (overall) Betweenness (10%)			1.00	-.90*	.17	-.12	-.09	.02	.16	.20
4. Nonlocal Pedestrian (overall) Betweenness (10%)				1.00	-.18	-.20	.14	-.02	-.09	-.09
5. Vehicular (overall) Betweenness (10%)					1.00	.20	-.28	.09	.02	-.15
6. Ethnic Heterogeneity (%)						1.00	.09	-.19	-.02	-.34
7. Residential Turnover (%)							1.00	-.43*	.01	.87*
8. Socioeconomic Heterogeneity (%)								1.00	-.01	-.16
9. Affluence (£10,000s)									1.00	.35
10. Number of Dwellings										1.00

* $p < .05$ (two-tailed).

preferred those roads that were located in areas of high residential turnover. Although only moderately correlated, residential mobility was also positively correlated with farness (.40) and negatively correlated with socioeconomic heterogeneity (–.43).

DISCUSSION

In this article, we employed novel approaches to test more directly aspects of theories of burglar location choice that have been largely unexplored in previous research. In particular, we introduced variants of existing graph theory metrics to (for the first time) disentangle the estimation of offender awareness, the effort (in terms of network travel time) involved in traveling to particular locations, and the potential for ambient guardianship at specific locations in the road network. Like Townsley, Birks, Ruiter, et al. (2015), we used a more sophisticated discrete choice model than is typically used by researchers in studies of offender location choice to test hypotheses, and the findings illustrate the benefits of so doing. For example, allowing parameters to vary to account for taste variation led to significant improvements in model fit and a better understanding of the consistency with which particular factors affect offender decision-making (something that cannot be estimated with a conditional logit model). In terms of the overall fit of the final model, interpretation of the RLH is not as simple as for the R squared values associated with (say) ordinary least-squares models, or even the pseudo R -squared values computed for conditional logit models (see McFadden, 1974). Nevertheless, the change in the RLH relative to the null (a factor of 15) and equivalent conditional logit (a factor of 3.8) models suggests that the ML model (3) fits the data reasonably well and provides an improvement over the conditional logit model. Townsley, Birks, Ruiter, et al.'s (2015) analysis of offender spatial decision-making at the area level (for which the improvements in model fits were 25.2 and 5.4, respectively) also demonstrates the value of using ML models in studies of offender location choice. This suggests the utility of the ML approach to modeling, regardless of the unit of analysis employed (street segments in the current article and large areal units in Townsley, Birks, Ruiter, et al., 2015).

When we consider the role of offender awareness and accessibility, we find “idiosyncratic farness” and “idiosyncratic betweenness” to be significant predictors of crime

location choice, as expected. That is, the effort required to reach locations was negatively associated with the likelihood that an offender would select a particular street segment on which to offend. When we accounted for this, and in line with crime pattern theory, our estimate of an offender's familiarity with a street segment was also (positively) correlated with the likelihood that they would select it.

Yet, it is important to note that there was evidence of individual variation in taste preferences for these two (idiosyncratic) variables. With respect to the distance traveled—the only estimate of offender awareness used by research teams in other studies—Townsend, Birks, Ruiter, et al. (2015) also reported variation in preferences for this variable (measured in Euclidian terms at the area level in their study). Thus, future research might be designed to explore what explains such variation. For example, is this associated with characteristics of the offenders, characteristics of the areas within which they live, or both? For example, awareness may play a more important role in target choice for less experienced burglars who are unwilling to seek out new opportunities for crime (e.g., Bennett and Wright, 1984). Alternatively, offender awareness may be more important in neighborhoods that have less regular road network configurations that would be more difficult to navigate without some awareness of them (see Beavon, Brantingham, and Brantingham, 1994; Bevis and Nutter, 1978).

The findings from qualitative research concerned with burglars' use of space (e.g., Rengert and Wasilchick, 2000; Wiles and Costello, 2000) has revealed that different activity nodes, such as schools for younger burglars and the workplace for older offenders, influence offender spatial decision-making. Thus, data permitting, in future quantitative research of the kind reported here, scholars may derive estimates of idiosyncratic awareness by using other likely significant activity nodes as origin points. They may also use the methodology to examine more precisely how an offender's awareness space evolves over time when he or she (for example) changes residential address (see Bernasco, 2010a; Rengert and Wasilchick, 1985).

When we consider ambient guardianship, existing graph theoretical measures (see Davies and Johnson, 2015) that can be used to estimate the level of passers-by (and guardianship) were also advanced in this article. This was achieved by weighting the metrics to account for the nonuniform distribution of journeys, and by deriving estimates of local and nonlocal movement potential. As found in Bennett and Wright's (1984) qualitative research, burglars seemed to avoid street segments with higher estimated levels of vehicular traffic. Moreover, street segments with greater estimated volumes of nonlocal passers-by and lower estimated volumes of local passers-by were found to be more likely to be targeted by burglars, although—and in line with findings from qualitative research (e.g., Bennett and Wright, 1984; Wright and Decker, 1994)—these "taste preferences" also varied across offenders. The correlation between the coefficients representing the estimated number of local and nonlocal passers-by (guardianship) was also significant. As a result, burglars who preferred street segments for which fewer local passers-by would be expected also simultaneously preferred those where more nonlocal passers-by would be expected (and vice versa). That is, rather than preferring street segments where no passers-by would be expected whatsoever, burglars tended to prefer streets where people would be expected but where fewer local people would be anticipated. These findings support predictions from the "defensible space" perspective for which nonlocal movement would be perceived to be detrimental to effective guardianship by suppressing the ability of local residents (and others) to exhibit territoriality and deter crime. This supports

Newman's (1972) suggestion that crime risk is influenced by both how much movement there is on a street and who is involved.

To some extent, these findings are also in keeping with the ideas underpinning social disorganization and associated theories (e.g., Sampson and Groves, 1989). That is, in areas where the estimated number of nonlocal passers-by is high, residents' ability to act collectively to deter crime may be impaired. Nevertheless, an alternative interpretation of this finding is that the key ingredient is not social disorganization but simply guardianship, and that effective guardianship is directly influenced by the way in which urban form shapes the movement of different people through places. In this way, there would still be a form of social organization (as who is present seems to matter), but it would be much simplified and more consistent with Newman's ideas than with those invoked by theories of social disorganization. In the current study, we included estimates of social disorganization as control variables, and so the effect of nonlocal movement was estimated net of area-level indicators of social disorganization. However, the indicators of social disorganization we used here were for larger spatial units than the modeled target locations (street segments), and the (census) data we used represent only indirect estimates of social processes. Thus, future research may seek to combine more precise approaches to measuring local social processes (Sampson and Groves, 1989; Sampson, Raudenbush, and Earls, 1997; see also, Weisburd, Groff, and Yang, 2012) with the approach to investigating the role of the road network employed here.

When we consider our estimates of local and nonlocal movement further, it is, of course, important to note that they are estimates. Their derivation was based on the principles of graph theory (and on common sense), which have been verified for pedestrian movement more generally (e.g., Hillier and Iida, 2005), but future studies might be designed to explore this further. For example, our implementation is a first step and is consequently a simple one. What is local may vary by person, area, and composition of the road network. For example, older adults may have a more extended sense of what they perceive as local when compared with their younger counterparts. Those who commute to work on foot may have a different perception of what is local when compared with those who use vehicular transport. Other possibilities exist. Areas will vary in terms of housing density, and in dense areas, only those homes very close to a person's residence might be perceived as local, whereas in low-density areas, people's perception of local might extend over larger geographic areas. The composition of the road network too can directly affect how aware people become of particular locations. For example, grid layouts offer uninterrupted sight lines making areas permeable and predictable (see Beavon, Brantingham, and Brantingham, 1994), facilitating awareness of locations and potentially what is perceived to be local. On the other hand, more irregular layouts decrease permeability and limit awareness of locations (Brantingham and Brantingham, 1993), even those nearby that, in turn, may reduce what people perceive as local. For simplicity, here we differentiate between local and nonlocal areas, which assumes a step-function in the way that people perceive areas. In reality, people's perceptions may vary along a continuous rather than a binary scale. For the reasons discussed, examining this issue in a more precise way was beyond the scope of this article, but we would encourage others to do so in the future. Such studies are likely to involve additional methods to those used here, such as interviews and field studies.

It is also important to acknowledge limitations associated with the police data analyzed here. Not all crimes are recorded by, or cleared by, the police, and consequently, the

current findings may only apply to the sample of offenders who came to the attention of the police. This is, of course, true of all studies that involve the analysis of crimes cleared by the police, but the outcomes of recent work (Johnson, Summers, and Pease, 2009; Lammers, 2014) have revealed that spatial patterns of offending observed for those who are cleared by the police and those who are not are similar. Nonetheless, replication is needed to establish the external validity of the findings reported here, and future research might seek to do so comprising other forms of data.

In summary, in the current study, we used graph theory metrics and a mixed logit approach to test theories of criminal location choice for the crime of burglary. Analyses were conducted at a much finer spatial scale than has been generally the case hitherto. This is important not because smaller is better but because the street segment is likely one key scale at which people navigate their environment and events (criminal or otherwise) take place. This choice of scale enabled the generation of novel “idiosyncratic” measures of offender awareness. These might be further developed in future research with other anchor points of importance to an offender, such as place of work or other locations. The more established (overall) betweenness measures could also be extended to consider (for example) temporal variation in traffic flows, public transportation systems, and other factors. The use of the mixed logit model also shows considerable promise, providing insight into variation in individual taste preferences across offenders that is not possible to detect with conditional logit variants. A challenge for future research will be to explain this variation. For now, our results provide further support for crime pattern theory, Newman’s concept of defensible space, and theories of social disorganization.

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

Appendix A. Map of the Study Area Showing the 1-Km Buffer Around the “Built-Up Areas” of High Wycombe, Beaconsfield, and Marlow within Buckinghamshire County

Appendix B. Comparison of the Inter-street Segment Euclidean Pedestrian Travel Times and Equivalent Street Network Pedestrian Travel Times

Appendix C. Summary of All Previous Crime Location Choice Studies that Used the Discrete Choice Framework

Appendix D. Estimated Average Odds Ratios (Top Panel), Standard Deviations of the Odds Ratios (Bottom Panel), and Model Fits for the Mixed Logit Models of Residential Burglar Preferences

Appendix E. Estimated Unscaled Average Odds Ratios (Top Panel), Standard Deviations of the Odds Ratios (Bottom Panel), and Model Fits for the Mixed Logit Models of Residential Burglar Preferences