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Burglar Target Selection: A Cross-national Comparison

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Abstract

Objectives: This study builds on research undertaken by Bernasco and Nieuwbeerta and explores the generalizability of a theoretically derived offender target selection model in three cross-national study regions. *Methods:* Taking a discrete spatial choice approach, we estimate the impact of both environment- and offender-level factors on residential burglary placement in the Netherlands, the United Kingdom, and Australia. Combining cleared burglary data from all study regions in a single statistical model, we make statistical comparisons between environments. *Results:* In all three

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study regions, the likelihood an offender selects an area for burglary is positively influenced by proximity to their home, the proportion of easily accessible targets, and the total number of targets available. Furthermore, in two of the three study regions, juvenile offenders under the legal driving age are significantly more influenced by target proximity than adult offenders. Post hoc tests indicate the magnitudes of these impacts vary significantly between study regions. *Conclusions:* While burglary target selection strategies are consistent with opportunity-based explanations of offending, the impact of environmental context is significant. As such, the approach undertaken in combining observations from multiple study regions may aid criminology scholars in assessing the generalizability of observed findings across multiple environments.

Keywords
offender mobility, residential burglary, discrete spatial choice, replication

Introduction

Understanding how offenders choose where to commit crime is a classic criminological problem. There is long-standing empirical evidence that offenders do not necessarily offend where they live (Boggs 1965; Lottier 1938a, 1938b; Schmid 1960). This has led researchers to focus on explaining the "push-pull" factors of offender choice (Brantingham and Brantingham 1995; Pyle and Hanten 1974; Schmid 1960) and importantly environmental factors that impede or facilitate mobility, such as public transport or street networks (Beavon, Brantingham, and Brantingham, 1994; Clare, Fernandez, and Morgan 2009; Johnson and Bowers 2010; Ratcliffe 2006).

Historically, however, two important issues have limited understanding of offender mobility: (1) lack of a general paradigm to study the spatial behavior of offenders and (2) lack of systematic replication studies. Addressing the first of these issues in their study of residential burglary, Bernasco and Nieuwbeerta (2005) propose the *discrete spatial choice* approach, consolidating extant methodologies—offender-, target-, and mobility-based studies—in a single analytical framework. Subsequently, this approach has enabled similar studies of burglary (Bernasco 2006; Clare et al. 2009) and has been applied to the analysis of different types of crime (Baudains, Braithwaite, and Johnson 2013; Bernasco 2010; Bernasco and Block 2009; Bernasco, Block, and Ruiter 2013; Bernasco and Kooistra 2010).

This study addresses the second issue—a lack of systematic replications. Replication allows researchers to rule out the role of unmeasured factors specific to a previous investigation, establishing whether previous findings were an exceptional case or representative of the phenomena being studied. However, such replications often result in disparities in observed impacts (Tilley 1993). Where differences are observed, it can be exceedingly difficult to establish their cause: a different mechanism influencing offending? different settings? differences in experimental units? differences in implementation, measurement, or analytic approaches? or some combination of the above. Confounding this problem, academic journals often prioritize novel insights and methods above strict replications of existing studies. Thus, publication bias may limit the extent to which the results of replications are disseminated, and in turn, the degree to which the generalizability of findings can be established (Rothstein 2008).

Drawing on initial research undertaken by Bernasco and Nieuwbeerta (2005), this article tests the applicability of their theoretical account of crime placement in multiple environments by comparing burglar target selection across different cities (i.e., multiple environments). Recorded crime data from three independent police services are used to analyze the location choices of residential burglars operating in The Hague (Netherlands), Birmingham (United Kingdom), and Brisbane (Australia).

Theoretical Framework

Introducing the discrete spatial choice approach to studies of individual offender mobility, Bernasco and Nieuwbeerta (2005)—hereafter abbreviated to B&N—describe three distinct approaches used in the analysis of criminal location choice, each delineated by unit of analysis and dependent variable. Offender-based studies typically analyze journey distances between offender home and offense locations (Block, Galary, and Brice 2007; Costello and Wiles 2001; Townsley and Sidebottom 2010). Conversely, target-based studies link attributes of potential targets with victimization rates (Hakim, Rengert, and Shachmurove 2001; Rountree and Land 2000; Vélez 2001). Finally, mobility-based studies, often referred to as "gravity models," use pairs of locations and examine the observed frequencies of crimes trips between them (Elffers et al. 2008; Rengert 1981; Reynald et al. 2008; Smith 1976). Each approach suffers from an inability to include data relating to the other dimensions of the offender–target–location interaction (see B&N for a full explanation).

B&N introduce a new method for studying the spatial preferences of offenders which incorporates information describing both offenders and targets (victimized and not)—the discrete spatial choice model. This approach allows estimates of the influence of area-specific characteristics (such as affluence) and interactions of individuals and areas (such as the proximity of an area to an offender's home), overcoming key weaknesses associated with conventional offender-, target-, and mobility-based studies.

Developing a behavioral rule for burglar spatial preferences, B&N draw on a range of theoretical perspectives and empirical findings including the routine activity approach, rational choice perspective, crime pattern, and social disorganization theories. Distilling the findings of a large number of ethnographic and place-based burglary studies, they specify a behavioral rule hypothesizing that offenders are likely to select neighborhoods (and subsequently, residential dwellings from within those neighborhoods) that (1) appear to contain valuable goods; (2) require little effort to travel to, reach, and enter; and (3) where the risks of detection are low.

B&N demonstrate that residential burglars in The Hague, Netherlands, are attracted to neighborhoods that (1) have low levels of guardianship, (2) offer easily accessible targets, and (3) are within close proximity of their homes. Conversely, they find no effect for neighborhood affluence (a measure of perceived reward), residential turnover (a measure of social cohesion), and proximity to the city center (a measure of offender environment familiarity). Furthermore, studying the differential impacts of proximity, they find no statistically significant differences between juvenile and adult offenders.

Research Hypotheses—Components of the Behavioral Rule

Seven distinct decision criteria were developed by B&N in specifying a hypothesized offender behavioral rule, two of which were hypothesized to differ between offender subgroups. In this study, we replicate six of these criteria and one difference between subgroups,[1] testing their consistency across three environments and offending populations: the first, sourcing data from the original study in The Hague, the Netherlands; the second from Birmingham, United Kingdom; and the third from Brisbane, Australia. Modeled decision criteria attempt to capture the influences of perceived reward, risk, and effort on criminal location choice at the area level. In what follows, each criterion is described by briefly reiterating the theoretical underpinnings initially specified by B&N and providing a hypothesis concerning the consistency of this result across the three study regions. Our primary goal is to assess the generalizability of these factors previously considered relevant in explaining burglar location choice in The Hague across two further environmental settings in the United Kingdom and Australia.

Rewards. The first model component relates to the perceived rewards associated with the successful commission of a burglary in a particular area. Studies show that burglars rate wealthy households over poor ones because of likely higher returns (Bennett and Wright 1984; Cromwell, Olson, and Avary 1991; Nee and Meenaghan 2006). Affluent neighborhoods have a substantially different appearance from neighborhoods with below average income, a difference that is obvious to anyone who has ever moved to and looked for property in an unfamiliar city. We hypothesize for each study region:

> **Hypothesis 1:** Reward (Affluence): The greater an area's residential real estate value, the greater the likelihood a burglar will select it for burglary.

Risks. The second model component relates to the perceived risks of detection associated with committing an offense in a particular area. Offenders are thought to be attracted to areas with low levels of social cohesion because residents are less able to distinguish between locals and strangers and are less likely (or willing) to intervene on their neighbor's behalf if they observe criminal acts (Sampson, Raudenbush, and Earls 1997; Sampson and Wooldredge 1987; Shaw and McKay 1942). This lack of social control to prevent crime contributes to an environment offenders may associate with a reduced risk of apprehension (Smith and Jarjoura 1989). We hypothesize for each study region:

> **Hypothesis 2:** Risk (Stable Areas): The greater the level of residential mobility in an area, the greater the likelihood a burglar will select it for burglary.

Effort. The following three model components relate to the effort involved in committing a burglary in a particular area. First, target vulnerability is evaluated in terms of physical accessibility. Single-family dwellings, which typically offer multiple on-street entry points, are likely both easier and less risky to physically access than flats, apartments, and attached dwellings. We hypothesize for each study region:

> **Hypothesis 3:** Effort (Target Accessibility): The higher the proportion of single-family dwellings in an area, the greater the likelihood a burglar will select it for burglary.

Our second measure of effort relates to the distance offenders travel to commit burglary. Empirical evidence consistently demonstrates that offenders operate under limited mobility with respect to criminal location choice (Rengert, Piquero, and Jones 1999; Smith, Bond, and Townsley 2009; Snook 2004; Townsley and Sidebottom 2010). This observation is likely the result of two interconnected factors. First, offenders tend to minimize the distance traveled to crime locations as, like all members of society, they are subject to constraints and have a fixed amount of time at their disposal; this is known as the *distance decay* observation (Ratcliffe 2006). Second, offenders prefer to operate in familiar areas, as they are less likely to "stand out" as an outsider and detailed local knowledge of an area can be employed in the planning and commission of offenses.

Combining the distance decay observation and the familiarity tendency suggests that offenders will be attracted to those areas that are in close spatial proximity to their home.[2] We hypothesize for each study region:

> **Hypothesis** 4: Effort (Proximity to Home): The closer an area is to a burglar's home, the greater the likelihood they will select it for burglary.

The third measure of effort relates to a neighborhood's proximity to the city center. It is expected that the city center will be a common node within the awareness space of residents by virtue of the concentration of public facilities and services located there. By extension, the city center is also likely better known and more visited by offenders than other areas within a given urban locality. We hypothesize for each study region:

> **Hypothesis 5:** Effort (Proximity to City Center): The closer an area is to the city center, the greater the likelihood a burglar will select it for burglary.

The final model component relates simply to the availability of potential targets in a given area. This hypothesis asserts that areas with more residential dwellings offer greater numbers of opportunities for residential burglary. We hypothesize for each study region:

Hypothesis 6: Effort (Target Availability): The greater the number of residential units in an area, the greater the likelihood a burglar will select it for burglary.

Whereas the previous six hypotheses apply to all decision makers, the next hypothesis differentiates between burglar categories. Studies have consistently found that older offenders travel further than younger offenders (Andresen, Frank, and Felson 2013; Levine and Lee 2013; Townsley and Sidebottom 2010; Wiles and Costello 2000), an observation that is thought to reflect the importance of ready access to vehicles in explaining differences in offender mobility. In examining this hypothesis, B&N categorize juvenile and adult offenders according to the legal driving age in the Netherlands—18 years. We hypothesize for each study region:

Hypothesis 7: The effect of proximity of a neighborhood to the home of the burglar is stronger for juvenile burglars under the legal driving age than for adult burglars.

Testing the Generalizability of Burglar Spatial Behavior

A conventional replication would compute separate statistical models for each study region and compare estimates. The disadvantage of this approach is that only differences in kind between regions (i.e., direction and significance) can be detected. The approach taken here allows differences in degree to be detected (i.e., magnitude of relationships) and statistically tested. To achieve this, a single consolidated model is estimated, integrating data from each study region, where parameters for all combinations of independent variables (IVs) and study region are calculated. Analyzing this single consolidated model, inferential tests are undertaken that allow testing of the behavioral rule both *within* and *between* study regions. This allows differences in kind and degree to be quantified across study regions. The following two sections provide complete details of the statistical model used and analytical strategy undertaken.

Discrete Spatial Choice Models

The discrete spatial choice approach is an application of the discrete choice method used extensively in micro economics to analyze choice behavior. The method envisages an actor faced with a choice set of discrete alternatives, from which one must be selected. Choosers evaluate the relative utility associated with each alternative. The spatial variant of discrete choice applied here differs by modeling decisions involving a spatially referenced alternative. In this scenario, each alternative/chooser combination typically includes a measure of distance between the origin location of the chooser and the location of the alternative.

Formalizing our initial hypotheses, the following utility function is derived:

$$U_{ij} = \beta x_{ij} + \varepsilon_{ij},$$

where

- U_{ij} is the expected utility of a burglary in neighborhood j for burglar i;
- β is a vector of coefficients to be estimated;
- x_{ij} are the values of the explanatory variables (corresponding to the elements of the behavioral rule) for neighborhood j for burglar i; and
- ε_{ij} is the random error component of the model.

If offenders select neighborhoods that maximize utility, the utility function can be estimated according to a conditional logit model (McFadden 1973). The probability of burglar i selecting neighborhood j can then be expressed in the following way:

$$\mathrm{Prob}(Y_i = j) = \frac{e^{\beta' x_{ij}}}{\sum_i^J e^{\beta' x_{ij}}},$$

where Y_i is the choice made by burglar i.

Data and Methods

The discrete spatial choice approach required the collection of three core data sets for each study region: (1) *alternatives*—the choice set of geographical spatial units (e.g., neighborhoods and suburbs) in which offenders may choose to offend; (2) *choosers*—charged residential burglary offenders who resided and committed burglaries within the study region in the study time frame; and (3) *choices*—cleared offense data comprising the locations (alternatives) where offenders (choosers) chose to offend.

In order to test our hypotheses, data describing cleared residential burglaries were collected from three cities: The Hague (Netherlands), Birmingham (United Kingdom), and Brisbane (Australia). Table 1 summarizes key features germane to the discrete spatial choice model for each study region.

Study regions and their associated choice set geographies (NL—neighborhoods, UK—Super Output Areas [medium layer], AU—Statistical

Table 1. Comparison of the Study Regions.

Variable	The Hague, NL	Birmingham, UK	Brisbane, AU
Number of choosers (unique offenders)	290	291	273
Number of choices made (cleared offenses)	548	398	889
Proportion of choices made by juvenile offenders	5.3	13.6	8.0
Number of alternatives (areas)	89	131	158
Mean number of households per alternative	2,380	3,086	2,537
Mean area of alternatives (km^2)	0.65	2.04	8.48
Target density (households per km^2)	3,652	1,513	299
Time period	1996–2001	2009	2006

Note: NL = Netherlands; UK = United Kingdom; AU = Australia.

Local Areas) were selected based on equivalence in size of the known burglar population, number of targets (households) within each area, and total number of areas in a study region. Study regions were purposefully selected based on differences in target density, aligning with our aims to assess the consistency of relationships across differing environmental settings. The Hague, Birmingham, and Brisbane can be characterized as having relatively high (3,652 households per km^2), medium (1,513 households per km^2), and low (299 households per km^2) target densities, respectively.

All additional differences are the result of an interaction between burglary and clearance rates: At a national level, the United Kingdom has 454 residential burglaries per 100,000 population with a clearance rate of 13 percent (Office of National Statistics [ONS] 2013; Taylor and Chaplin 2011), Australia has 592 residential burglaries per 100,000 population and 8.7 percent clearance rate (Australian Bureau of Statistics 2011; Australian Institute of Criminology 2012), and the Netherlands has 427 residential burglaries per 100,000 population with a clearance rate of 7 percent (Bernasco and Nieuwbeerta 2005).

Alternatives—Census Data

Characteristics of each study region were obtained through statistical agencies, the Municipal Agency for Urban Development (The Hague, Netherlands), the ONS (United Kingdom), and the Australian Bureau of Statistics. Six variables were used in the modeling, of which five could be defined and measured consistently for all study regions: (i) number of households, (ii) proportion of single-family dwellings, (iii) residential mobility, (iv) proximity of spatial units to offender residence, and (v) proximity of spatial units to the city center. It was not possible to measure residential real estate value entirely consistently across the three study regions.

The variable *number of households* is an operationalization of the target availability construct and simply represents the total number of residential dwellings, and thus potential targets for residential burglary, found within the area.[3] For consistency with B&N, this variable is measured in units of 1,000. As a result, a one-unit increase in this variable corresponds to an increase of 1,000 households in an area.

The variable *proportion of single-family dwellings* is an operationalization of the target accessibility construct and is measured as the proportion of residential dwellings in a given area not categorized as flats/apartments. As stated previously, for consistency with B&N, this proportion is multiplied by a factor of 10.

The variable *residential mobility* is an operationalization of the community stability construct and is calculated by estimating the resident "turnover" for an area. In calculating this variable, two values are summed: the proportion of residents who moved into an area in the last 12-month period (incoming proportion) and the proportion of residents who moved out of an area in the last 12 months (outgoing proportion). The maximum score possible is 2 (or 200 percent), whereby every person leaves the area (100 percent outgoing) and is replaced by entirely new residents (100 percent incoming). This variable was measured consistently across the three study regions. This value is also multiplied by a factor of 10 for the reason discussed previously.

The variables *proximity* and *proximity to city center* describe the distance between an offender's home area and the alternative in question, and the distance between the alternative and the city center of the study region, respectively. Both measures of proximity were calculated as the Euclidian distance between each pair of area centroids. A Ghosh (1951) correction was applied to all zero distances (where an offender chose to commit a crime within their home area). To aid interpretation, distance variables were multiplied by negative one (-1) and interpreted as proximities, with positive estimates implying that the odds of a neighborhood being selected increase when it is closer to the offender's home or the city center.[4]

The variable *residential real estate value* represents the average price of residential property in an area and is an operationalization of the affluence construct. The data set for The Hague contains mean real estate values for each area, as recorded through tax assessments. For the United Kingdom, the data used are the mean House Price sale as recorded by the U.K. Land Registry (in the United Kingdom, it is a legal requirement that all purchases are registered with the Land Registry) at the Super Output Area (medium layer), which were obtained from the ONS. An equivalent metric was not available in Australia. Instead, the Australian census records monthly housing repayment, which we consider to be highly correlated with property values. As these are provided as ordinal variables (interval bands such as \$200—\$249/week, \$250—\$300/week, . . .), weighted averages were used to compute an average housing payment or house price index. Even if equivalent measures were available, given differing housing markets directly comparing monetary values across study regions are likely invalid. As a result, the mean home price for spatial units was aggregated into deciles within their respective study region.

Descriptive statistics for all study regions are provided in Table 2. Furthermore, correlation tables of these variables for each study region are presented in the Appendix.

Choices and Choosers—Recorded Crime Data

Recorded crime data describing all cleared burglaries located within the study region and attributed to an offender also living within the study region at the time of the offence were collated for each respective region. Variables include the date of the offense, the area in which the offense occurred, the area in which the offender resided, and their age at the time of the offense. In keeping with B&N, all burglary incidents associated with multiple offenders were removed from each data set (totaling 276, 94, and 247 crimes in The Hague, Birmingham, and Brisbane data sets, respectively). Restricting the sample to choices involving offenders operating by themselves provides a clearer test of the behavioral rule than if choices involving multiple offenders were included.[5] Finally, following B&N, the categorization of juvenile and adult offenders is defined by the legal driving age in each respective region; 18 in The Netherlands and 17 in the United Kingdom and Australia.

Modeling

The conditional logit model was used to estimate parameters of the behavioral rule using maximum likelihood methods. In order to test for relationships across the three study regions, source data from each region were combined into a single consolidated data set. Two equations were estimated

Table 2. Descriptive Statistics of Census Variables for Alternatives in Three Study Regions.

	The Hague, NL			Birmingham, UK			Brisbane, AU		
Variable	Mean (*SD*)	Min.	Max	Mean (*SD*)	Min.	Max	Mean (*SD*)	Min.	Max
Area (km^2)	0.65 (0.51)	0.13	3.18	2.04 (1.56)	0.53	13.11	8.48 (21.93)	0.7	184.85
Proximity to city center (km)	3.00 (1.5)	0.2	6.99	6.52 (2.80)	0.16	14.22	10.04 (6.1)	0.42	51.59
Residential mobility (in% + out%)	36.92 (12.33)	13.45	63.2	17.92 (8.58)	8.81	71.03	30.78 (12.51)	10.84	76.85
Single-family dwelling (%)	16.67 (17.14)	0.31	93.82	77.82 (14.53)	19.28	96.62	82.94 (22.85)	3.15	100
Number of households	2,380 (1,462)	212	7,476	3,086 (565)	2,092	5,067	2,537 (1,505)	94	7,344

Note: NL = Netherlands; UK = United Kingdom; AU = Australia.

Table 3. Conditional Logit Model Results (Odds Ratios) for the Three Study Regions Estimated Simultaneously.

Variable (Unit)	The Hague, NL	Birmingham, UK	Brisbane, AU
Real estate value (Deciles)	0.92 (0.03)**	0.98 (0.03)	1.01 (0.04)
Residential mobility (10%)	1.03 (0.06)	1.04 (0.09)	1.14 (0.15)
Single-family dwellings (10%)	1.19 (0.08)**	1.12 (0.05)**	1.13 (0.07)*
Proximity (km)	1.67 (0.14)**	1.90 (0.12)**	1.21 (0.03)**
Proximity to city center (km)	1.02 (0.07)	1.00 (0.02)	1.06 (0.04)*
Residential units (1,000)	1.34 (0.04)**	1.76 (0.18)**	1.47 (0.07)**

Note: NL = Netherlands; UK = United Kingdom; AU = Australia. Figures in parentheses refer to standard errors (robust Huber–White "sandwich" estimates based on clustering of multiple burglaries per burglar).
$^{**}p < .01$, $^{*}p < .05$, all tests one-tailed.

to test hypotheses *within* study regions. The first equation (equation (A1) in the Appendix) included terms corresponding to each of the Hypotheses 1−6, the second (equation (A2) in the Appendix) included the same terms, except that (in order to test Hypothesis 7) the proximity term was replaced by two proximity terms, one for adults and other for juveniles. The Appendix describes these two equations in detail and specifies which tests were performed within and between study regions.

Tests of cross-region hypotheses were conducted in two stages for each hypothesis. The first stage established whether the model terms for the different study regions were consistent. If the parameter estimates for an explanatory variable were consistent in direction and statistical significance[6] across study regions, we inferred the relationship was consistent and there were no differences in kind. The second stage, assuming consistency was observed, investigated area effects by comparing the magnitude of parameter estimates for the study regions. In doing so, bivariate Wald tests of the parameter estimates were used to locate interstudy region differences in the corresponding estimated relationships.[7]

As evidenced in Table 1, data on burglaries (choices) are nested in burglars (choosers) because some burglars committed multiple burglaries. Robust standard errors were estimated to correct for the nested structure of the data.

Findings

Table 3 summarizes the first estimated conditional logit model for the consolidated data set, corresponding to equation (A1) in the Appendix. It reports multiplicative odds ratios (ORs) describing the amount the odds of a neighborhood being chosen will increase given a one-unit increment in the explanatory variable. For example, the OR estimate for the proximity variable in The Hague is 1.67. This indicates that, all other things being equal, the odds of an area being chosen increase 1.67 times (or by 67 percent) for each kilometer closer it is to an offender's home. While estimated simultaneously, for the purposes of cross-region comparisons, coefficients are placed in columns by study region. Recall that all explanatory variables have been coded so that if hypothesized relationships hold true, the estimated ORs should be greater than 1.

Within Region Results

For The Hague, five of the six variables had coefficient estimates consistent with the behavioral rule. Only real estate value displayed a negative relationship, which was statistically significant. Of the positive relationships, three were statistically significantly different from the null. For Birmingham, five of the six had positive relationships, three of which were statistically significant. Brisbane had all six variables displaying positive coefficients, four of which were statistically significant.

Between Region Results

Consistency: differences in kind: Hypotheses 1 to 7. Hypothesis 1 stated that neighborhood affluence would increase the likelihood of target selection; however, this was not the case. In The Hague, the effect of affluence was negative, such that a decile increase in real-estate value reduces the odds of an area being selected for burglary by eight percent; thus, suggesting that all other things being equal, The Hague burglars prefer to target areas of lower affluence.[8] In Brisbane and Birmingham, neighborhood affluence had no discernible effect on target selection.

Hypothesis 2 states that a lack of social cohesion (as operationalized by levels of residential mobility) would be positively correlated with the chance of a neighborhood being selected for burglary. Again, this turns out not to be the case. In all of the study regions, the strength of the relationship could not reliably be distinguished from an OR of 1.

Hypothesis 3 proposes that the impact of available, easily accessible targets (operationalized via the proportion of single-family dwellings) will increase the chance of a neighborhood being selected for burglary. Results demonstrate that this is indeed the case in all study regions, with an increase

Table 4. Conditional Logit Model Results (Odds Ratios) for the Three Study Regions Estimated Simultaneously with Proximity Conditioned by Age-Group.

Variable (Unit)	The Hague, NL	Birmingham, UK	Brisbane, AU
Real estate value (Deciles)	0.92 (0.03)**	0.98 (0.03)	1.01 (0.04)
Residential mobility (10%)	1.03 (0.06)	1.03 (0.09)	1.14 (0.15)
Single-family dwellings (10%)	1.19 (0.08)**	1.11 (0.05)*	1.13 (0.07)*
Proximity (km)—Adults	1.65 (0.15)**	1.81 (0.12)**	1.20 (0.03)**
Proximity (km)—Juveniles	2.22 (0.54)**	3.81 (1.03)**	1.35 (0.09)**
Proximity to city center (km)	1.01 (0.07)	1.00 (0.02)	1.06 (0.04)*
Residential units (1,000)	1.34 (0.04)**	1.77 (0.18)**	1.47 (0.07)**

Note: NL = Netherlands; UK = United Kingdom; AU = Australia. Figures in parentheses refer to standard errors (robust Huber–White "sandwich" estimates based on clustering of multiple burglaries per burglar).
**$p < 0.01$, *$p < 0.05$, all tests one-tailed.

of 10 percent in the proportion of single-family dwellings in a neighborhood increasing the odds that it will be selected for burglary by a factor of 1.19, 1.12, and 1.13 in The Hague, Birmingham, and Brisbane, respectively.

Hypotheses 4 and 5 relate to the effect that proximity of a neighborhood to an offender's home and to the city center, respectively, has on target selection. Results demonstrate that offenders in all three study regions prefer to offend in neighborhoods closer to their homes—the odds of a neighborhood being selected increasing by 67 percent in The Hague, 90 percent in Birmingham, and 21 percent in Brisbane for each kilometer closer a neighborhood is to an offender's home (Hypothesis 4). Testing Hypothesis 5, results show that proximity to city center was only important in Brisbane, although the magnitude of this relationship was small—the estimated odds of a neighborhood being selected for burglary increased by only 6 percent for each kilometer closer to the city center it was located.

Hypothesis 6 states that the greater the number of targets in a neighborhood, the more likely it is to be selected for burglary. Our results confirm this; increasing the number of households in a neighborhood by 1,000 increases the odds it will be selected for burglary by a factor of 1.34 in The Hague, 1.76 in Birmingham, and 1.47 in Brisbane.

According to Hypothesis 7, the effect of proximity of a neighborhood to the home of the burglar is stronger for juvenile burglars than for adult burglars. To test this hypothesis, equation (A1) in the Appendix was modified, so that effects of proximity are estimated separately for adults and juveniles (as defined by the legal driving age in each study region—under 18 years of age in The Netherlands and under 17 in the United Kingdom and Australia[9]),

Table 5. *p*-Values of Wald Tests of Differences in Effect Size for Relationships Observed to be Consistent.

Variable (Unit)	*Brisbane v. Hague*	*Brisbane v. Birmingham*	*Hague v. Birmingham*
Single-family dwellings (10%)	0.57	0.89	0.44
Proximity (km)	<0.05*	<0.05*	0.23
Residential units (1,000 s)	0.10	0.11	<0.05*

Note: $^{*}p$ < .05, all tests two-tailed.

giving rise to equation (A2) in the Appendix. The results are presented in Table 4. Because the other five variables are almost identical to those in Table 3, we focus solely on the estimated effects of proximity. For both juveniles and adults, the effects of proximity are positive and significant. Moreover, in support of Hypothesis 7, in all three study regions, the proximity effects are larger for juveniles under the legal driving age than for adults.

To test the significance of these differences, Wald tests of the juvenile–adult differential corresponding to the three study regions were conducted. Results demonstrate that the juvenile–adult differential is statistically significant in Birmingham ($\chi^2 = 7.14$, $p = .004$), marginally significant in Brisbane ($\chi^2 = 2.56$, $p = .05$), and, in line with B&N, not significant in The Hague ($\chi^2 = 1.36$, $p = .12$).

Consistency: differences in degree. The cross-region comparisons described previously demonstrate that three variables show consistent relationships (defined as uniform direction and significance across study regions): proportion of single-family dwellings, proximity to an offender's home, and number of residential units in an area. Evaluating these relationships between study regions, Table 5 displays results of Wald tests ($p < .05$) performed to detect statistically significant differences in parameter estimates across all pairs of study regions.

Results of these tests demonstrate no statistically significant difference between the effect sizes in each study region for the proportion of accessible targets. As such, offenders in each study region place comparable importance on the proportion of accessible targets in an area. The proximity of a potential target to an offender's home is a statistically more important decision criterion in The Hague (OR = 1.67) and Birmingham (OR =

Table 6. *p*-Values of Post hoc Wald Tests of Differences in Proximity Effects by Age of Offender—between Study Regions.

Variable (Unit)	*Brisbane v. Hague*	*Brisbane v. Birmingham*	*Hague v. Birmingham*
Proximity (km)—Adults	<0.05*	<0.05*	0.41
Proximity (km)—Juveniles	<0.05*	<0.05*	0.14

Note: *p < .05—all tests two-tailed.

1.90) compared to Brisbane (OR = 1.21). One potential explanation for this lies in the size of Brisbane neighborhoods, and in turn, the spatial densities of potential targets found within them, which are considerably lower than in The Hague and Birmingham. The importance of target availability as a decision criterion is statistically different between The Hague (OR = 1.34) and Birmingham (OR = 1.76) but no other pair of study regions.

Finally, cross-regional differences in the effects of proximity are tested for juveniles and adults separately (see Table 6). Results of these tests demonstrate that both adult and juvenile offenders in Brisbane place significantly less importance on proximity with respect to location than their counterparts in The Hague and Birmingham. This finding likely further reflects differences in target densities between Brisbane, a sprawling conurbation, and the more closely packed urban areas of The Hague and Birmingham.

Discussion

This cross-national study applied the discrete spatial choice model to analyze factors influencing burglar target selection in three study regions, and in particularly aimed to investigate the consistency of relationships described by Bernasco and Nieuwbeerta (2005) across multiple environments. Data from study regions in the Netherlands, United Kingdom, and Australia were consolidated into a single statistical model that allowed the formal quantification of study region effects on factors hypothesized to influence criminal location choice.

Primary findings of these analyses demonstrate that in The Hague, Birmingham, and Brisbane, the likelihood that an area will be selected for burglary is consistently positively influenced by (i) proximity to an offender's home, (ii) the proportion of easily accessible targets, and (iii) the number of targets in an area. Additional analyses demonstrate that in all study regions, the influence of proximity of target areas to an offender's home is greater for juvenile offenders under the legal driving age than adults. This difference is statistically significant in both Birmingham and Brisbane.

These findings support both opportunity-based accounts of offending, those that portray offenders as optimal foragers, and the principle of least effort; such that offenders are consistently attracted to those areas that can be reached quickly and easily, and in which there are an abundance of viable targets. Furthermore, results from two of the three regions studied are compatible with hypotheses that assert the importance of access to vehicles in shaping patterns of offender mobility.

Subsequent analyses do, however, demonstrate that the magnitude of impact for two of these three consistently attractive choice criteria varies significantly across environments. Considering these findings, differences in the magnitude of impact that target proximity has on location choices of offenders are of particular interest because it may suggest that the commonly observed distance decay curve is at least in part reflective of the number of potential targets available to offenders within a given distance. To illustrate, in the study regions where the spatial density of targets was relatively high—The Hague (3,652 households per km^2) and Birmingham (1,513 households per km^2) offenders displayed comparatively limited search spaces; conversely, in Brisbane where target density was relatively low (299 households per km^2), offenders were less influenced by the proximity of target areas—perhaps by necessity. This observation is consistent with the notion of intervening opportunities (Stouffer 1940), which posits the likelihood of travel to a given location (in the context of migration) is determined by the opportunities at competing destinations, and less so by the distance involved.

We did not observe an effect of residential mobility on location choice in any study region, a finding inconsistent with social disorganization theory. Because this study used a regression-style model, estimated relationships will always have the ceteris paribus caveat and need to be interpreted in the context of the other IVs included in the model. Moreover, differences in measurement precision may exist between constructs that explain this finding. For example, the social cohesion construct is more challenging to operationalize than area affluence or number of dwellings.

Mixed effects were observed for (i) area affluence, which was negatively correlated with burglar spatial preference in The Hague and nonsignificant elsewhere and (ii) proximity to the city center, which was positively correlated with burglary spatial preferences in Brisbane but not statistically significant elsewhere. The lack of consistent impact of affluence mirrors the mixed findings of previous studies (Rountree, Land, and Miethe 1994; Sampson and Groves 1989; Vélez 2001) and may reflect the penetration of highly desirable goods such as smartphones, laptop computers, and jewelry throughout society; viable rewards for offending are widespread and therefore do not play a major role in spatial target choices of burglars. With respect to the impact that proximity to city center has on location choices in Brisbane, this finding may reflect the location/size of Brisbane, which is significantly larger than other conurbations within South East Queensland. As such, we speculate that Brisbane confers a greater draw of activities relative to other locations in South East Queensland. By extension, we also suggest that offenders in The Hague and Birmingham (particularly those who live near the periphery of a region) may be influenced by other locales in relative close proximity to, but not included in, their respective study region.

Differences in kind and degree such as those observed in this study present a challenge for scholars in providing a parsimonious explanation of the role that environments play in shaping offender calculus. Here, we speculate the existence of such effects is likely the result of two interconnected mechanisms. First, *offender cohort effects*—that is, the manner in which different active offender populations conform to the behavioral rule hypothesized to govern spatial preferences. Broadly thought of as differences between offending groups, in practice, this will translate into differences (in kind and degree) in the distinct dimensions of criminal careers—onset, prevalence, offending rate, specialization, and desistance—observed in offender cohorts. Such differences will likely impact the role that reward, risk, and effort play in influencing spatial preferences between offenders, and as a result across areas. Second, *environmental differences*—that is, the influence that urban environment morphology has on the volume and nature of crime. While the samples used in this study share many characteristics, they also differ in key ways. The most obvious being the size of the neighborhoods and the density of potential targets for burglary found within them. Public transport systems also differ greatly between countries, a factor likely to influence spatial preferences but not quantified in this study. These and related differences underscore the value of cross-national replications in testing criminological theories.

Considering these issues, we believe the approach taken in this study is noteworthy for two reasons. First, the nature of the statistical model and the variables of interest allow replications to be highly aligned with respect to study design. Second, consolidating multiple study regions into a single model enabled statistical rather than descriptive comparisons of the hypothesized behavioral rule across study regions; thus, formally quantifying study setting effects on parameter estimates between environments. To our knowledge, this approach to examining the generalizability of research findings across multiple environmental settings has not previously appeared in the criminological literature.

It is important to acknowledge several limitations of our analyses. First, and likely most importantly, as with previous studies, it is acknowledged that findings rely solely on cleared offense data. While undesirable, this is an inevitable ramification of any study of criminal location choice that aims to examine the interaction between area- and individual-level characteristics using police-recorded crime data. More generally, alternative methodologies such as offender interviews and ethnographic studies suffer from the same nonprobabilistic sampling issue, typically concentrating on prolific offenders. Indeed, the appeal of the discrete spatial choice approach is that findings derived from various methodologies can be incorporated into a single framework for investigation. Second, analyses presented assume crime trips originate from an offender's residence. While this assumption is widely held in studies of offender mobility, it may influence observed results. Third, while the approach to replication undertaken confers several advantages over discrete replications, it is subject to two weaknesses—(1) the notion that all subsequent replications are constrained by the quality of the initial study with respect to hypotheses, measurement instruments, and so on and (2) the requirement to build a consolidated model is limited by the lowest common denominator of all available data. To illustrate, while directly aligning six of the seven criteria originally presented by B&N, data recorded from the United Kingdom and Australia could not provide an indicator of ethnic heterogeneity equivalent to that explored in the original study of The Hague. Moreover, this study required considerable administrative efforts in sharing (deidentified) data between study regions to estimate the consolidated model.

To conclude, we outline several avenues of future research that could extend the ideas presented here in terms of breadth and depth. First, criminological knowledge can be made broader by applying the specified behavioral rule in more study regions. Differences between study regions are expected, but whether these are meaningful can only be assessed in relation to many more study regions. Thankfully, as the administrative and census data required for these types of study become increasingly commonplace, barriers to replication are reduced.

Second, our understanding about spatial preferences of offenders can be deepened by expanding the behavioral rule to include more nuanced factors underpinned by theory. For instance, Beavon et al. (1994), later replicated by Johnson and Bowers (2010), demonstrate that characteristics of street networks influence the volume and distribution of crimes. Incorporating the permeability and connectedness of alternatives might shed light on spatial preferences. Equally, the role that public transport networks play in connecting spatial areas could be investigated.

Finally, while the conditional logit model presented here provides an elegant means to test hypotheses concerning offender location choices, as currently implemented, it operates under a number of assumptions that warrant further investigation. The most obvious is the assumption that the influence of choice-level characteristics is systematic, that is, constant for all offenders. Recent research in the study of offender mobility suggests that for at least target proximity, this may not be the case (Smith et al. 2009; Townsley and Sidebottom 2010). Relaxing this assumption involves the use of a more complex statistical model, the mixed logit (Train 2009), but should yield more precise estimates of spatial preferences.

Appendix

The utility equation that is estimated to test Hypotheses 1 to 6 and the corresponding hypotheses on cross-region equality is given by:

$$\begin{aligned} U_{ij} = {} & H_i(\beta_1 V_j + \beta_2 R_j + \beta_3 S_j + \beta_4 P_{ij} + \beta_5 C_j + \beta_6 T_j) \\ & + Bh_i(\beta_7 V_j + \beta_8 R_j + \beta_9 S_j + \beta_{10} P_{ij} + \beta_{11} C_j + \beta_{12} T_j) \\ & + Br_i(\beta_{13} V_j + \beta_{14} R_j + \beta_{15} S_j + \beta_{16} P_{ij} + \beta_{17} C_j + \beta_{18} T_j) + \varepsilon_{ij}, \end{aligned} \tag{A1}$$

where

- U_{ij} is the expected utility of a burglary in neighborhood j for burglar i;
- V_j is the decile of the average value of residential real estate in neighborhood j;
- R_j is the residential mobility in neighborhood j;
- S_j is the percentage of single-family dwellings in neighborhood j;
- P_{ij} is the proximity of neighborhood j to the home neighborhood of burglar i;
- C_j is the proximity to neighborhood j to the city center;

- T_j is the number of potential targets (residential units) in neighborhood j;
- H_i is a dummy variable indicating The Hague study region;
- Bh_i is a dummy variable indicating the Birmingham study region;
- Br_i is a dummy variable indicating the Brisbane study region.

Tests of Hypotheses 1−6 are $\beta_k > 0$ for all 18 estimates of β presented in Table 3. The six cross-region equality tests are $\beta_1 = \beta_7 = \beta_{13}$, $\beta_2 = \beta_8 = \beta_{14}$, $\beta_3 = \beta_9 = \beta_{15}$, $\beta_4 = \beta_{10} = \beta_{16}$, $\beta_5 = \beta_{11} = \beta_{17}$, and $\beta_6 = \beta_{12} = \beta_{18}$. A selection of these is reported in Table 5.

To test the additional hypothesis that target proximity is a more important choice criterion for juveniles than for adults (Hypothesis 7), a new equation is estimated in which the proximity parameter is allowed to vary between juveniles and adults:

$$\begin{aligned} U_{ij} = {} & H_i\left(\gamma_1 V_j + \gamma_2 R_j + \gamma_3 S_j + \gamma_4 P_{ij} A_i + \gamma_5 P_{ij} J_i + \gamma_6 C_j + \gamma_7 T_j\right) \\ & + Bh_i\left(\gamma_8 V_j + \gamma_9 R_j + \gamma_{10} S_j + \gamma_{11} P_{ij} A_i + \gamma_{12} P_{ij} J_i + \gamma_{13} C_j + \gamma_{14} T_j\right) \\ & + Br_i\left(\gamma_{15} V_j + \gamma_{16} R_j + \gamma_{17} S_j + \gamma_{18} P_{ij} A_i + \gamma_{19} P_{ij} J_i + \gamma_{20} C_j + \gamma_{21} T_j\right) \\ & + \varepsilon_{ij}\,, \end{aligned} \tag{A2}$$

where we use γ instead of β to make explicit that the estimates differ from those in equation (A1), where all other symbols have the same meaning as in equation (A1), and where, in addition

- J_i is a dummy variable indicating the burglar was under legal driving age;
- A_i is a dummy variable indicating the burglar was over legal driving age.

In equation (A2), $\gamma_k > 0$ represents the tests of Hypotheses 1−6 for The Hague, Birmingham, and Brisbane, with proximity effects tested separately for adults and juveniles. These are the 21 estimates presented in Table 4. In addition, the juvenile–adult difference in Hypothesis 7 is $\gamma_5 > \gamma_4$ for The Hague, $\gamma_{12} > \gamma_{11}$ for Birmingham, and $\gamma_{19} > \gamma_{18}$ for Brisbane. The cross-national equality tests for juvenile and adult proximity effects are $\gamma_4 = \gamma_{11} = \gamma_{18}$, and $\gamma_5 = \gamma_{12} = \gamma_{19}$. The test results are displayed in Table A1.

Table A1. Correlations between Neighborhood Variables, The Hague (n = 89), Birmingham (n = 131), and Brisbane (n = 158).

Variable	A	B	C	D
The Hague				
A. Proximity to city centre				
B. Residential mobility	0.70*			
C. Real estate value	–0.19	–0.32*		
D. Single-family dwellings	–0.31*	–0.35*	0.65*	
E. Residential units	0.08	0.11	–0.38*	–0.26*
Birmingham				
A. Proximity to city center				
B. Residential mobility	−0.12			
C. Real estate value	−0.34*	0.28*		
D. Single-family dwellings	−0.15	−0.49*	−0.07	
E. Residential units	−0.11	0.10	0.07	−0.25*
Brisbane				
A. Proximity to city centre				
B. Residential mobility	0.51*			
C. Real estate value	0.42*	0.39*		
D. Single-family dwellings	–0.63*	–0.84*	–0.43*	
E. Residential units	0.22*	0.08	–0.10	–0.22*

*p < .05, two-sided.

Authors' Note

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Notes

1. There are two differences between the behavioral rule presented here and the original rule appearing in B&N: (1) The hypothesis relating to the impact of neighborhood ethnic heterogeneity (Hypothesis 2b in B&N) is omitted due to

disparities in the census data collected in the Netherlands, United Kingdom, and Australia that preclude identification of parental ethnicity across all three study regions; (2) Given the above, the interaction effect between ethnicity and neighborhood ethnic heterogeneity (Hypothesis 6 in B&N) is also not investigated here.

2. In the absence of further data describing offender activity spaces, here we make the necessary assumption that all crime trips originate from an offender's home location.
3. Areas containing no residential households are removed from the choice set before analysis.
4. In theory, both distance measures cannot vary completely independently as they are two distances in a triad. To ensure integrity, additional models were estimated omitting the proximity to city center variable. No discernible impact on proximity to offender residence coefficients (or any other variables) was observed.
5. While beyond the scope of the behavioral rule replicated here, interested readers are directed to Bernasco (2006) where the impact of co-offending on location choice is examined in more detail.
6. Interpreted as statistically significantly different from an OR of 1.
7. To validate this approach, another series of tests was conducted. A pooled model was specified where study region was not observed for the independent variables (IVs), that is a single parameter for each IV was estimated. This model was then compared to six (expanded) models where dummy variables for each corresponding IV were included. Comparisons between the pooled and expanded models were made using bivariate Wald tests. We found no meaningful differences between the results reported here for the consolidated versus restricted model comparisons and the pooled versus expanded model comparisons.
8. The observed relationship between real estate value and spatial preference in The Hague in this study (negative and statistically significant) runs counter to that reported in B&N (positive and nonsignificant). This disparity is explained by the necessary omission of the ethnic heterogeneity variable and the transformation of the property value variable into deciles. Supplementary analysis confirms this explanation, demonstrating that the effect of (deciled) property value was not statistically significant for The Hague when ethnic heterogeneity was included.
9. To validate this approach, a further model was estimated examining the influence of target proximity on adult and juvenile offenders consistently across regions (18 and above, and below 18, respectively). While the direction and significance of relationships remained consistent between this simplified model and the one presented in Table 4, results of this analysis demonstrated that the model using definitions of juveniles based on the legal driving age in each region provided a better fit to the observed data.

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