



# Relationships Between Offenders' Crime Locations and Different Prior Activity Locations as Recorded in Police Data

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## Abstract

Understanding the relationships between individual offenders' crime locations and their prior activity locations is important to enable individual level predictions to support crime prevention and investigation strategies. This study examined a wider range of crimes and activity locations than included in previous studies, to determine whether offenders are more likely to commit crime near some types of activity locations than others. Using discrete spatial choice models, we identified relationships between proximity to pre-crime activity locations recorded in a police database (e.g., offenders' homes, family members' homes, schools, prior crimes, and other police interactions) and the locations of 17,054 residential burglaries, 10,353 non-residential burglaries, 1,977 commercial robberies, 4,315 personal robberies, and 4,421 extra-familial sex offences in New Zealand. Offenders were generally more likely to commit crime closer to their activity locations than farther away, and closer to those visited more frequently (e.g., home versus family homes) or more likely to impart relevant knowledge about crime opportunities (e.g., prior crimes versus prior victim or witness locations). The observed patterns for different activity locations and crime types broadly support a recently proposed extension to crime pattern theory and illustrate the benefits of differentiating activity location and crime types when examining criminal spatial behaviour. The results have implications for offender risk assessment and management, and geographic profiling in police investigations.

**Keywords** Crime location choice · Crime pattern theory · Discrete spatial choice · Police data · Routine activity locations

## Introduction

We know from routine activity theory (Cohen and Felson 1979) and crime pattern theory (Brantingham and Brantingham 1991, 1993a) that crimes occur where opportunity (i.e., the presence of a suitable and available target) overlaps with offenders' awareness spaces: the

locations known to offenders through their routine non-criminal activities such as where they live, work, or socialise with family or friends. Recent theoretical development suggests that some types of activity locations are more salient to offenders' crime location choices than others (Curtis-Ham et al. 2020). Understanding which of their activity locations people are more likely to commit crime near has important implications for crime prevention and investigation. It can assist in identifying offenders' high-risk locations for offending, to inform risk management strategies (Schaefer et al. 2016; Serin et al. 2016). It can also assist in geographic profiling for crime investigations (Rossmo 2000). For example, suspects could be prioritised by comparing their high-risk locations for offending with the location of a given crime (as implemented by Curtis-Ham et al. 2022), or with likely 'anchor point' areas predicted by analysing the locations of a crime series (as raised by Goodwill et al. 2014; van der Kemp 2021).

But despite the practical importance of being able to predict—at an individual level—where a person will commit crime, given knowledge of their different activity locations,

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little research has explored empirically the extent to which various types of activity locations differ in their effects on crime location choices. Studies to date have only compared a limited subset of activity locations (e.g., offenders' homes, homes of family members and locations of previous offences; Ruiter 2017). This study leverages a large national dataset of offenders' pre-crime activity locations recorded in a police database, in a previously unresearched context (New Zealand). It expands our understanding of offenders' crime location choices—and thus our ability to predict their future crime locations—by comparing the associations between a wider range of activity locations and offenders' crime location choices, for a wider range of crime types separately, than included in prior studies. It also expands the empirical evidence for crime pattern theory and its recent extension by Curtis-Ham et al. (2020) through testing theory-derived hypotheses about these comparisons, as described next.

### Activity Locations and Distance Decay

Drawing on environmental psychology, crime pattern theory emphasises the role of people's routine activities in generating awareness of crime opportunities (Brantingham and Brantingham 1991, 1993a, b). The consequences of this theory for present purposes are two-fold. First, in principle, offenders could identify crime opportunities near any of their activity locations (also referred to as 'nodes'). Qualitative studies have confirmed that home, work, and other non-criminal activity locations have potential to generate awareness of crime opportunities (e.g., Alston 1994; Costello and Wiles 2001; Davies and Dale 1996; van Daele 2009). Recent quantitative studies have estimated the increased likelihood of offenders to commit crime near their homes, the homes of close relatives (parents, children and siblings), and the locations of previous offences, compared with elsewhere (Menting et al. 2016; Ruiter 2017; van Sleeuwen et al. 2018). This increased likelihood also applies to former, rather than current, homes of offenders and of their relatives (Bernasco 2010b; Bernasco and Kooistra 2010; Menting et al. 2016).

Two studies have included a wider range of activity locations and demonstrated that offenders are more likely to commit crime near these activity locations—collectively—than farther away. Bernasco (2019) included all locations frequented by 70 Dutch adolescents during a 4-day period up to 4 years before their offences; Menting et al. (2020) included friends' and partners' homes, victimisation locations, school, work, and leisure locations visited by 78 Dutch offenders (aged 18–26) in the month before their offences. However, the small sample sizes in both studies precluded disaggregate analysis to test each activity location type's association with crime location choice. Considering the potential of any activity location to generate awareness of

crime opportunities, and the empirical confirmation of activity locations studied separately or in the aggregate to date, we therefore expected that each type of activity location in the present data would be positively associated with crime location choice.

Second, the role of routine activities in generating awareness of crime opportunities means that the likelihood of offending is typically highest nearest to activity nodes and declines with distance. This 'distance decay' pattern reflects that people are more familiar with areas closer to than farther away from their activity locations (Brantingham and Brantingham 1991, 1993a, b), and familiarity is an important factor in crime location choice (as expanded upon in Curtis-Ham et al. 2020). It also reflects the 'principle of least effort' (Zipf 1949): if setting out from an activity location to commit crime, people will travel the least distance necessary to find a crime opportunity—or exploit a known one (Goodwill et al. 2014). This pattern was observed in the studies described above and many past analyses of the frequency of offending at different distances to offenders' current homes (see Ackerman and Rossmo 2015; Townsley 2016). Further, distance decay is not simply a by-product of such studies aggregating across offenders, nor a pattern specific to crime, but reflects individuals' tendencies to conduct their everyday activities closer to existing activity nodes than farther away (Bernasco 2022). We therefore expected to observe a distance decay pattern with respect to each activity location type analysed in the present study.<sup>1</sup>

Hypothesis 1 reflects the stated expectations that each activity location type would be associated with crime location choice and that this association would become weaker with distance from the activity location. However, we set no a priori hypotheses regarding differences in decay rates (the steepness of the decline) between different activity nodes. We considered this aspect to be subject to exploratory analysis.

H1 Offenders are more likely to commit crime in closer proximity to each activity location than farther away.

### Relative Influence of Different Activity Locations

Although we expected each activity location to have at least some association with crime location choice, the main aim of this paper was to expand our understanding of how

<sup>1</sup> Buffer zones of reduced crime likelihood *immediately* surrounding home or other activity nodes (Rossmo 2000) would not have been detectable given the spatial units of analysis used in this study—neighbourhoods—because these units cover more than the immediate area of activity nodes. We thus expected monotonic decay as found in other neighbourhood level studies (Bernasco 2019; Bernasco and Block 2009; Menting et al. 2020).

these associations differ between activity locations. To guide expectations about the relative influence of different activity locations, we drew on the theoretical framework of Curtis-Ham et al. (2020). Synthesising existing theory and empirical evidence from psychology, criminology, and geography, the framework proposes that offenders' crime location choices are a product of both the *reliability* and the *relevance* of their knowledge of the areas around their activity nodes. People are more likely to commit crime near nodes that have produced reliable knowledge (i.e., greater familiarity) that is relevant to the crime (i.e., suggestive of a good crime opportunity). Specific attributes of offenders' activities at these locations affect how much reliable and crime-relevant knowledge they obtain. The frequency, recency, and duration of offenders' activities at their activity nodes determine how reliable is their knowledge of the area. The similarity of their activities to the crime at hand determines the extent to which they have obtained relevant knowledge of opportunities for that crime. The more similar the activities in terms of the behaviour, timing or type of location involved, the more conducive they are to identifying the crime opportunities in the vicinity.

Our hypotheses comparing different activity nodes' associations with crime location choice reflect their differences on single factors set out in the theoretical framework where other factors can be assumed constant. The second hypothesis compares types of node that vary in terms of how frequently they are visited: offenders' own homes and homes of their family members. These nodes are likely comparable in recency (i.e., whether they are a current or former address) and duration (i.e., how long the offender or family member lived there). They are also comparable in terms of type of location (residential), timing (one might visit or stay with family at any time of day or day of week) and general behaviour ("hanging out", sleeping). Given that—on average—offenders will visit their own home more frequently than their family members' homes, we hypothesised:

H2 Offenders are more likely to commit crime near their own homes than the homes of family members.

We also compared between homes of different categories of family members. Given that offenders' associations with intimate partners and their addresses are likely to have been of shorter duration (on average) than for immediate family, we hypothesised:

H3a Offenders are more likely to commit crime near to the homes of immediate family members (parents, children and siblings), than those of current or former

intimate partners (ex or current spouses and other intimate relationships)<sup>2</sup>

Given the likelihood that immediate family members are visited more frequently than other relatives due to their likely closer relationships (Agneessens et al. 2006; Wellman and Wortley 1989), we hypothesised:

H3b Offenders are more likely to commit crime near to the homes of immediate family members (parents, children and siblings), than those of other relatives (grandparents, grandchildren and other relatives).

Curtis-Ham et al. (2020) suggest that one dimension of behavioural similarity would be exposure to criminal behaviour in different roles. *Committing* a crime is a similar activity to committing a future crime and likely to provide relevant knowledge of the location's crime opportunities. Experiencing crime as a *victim or witness* is less similar, and so would provide less directly relevant knowledge of the location's crime opportunities. The behavioural similarity factor reflects how people transfer learning from one situation to another: knowledge about a location gained from the actual commission of a crime is more directly transferrable to a future crime than knowledge gained from observing another person committing it (Curtis-Ham et al. 2020).<sup>3</sup> We therefore tested:

H4 Offenders are more likely to commit crime near to places they have previously offended than to places where they have previously been a crime victim or witness.

Hypotheses H1 to H4 apply to all crime types because the same mechanisms—prior activities generating reliable and relevant location knowledge—are theorised for all crime. However, through these mechanisms, different types of activity node can also generate knowledge relevant to different types of crime (Curtis-Ham et al. 2020). The next section therefore considers the interaction of node type and crime type.

<sup>2</sup> This hypothesis assumes that the shorter duration of intimate relationships offsets the likely higher frequency of visiting intimate partners compared with other family members.

<sup>3</sup> The acquisition of location knowledge affects *where* a future crime is committed. A person's experience of a crime as a victim or witness may also affect their motivation to commit a future crime, but this research is concerned with *where*, not *whether*, they commit a future crime.

## Activity Locations and Different Crime Types

Here we consider how different activity locations generate knowledge that is specific to different types of crime. Curtis-Ham et al.'s (2020) theoretical framework includes a 'location type similarity' factor that reflects that activities that involve the same type of location (e.g., residential or commercial) as targeted by a certain crime are more likely to generate knowledge of nearby targets for that crime. Thus, residential nodes such as offenders' homes or their family's homes would yield relevant knowledge of nearby residential burglary targets and less relevant knowledge with respect to commercial targets. In line with this suggestion, home-crime distances tend to be longer for commercially than residentially focused crimes (Ackerman and Rossmo 2015; Townsley 2016). Accordingly, we tested:

H5 Residential burglars are more likely to commit crime near to home and family homes than non-residential burglars and commercial robbers.

H5 excludes personal robberies and extra-familial sex offences, which involve moving targets—people—rather than specific types of premises from which to gauge location type similarity. Although personal robberies tend to concentrate in places with high numbers of potential victims (e.g., commercial, nightlife and transit hubs), many occur in residential areas (Bernasco and Block 2009; Block and Davis 1996; Hart and Miethe 2015). Similarly, victims of extra-familial sex offences could be identified and first contacted in a target rich environment such as a bar or club, or through the offender's social network, or in their residential neighbourhood, but the offence itself could occur away from these initial 'encounter' locations, even at the offender's home (Chopin and Caneppele 2018, 2019; Hewitt et al. 2012, 2020).

## Opportunity and Crime Location Choice

Crime occurs where offenders' awareness space—the locations they are aware of around their activity nodes—converges with crime opportunities (Brantingham and Brantingham 1991). Opportunities exist where suitable targets (for a given crime) are present in the absence of capable guardians (Cohen and Felson 1979). Crime location choice is typically modelled as the product of activity node proximity while controlling for the locations of crime opportunities using covariates such as the number of potential targets, or presence of crime generators (Ruiter 2017). We therefore expected hypotheses 1 to 5 to hold while controlling for the presence of opportunities—operationalised via indicators of the number of potential targets in each spatial unit, relevant to each crime type analysed.<sup>4</sup>

Additionally, including opportunity variables in models of crime location choice explains variance beyond that accounted for by proximity to activity nodes alone (Bernasco 2019). Studies have frequently found that opportunity measures are associated with crime location choice while controlling for proximity to activity nodes (Ruiter 2017). This finding could reflect unmeasured activity locations that concentrate where crime opportunities—and people in general—concentrate (Boivin and Felson 2018; Frank et al. 2011) or crimes committed outside of awareness space where opportunities that have been either stumbled upon or sought out (Curtis-Ham et al. 2020). We therefore expected opportunity to be associated with crime location choice while controlling for the presence of activity nodes.

## Data and Method

To test our hypotheses, we employed discrete crime location choice modelling (DSCM). DSCM is specifically designed and therefore frequently used to analyse hypotheses such as ours about the relative likelihood of an offender choosing a location to commit crime, given attributes of the location such as its distance from an activity node or its crime opportunities (Bernasco 2021; Ruiter 2017). This section describes the data, variable construction, and DSCM method.

## Offender and Activity Node Data

Data on offences and offenders' activity nodes were extracted from the New Zealand Police National Intelligence Application (NIA). Offences included all residential and non-residential burglaries, commercial and personal robberies, and extra-familial sex offences committed between 2009 and 2018 for which an offender had been identified with sufficient evidence to proceed against. Including these offences balanced considerations of scope, volume, seriousness and priority to police; and coverage of crimes included in previous DSCM studies—residential burglary and robbery—and other crimes considered by research on offender mobility: non-residential burglary and extra-familial sex offences (Chopin and Caneppele 2018, 2019).<sup>5</sup> Including

<sup>4</sup> Note that crime locations are a product of an *interaction* between offenders' awareness space and opportunities (Menting 2018), an interaction that is reflected in the statistical model we use to test the hypotheses.

<sup>5</sup> Sex offences ranged from indecent exposure to rape. Some would have occurred at offenders' homes (regardless of how and where the victim was identified) reflecting the ability of offenders to make this choice. The dataset did not enable separation of known and stranger victims, nor adult and child victims, to explore how this choice depended on victimology.

crimes with different target types (residential versus commercial and buildings versus people) and motivations (property acquisition versus sexual violence) enabled us to verify whether the crime-independent hypotheses (H1-H4) were robust across crime types—important given the theories from which these hypotheses derived expressly apply for all crime. Using a national dataset overcame limitations of previous studies which typically considered smaller areas and excluded offenders with no activity locations in the study area, likely inflating associations between activity locations and crime locations (the exceptions are limited to small European countries: Bernasco and Kooistra 2010; Menting et al. 2020; van Sleuwen et al. 2021).

Activity node data derived from a range of records including address history, linked persons and their address histories, employment, education, offences, incidents/call-outs, arrests, stops, and intelligence. These were grouped into ten node types as described below. Because police do not comprehensively monitor people's whereabouts, not all activity locations are on record for each offender. The data are therefore a sample of each offender's true population of activity locations. For example, home addresses often only become known when offenders are arrested for an offence; address changes between offences or arrests are thus not necessarily on record. Not all family members will have address records in the database; 'links' between family members are not always recorded. Employment and education records were more rarely on file. Crime, victimisation, and incident locations depend on these being reported to the police.

We included activity locations that were less common in the data, less routinely visited, and less recent, erring towards inclusion of data. Activity locations generate awareness of crime opportunities that can result in the offender returning to commit crime years after their activities, at least as captured in available data (Bernasco 2010b, 2019; Bernasco et al. 2015; Bernasco and Kooistra 2010; Lammers et al. 2015; Menting et al. 2016). A single prior crime in a neighbourhood is associated with an increased likelihood of future offending there (Bernasco et al. 2015; Long et al. 2018), as are activities with relatively low frequency in short activity sampling periods (Bernasco 2019: four days; Menting et al. 2020: one month). Thus, activities do not have to be particularly recent or 'routine' to impart knowledge of crime opportunities that operates on future crime location choices (though the more recent or routine, the higher the likelihood of future crime). Further, single data points such as prior offences and incidents can be indicative of other activities carried out more routinely in those locations that are not captured in the data.

The raw data included almost 5.5 million activity node records, for approximately 66,000 offenders. After removing offence and activity node records that did not reliably establish the presence of the offender (e.g., some specific frauds and offences involving publication or remote

communication), or the time or location with sufficient specificity, approximately 60,000 offenders and 4.5 million nodes remained (see Curtis-Ham et al. 2021a for more detail on the data cleaning steps). To ensure comparability in recency between different node types, we only included nodes dated within 5 years of the reference offence.<sup>6</sup> See Tables S1.1 and S2.2 in the online supplementary materials for detailed definitions and the distribution of nodes per offender, respectively.

To yield as many prior activity locations as possible per crime location choice and to prevent nesting, for each of the five offence types—modelled separately—each offender's most recent offence was identified as their 'reference offence' (following Bernasco 2010a); its location was the variable of interest. An offender could appear in multiple models if they committed more than one type of offence (e.g., both a residential burglary and a personal robbery). An offence could recur in the reference offences if it was also a co-offender's reference offence (following Menting et al. 2020; Chamberlain and Boggess 2016 who found that statistically adjusting for nesting of offenders in offences made no difference to the results). We included only offenders with at least one pre-offence activity node and only their nodes that pre-dated the reference offence.<sup>7</sup> The data included both serial offenders, whose crimes prior to the reference offence counted as prior crime nodes, and one-off offenders with no prior crimes but at least one other pre-offence activity node. We analysed 17,054 residential burglaries, 10,353 non-residential burglaries, 1,977 commercial robberies, 4,315 personal robberies, and 4,421 extra-familial sex offences.<sup>8</sup> Demographic characteristics of the offenders are provided in Table S2.1 in the online supplementary materials.

## Unit of Analysis

The question that the discrete spatial choice model sets out to answer is as follows: which attributes of locations make offenders decide to choose them (or avoid them) for committing crime? The 'locations' are the spatial units of analysis of the model, an advantage of DSCM being that it considers both units that were chosen, and those that could have been but were not. The units can range from specific addresses (Vandeviver and Bernasco 2020) to administrative units such as census tracts or postcodes (e.g., Townsley

<sup>6</sup> The data initially included crime and incident records dating back to 2004—reflecting the start of the database and limited capture of historical records—and address records dating back to the offender's date of birth.

<sup>7</sup> Resulting in the removal of 1.2% of residential burglars, 1.6% of non-residential burglars, 0.5% of commercial robbers, 0.9% of personal robbers, and 8.9% of sex offenders.

<sup>8</sup> We randomly sampled 50% of reference offences to train each model, reserving the rest for future studies testing models' predictions.

et al. 2015). Selecting the spatial unit involves balancing a range of considerations by the analyst (Bernasco 2010a). These include theoretical relevance (how big is one unit of ‘activity space’?), spatial spill-over (if the unit is too small the choice is influenced by the attributes of surrounding units), spatial heterogeneity (if the unit is too big then variation within the unit that could affect the choice is not captured), and computational processing (if there are too many units the capacity of available computing equipment may be exceeded).

We used the New Zealand Census Unit ‘Statistical Area 2’ (SA2).<sup>9</sup> SA2s approximate neighbourhoods, typically containing 2000–4000 residents in urban areas and 1000–3000 residents in rural areas. Outliers with smaller populations represent industrial and commercial areas, remote regions, and bodies of water with no residential population. SA2s are comparable to the units used in other neighbourhood level DSCM studies (e.g., Clare et al. 2009; Townsley et al. 2015).

In DSCM analysis, the dataset needs to include not only the attributes of chosen locations but those of alternative locations that could have been chosen but were not. To overcome computational challenges involved in including every SA2 in each offender’s ‘choice set’ of possible alternatives—given the number of alternatives, offenders, variables and available computing capacity—we sampled from all potential SA2 alternatives ( $n = 2153$ ) to construct a manageable set for each offender. We followed a stratified importance sampling approach (Ben-Akiva and Lerman 1985; McFadden 1977) shown to yield estimates consistent with those produced by including all alternatives when modelling crime location choice (Curtis-Ham et al. 2021b). Each offender’s choice set included the chosen SA2; all SA2s that contained an activity node or had an activity node within 5 km (from the SA2 boundary); and 10 SA2s randomly selected from the remaining SA2s (i.e., those that were more than 5 km away from any activity nodes). The median land area of the sampled SA2s was 1.2km<sup>2</sup> (quartiles 0.84, 2.2 km<sup>2</sup>) on average across the five offences modelled. The small and relatively homogenous size of the sampled SA2s reflects that the vast majority were in urban areas.

## Outcome Variable

The outcome variable reflects the location choice for each offender; from their set of potential SA2s, it is the one in which their reference offence was committed.

<sup>9</sup> The 2018 SA2 shapefile and metadata were downloaded from <https://datafinder.stats.govt.nz/layer/92212-statistical-area-2-2018-generalised/>. We excluded 83 SA2s made up of bodies of water from the analysis.

## Activity Node Variables

To assess our hypotheses about the relationships between different types of activity nodes and crime location choice, each SA2 alternative in each offender’s choice set was dummy coded depending on the presence (1) or absence (0) of each type of node in the SA2. *Home* included any residential address of the offender. Family homes included the residential addresses of persons linked to the offender in NIA as *immediate family* (parents, children, and siblings, including step relationships), past or present *intimate partners* (spouses, partners, and boy/girlfriends), and *other relatives* (grandparents/children, other relatives, foster, and other care/guardianship relationships).<sup>10</sup> *School* included school and tertiary education locations. *Work* addresses were included where available, as a distinct type of activity node from education. *Prior offences* included crimes committed by the offender with sufficient evidence to prosecute. *Prior victim/witness* included offences involving the offender in a non-offending role such as a victim or witness, but not as an offender or suspect. *Prior incidents* included non-crime events reported to or detected by police such as domestic disputes, drunk and disorderly behaviour, mental distress, suspicious behaviour and truancy. Finally, the category *Other location* captured addresses recorded in the offender’s address history with codes such as ‘arrested at’, ‘seen at’, ‘frequents’, ‘trespassed from’, ‘spoken to at’, ‘stopped at’, ‘other’ and ‘unknown’.

Each SA2 alternative was also coded 1 or 0 based on the presence or absence of the nearest of each type of node within five distance bands extending to 5 km from the SA2 (with thresholds at 200 m, 500 m, 1 km, 2 km, and 5 km from the SA2 boundary). Prior studies have shown significant associations between crime location choice and presence of activity nodes at an average of 3 km away (Menting et al. 2020). In choosing 5 km, we balanced exploring the extent to which activity nodes farther away were associated with crime location choice with minimising the number of distance bands included, given that each distance band added 10 variables indicating the presence or absence of each of the 10 node types. Using these dichotomous variables per distance band rather than the linear distance to each type of node enabled us to visualise and compare the pattern of distance decay across node and crime types. Additionally, using distance bands provided a more easily interpretable

<sup>10</sup> Family nodes were coded mutually exclusively, prioritising immediate family then intimate partners over other relatives. A limitation is that home addresses of some family members, especially intimate partners, may pre- or post-date the relationship and therefore may not have been visited by the offender. The data did not include relationship dates to enable restriction of activity locations to relationship periods.

scale than using contiguous spatial units at increasing lag orders (e.g., Menting et al. 2020), including distance bands both shorter and longer than the typical distance between neighbouring SA2s.<sup>11</sup>

As an example, if a given SA2 alternative contained a home node, it was coded 1 for the variable ‘home in SA2’ and 0 for the variables ‘home at 0–200 m’, ‘home at 200–500 m’, and so on for the remaining distance bands. If a given SA2 alternative did *not* contain a home node, but the nearest home node was between 200 and 500 m of the SA2, the SA2 was coded 0 for the variable ‘home in SA2’, 1 for the variable ‘home node at 200–500 m’ and 0 for all other home node × distance band variables. If there were no nodes of any kind within 5 km of a given SA2 alternative, the SA2 was coded 0 for all node type × distance band variables. Consistent with previous DSCM studies (e.g., Menting et al. 2020), this method prioritised the most proximal activity nodes while controlling for the presence of activity nodes farther away. The reference category for each type of node at each distance band was no node of that type within 5 km of the SA2, which could either mean that the node did not exist in the first place (e.g., no police-recorded prior offences), or that it existed but the nearest one was farther than 5 km away. A stable model for commercial robbery was only achievable using three distance bands for work nodes (applied for all crime types for comparability): ‘in SA2 to 200 m’, ‘200 m–1 km’, and ‘1–5 km’.<sup>12</sup> See Table S2.3 in the online supplementary materials for descriptive statistics for the node type × distance band variables.

## Opportunity Variables

In line with previous DSCM studies, we operationalised opportunity as the number of potential targets, or an indicator thereof, in each spatial unit. Because the focus of this study was on offenders’ activity locations rather than differentiating criminogenic features of the environment, we identified one opportunity variable for each crime type indicative of the number of potential targets per SA2. These variables came from New Zealand Statistics Census and Business Demography data (<http://nzdotstat.stats.govt.nz/>) and are further detailed in Table S1.2 in the online supplementary materials. For residential burglary, we used the number of dwellings (see similarly Bernasco and Nieuwbeerta 2005; Frith 2019; Townsley et al. 2015). For non-residential burglary, we used the total number of business units, which directly measures

the number of non-residential burglary targets in the SA2. For commercial robbery, we used the number of business units in industry categories that mapped to the types of crime locations used to identify commercial robberies. This was a more direct measure of potential targets than previous studies which used indirect measures such as retail footprint (Bernasco and Kooistra 2010) and number of retail employees (Bernasco and Block 2009). For personal robbery, we used the number of business units in commercial or public industries, combining the types of facilities included in prior DSCM studies as separate covariates (Bernasco et al. 2013; Long et al. 2018; Song et al. 2019). This measure is a proxy indicator of the ambient population in a given spatial unit: how many potential targets are there, on average, for work, education, shopping, or recreation purposes (Andresen 2011). Ambient population predicts personal robbery and other offences against mobile targets (such as sexual assaults) better than residential population, thus forming the better single indicator of target distribution (Andresen 2011; Andresen and Jenion 2010; Rummens et al. 2021). We thus adopted the same measure of opportunity for sex offences.

## Modelling Method

Consistent with most previous DSCM studies, we used conditional logit models to test our hypotheses (McFadden 1984). The conditional logit model evaluates the likelihood of a choice alternative (SA2) being selected given its attributes (e.g. presence of a home in the SA2, presence of nearest crime 200–500 m away). In each model (one per crime type), there were 61 variables: 10 node types × 6 distances (SA2 plus 5 bands) + 1 opportunity variable. We report model coefficients as odds ratios (ORs). For node types, the ORs reflect the increase in odds of an SA2 being chosen given the presence of an activity node of that type at that distance band, compared to no node of that type within 5 km of the SA2. For opportunity, the ORs reflect the increase in odds for every additional 100 opportunity units (e.g., households, businesses) in the SA2. When comparing ORs within models, if the ORs’ 95% confidence intervals (CIs) overlapped, we used Wald’s Chi-Square tests of difference.

## Results

The models provided a good fit to the data with pseudo  $R^2$  values between 0.35 and 0.42 (McFadden 1973), which are at the upper end of the range of values found in other DSCM studies (Table 1). Figure 1 displays the 95% CIs of the ORs for each model (crime type), simultaneously enabling visual comparison distance-wise (H1), node-wise (H2–5), and crime-wise (H5). Tables S3.1 and S4.1 in the online supplementary materials provide the ORs and CIs, and the Wald test results, respectively.

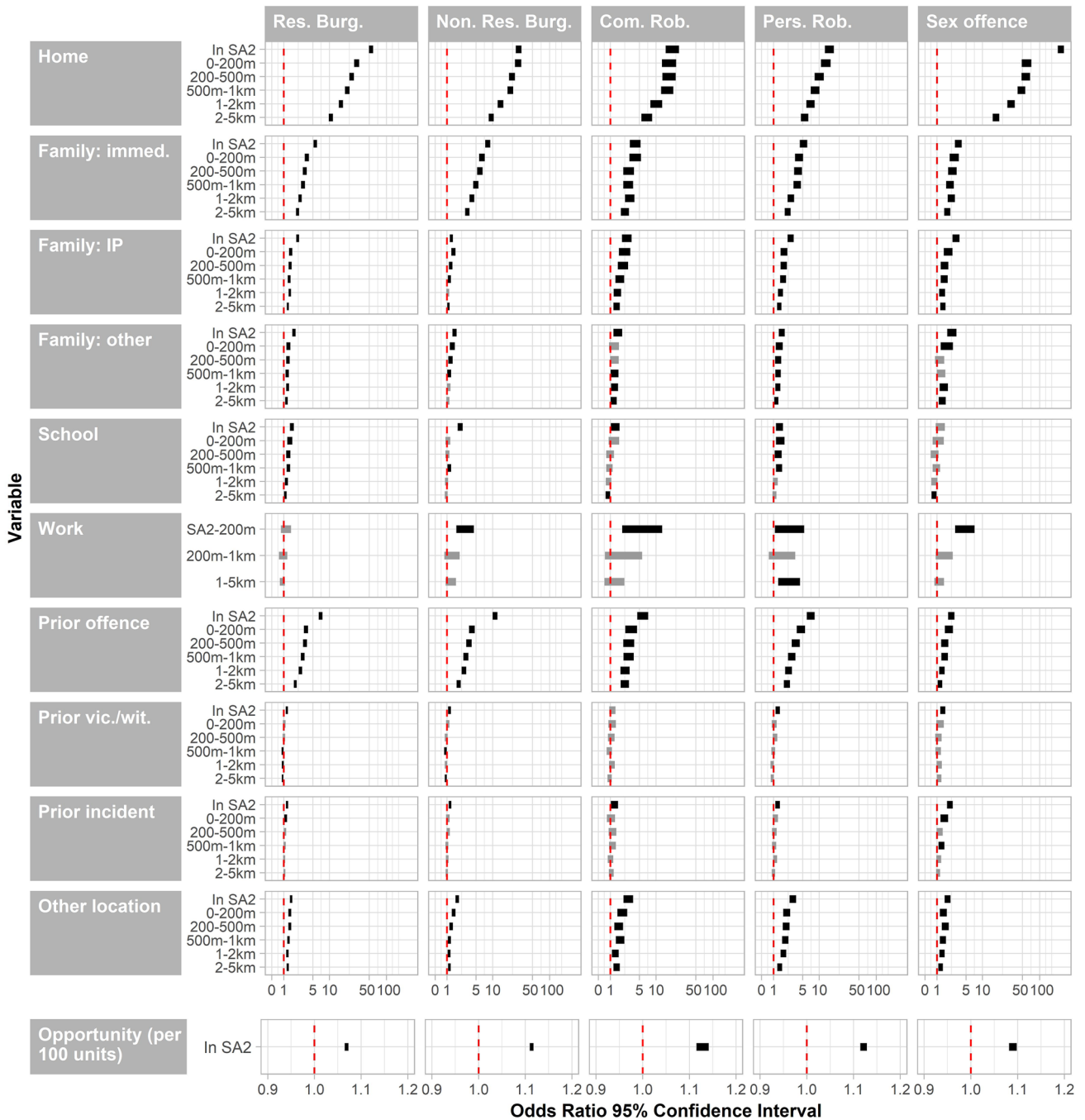
<sup>11</sup> Median nearest neighbour distance between centroids of sampled SA2s = 893 m (average across models).

<sup>12</sup> This method enabled the model to converge and produce Variation Inflation Factors (VIFs) demonstrating no problematic multicollinearity. Across all crime types, the median VIF was 1.56 and the maximum was 5.69, well under the commonly applied threshold of 10 (Bernasco and Block 2011; O’Brien 2007).

**Table 1** Model summary statistics

Statistic	Res. burg.	Non-res. burg.	Com. rob.	Pers. rob.	Sex offences
N offence choices	17,054	10,353	1,977	4,315	4,421
N SA2 choice alternatives	4,213,998	2,417,735	563,161	1,243,204	784,537
Pseudo R <sup>2</sup>	0.42	0.42	0.35	0.38	0.37

SA2 statistical area 2



**Fig. 1** Odds ratio (OR) 95% confidence intervals (CIs) for node type and opportunity variables per distance band for each model (crime type). Note: The shorter the bar, the smaller the CI. Grey bars indicate non-significant associations with CIs that cross the vertical line

at 1. Bars that do not overlap indicate significant differences between ORs. Bars that overlap indicate possible non-significant differences between ORs (see Wald test results)

As predicted by hypothesis 1, offenders were generally more likely to commit crime closer to activity nodes than farther away. Of the 50 associations between crime location choice and the presence of a node in the same SA2, 47 were significant and positive (Fig. 1: where the top bar in the cell is black and to the right of the vertical line). Offenders were between 1.22 times (victim/witness node + non-residential burglary) and 235 times (home node + sex offence) more likely to offend in an SA2 containing that type of activity node than if the nearest activity node of that type were more than 5 km away. The three non-significant associations were work for residential burglary, prior victim/witness events for commercial robbery, and school for sex offences (Fig. 1: where the top bar in the cell is grey). In several instances, contrary to expectation, offenders were less likely to commit crimes in SA2s with activity nodes present at the longest distance bands, than if those nodes were not present in any distance band: prior victim/witness events for burglary; school for commercial robbery; and sex offences (Fig. 1: where the black bar is to the left of the vertical line).

A distance decay pattern is evident for most nodes (Fig. 1: where the bars within each cell get closer to the vertical line from top to bottom). For example, in the top leftmost cell (home nodes and residential burglary), the ORs monotonically decrease with increasing distance bands, meaning the odds of an SA2 being chosen for a residential burglary decrease the further that SA2 is from a home node. ORs were not always significantly different from one distance band to the next, but ORs for the shortest distance band (in SA2) were significantly greater than ORs for the longest distance band for 47 of the 50 comparisons (Fig. 1: comparing the top and bottom bars within each cell). The three exceptions were as follows: other family homes and incidents for commercial robbery and work for personal robbery. The only other statistically significant exception to monotonic decay was intimate partner homes for non-residential burglary with slightly higher odds at 0–200 m (OR 1.40) than in the SA2 (OR 1.61).

Confirming hypothesis 2, offenders were more likely to commit crime near their own homes than their family members' homes: all differences between 'home in SA2' and each type of 'family home in SA2' were significant (Fig. 1: comparing the top bars of the top and second to top cells). Regarding hypotheses 3(a) and 3(b), offenders were significantly more likely to commit crime in the same SA2 as immediate family members' homes than in the same SA2 as homes of current or former intimate partners (except sex offenders and commercial robbers) and of other relatives (Fig. 1: 3(a) comparing the top bars of the second and third to top cells; 3(b) comparing top bars of the second and fourth to top cells). Hypothesis 4 was supported. Offenders were more likely to commit crime

near to places they previously offended than places where they had previously been a crime victim or witness: no prior offence CIs overlapped with prior victim/witness CIs for 'in SA2' (Fig. 1: comparing the top bars of the prior offence and prior victim/witness cells).

We found partial support for hypothesis 5. Residential burglars were roughly twice as likely to commit crime near home (OR 53.97) than were non-residential burglars (OR 28.66) and commercial robbers (OR 19.43; Fig. 1: comparing the top bars of the top cells across columns). Residential burglars were—as hypothesised—more likely to offend near intimate partner homes (OR 2.46) than non-residential burglars (OR 1.40; Fig. 1: comparing the top bars of the third to top cells across columns). But they were less likely to offend near immediate family homes (OR 5.55) than non-residential burglars (OR 8.17; Fig. 1: comparing the top bars of the second to top cells across columns), and CIs overlapped for the remaining H5 comparisons (with non-residential burglary for other family homes, and with commercial robbery for all family home categories).

Lastly, crime opportunity was positively associated with crime location choice, when controlling for the presence of activity nodes. For every increase of 100 households or relevant businesses (depending on crime type) in the SA2, the odds of an offence in that SA2 increased by 7% for residential burglary, 12% for non-residential burglary, 14% for commercial robbery, 13% for personal robbery, and 10% for sex offences.

## Discussion

This study aimed to identify near which of a range of activity locations (nodes) recorded in police data offenders are more likely to commit crime. Almost all nodes—including those not considered separately in previous studies: intimate partner and other relatives' homes, school, work, police involved incidents and other police contacts—were significantly and positively associated with crime location choice, at least at short distances. The lack of association between work nodes and residential burglary could reflect a lack of residential burglary opportunities around work nodes likely concentrated in non-residential areas. The lack of association between prior victim/witness events and commercial robbery indicates that these events were not conducive to the acquisition of knowledge of commercial robbery opportunities. There are several possible explanations for the lack of association between offenders' school/education nodes and sex offences. First, the aggregation of offences against children and adults in the present dataset could have masked any victim age-specific association. Second, past research suggests that relatively few extra-familial child sex offenders access their victims at or near schools (14%: Leclerc

and Felson 2016) and that those who do tend to carry out the offence elsewhere (Mogavero and Hsu 2017). The few negative associations—at longer distances—were marginally significant and small. We treat these results with caution, but they could reflect the unobserved underlying environmental backcloth that shapes different activities (Brantingham and Brantingham 1993a, b) and the distribution of crime opportunity, or idiosyncrasies of the present dataset. Replicating this study elsewhere to see if similar patterns emerge would assist in resolving whether these exceptions were mere anomalies or not (and if not, the implications for theory).

Consistent with our expectations based on crime pattern theory (Brantingham and Brantingham 1991, 1993a), crime was almost always most likely in the immediate vicinity of activity nodes, declining monotonically with distance. We place more weight on the general pattern and treat the few marginal exceptions with caution given the number of comparisons and limitations of the data (discussed below). The patterns of distance decay for different activity nodes evidence the extent of offenders' awareness space around different activity nodes and the likelihood that they will identify criminal opportunities within that space. Home and prior crimes showed the strongest associations with crime location choice, over longer distances, followed by homes of immediate family. These results are consistent with prior studies of residential burglary, robbery, and crime in general (Menting et al. 2016), but provide novel confirmation for non-residential burglaries and extra-familial sex offences specifically. The apparent wider awareness space around home nodes likely reflects that home nodes tend to anchor other routine activity locations that might not appear in the data (Golledge 1999; Wang et al. 2013). Further, more 'paths' exist between home and other nodes, generating familiarity with a wider area around home (Schönfelder and Axhausen 2002; Wang et al. 2013). In contrast, associations between prior victim/witness events and incidents and offenders' crime locations were largely limited to the same SA2, suggesting more constrained awareness space around these nodes. That the sex offenders were much more likely to offend in the same SA2 as they lived (OR 235) than other offenders likely reflects that some of these offences occurred at home.

That home, and to a lesser extent, immediate family homes and prior offence sites, were strongly associated with crime locations even at the 2–5 km distance range could be explained by the relatively low urban population density of New Zealand (Demographia 2019). When targets are more dispersed there are fewer crime opportunities within a given distance range, resulting in longer distances between activity nodes and crime and an extended decay curve. Accordingly, New Zealand burglary and sex offenders' home-crime distances are longer on average than those of offenders from other countries (Hammond 2014; Lundrigan et al. 2010;

Lundrigan and Czarnomski 2006; Scott 2012). Likewise, Townsley et al. (2015) found a smaller association between distance to home and residential burglary location choice in Australia than in the UK and the Netherlands, reflecting differences in urban population density. Our results are likely to generalise to other low population density jurisdictions and imply that studies in such jurisdictions could benefit from using an even longer distance range.

Differences in relative associations between crime locations and different nodes were largely consistent with the hypotheses derived from Curtis-Ham et al.'s (2020) theoretical model, thus lending further empirical support to this extension of crime pattern theory. Offenders were generally more likely to commit crime closer to activity nodes that were higher frequency (home versus family homes; immediate family versus other relatives); likely to impart more relevant knowledge about crime opportunities (prior crimes versus prior victim or witness locations); and of the same location type as the crime target (home for residential burglary versus non-residential burglary and commercial robbery). They were also more likely to offend near immediate family homes—presumed to be more enduring nodes—than near intimate partners' homes, though this difference was less pronounced for the commercial robbery and sex offenders. It is unclear why residential burglars were much more likely to offend near home than offenders targeting non-residential properties but not always more likely near family homes. Offenders' homes are just as likely as their family members' homes have more residential and fewer non-residential crime opportunities nearby. The difference must therefore lie in how knowledge of those opportunities is acquired through their activities at different residential nodes, a question that could be explored via survey or interview research in the future.

Several limitations of this study affect how our results can be interpreted. First, although the results demonstrate the ability of police data to indicate crime-salient elements of offenders' activity spaces, we may have missed or understated theoretically important relationships for under-represented nodes. For example, the offenders would likely have additional activity nodes not recorded in police data near which they could be offending when committing offences away from their police recorded activity nodes. To the extent that these activity nodes are missing from police data, our results underestimate the association between activity node proximity and crime location choice. This impact is most extreme in the cases of rarely recorded nodes such as school and work, so our results for those nodes should be treated with caution. Future research could supplement police data with other administrative datasets that comprehensively capture these locations, akin to the use of government address registry data by Bernasco and colleagues (Bernasco 2006; Bernasco and Kooistra 2010; Menting et al. 2016).

Second, because we studied solved cases—albeit a common practice in discrete crime location choice research—the results may not generalise to all offenders (Bernasco et al. 2013; Ruiter 2017). For example, if those who offend close to home are more likely to be identified, relationships between home and offence locations would be stronger for solved than unsolved crimes. Similarly, if police are more likely to link an offender to a crime committed in a place that the police *know* the offender has visited, than to a crime committed in a place with no recorded link to the offender, we would also find stronger node-crime associations for solved than unsolved crimes. Conversely, if offenders are more likely to return to locations of prior crimes they were not caught for (not captured in the present data), relationships between prior crimes and offence locations would be weaker for solved than unsolved prior crimes. Correspondingly, Long et al. (2018) found that offenders were less likely to return to the location of a crime for which they were immediately caught than of a crime for which they initially avoided capture. However, they still were more likely to return to the location of a prior crime with immediate capture, than somewhere they had not previously offended. Further, the few studies to examine the spatial decision-making of offenders in solved versus unsolved crimes suggest that differences between these groups are minimal (Bernasco et al. 2013; Lammers 2014).

Lastly, variation may exist between offenders within offence types. For example, the sex offence data includes a range of offences, from indecent exposure to rape, against both adults and children, and known and stranger victims, and sex offenders employ a range of methods for identifying, selecting and approaching victims (Balemba and Beauregard 2013; Beauregard and Busina 2013; Mogavero and Hsu 2017). Similarly, several prior studies have highlighted differences between offenders in the association between home or prior offence locations and future crime locations: for example, based on age and criminal history (Frith 2019; Townsley et al. 2016). Relatedly, although the conditional logit model used in this study provides useful insight into the ‘average’ offender, it does not yield a distribution across offenders that would provide insight into the relative proportion who prefer to offend close to activity nodes. Future research could separately examine relationships between different activity nodes and crime location choice for specific subtypes of offences and groups of offenders, and examine individual differences across the distribution of offenders using mixed logit models (see for example Frith 2019; Townsley et al. 2016).

Future research might also benefit from a more granular approach when examining the relationship between offence locations and offenders’ prior victim/witness, police incident and other police-recorded activity locations. Within these categories there is likely variation in factors that influence whether those activities generate relevant knowledge of nearby crime opportunities, such as the type of offence or

incident and its timing (Curtis-Ham et al. 2020).<sup>13</sup> Exploring this variation by measuring, more directly, the factors that mediate the influence of prior activity locations on crime location choice would help to identify why, for example, commercial robbers were no more likely to offend near prior victim/witness locations than farther away.

We conclude by highlighting the practical implications of quantifying the links between offenders’ different activity locations and their crime locations, as we did in this study. This quantification enables prediction of the most likely locations at which an individual will offend, given the locations, and nature, of their activity nodes. Such predictions could be used in community corrections settings, incorporated into risk assessments to identify offenders’ high-risk locations for offending, informing strategies to mitigate risk accordingly (Schaefer et al. 2016; Serin et al. 2016). In crime investigations, geographic profiling involves using offence locations to infer the likely location of an offender’s home or other node (Canter and Youngs 2008; Rossmo 2000; Rossmo and Rombouts 2008; Rossmo and Summers 2015). Our results could help to identify the kind of node that is more likely to be (e.g., home, school, prior crime), thus enabling prioritisation of suspects with higher likelihood nodes in the area predicted by the geographic profile (building on the approaches suggested by Goodwill et al. 2014; van der Kemp 2021, for incorporating consideration of suspects’ activity nodes other than home addresses). Alternatively, given a list of suspects, our results could help identify who is more likely to have committed a crime at the location of an unsolved crime, given the nature and proximity of their activity nodes (e.g., Curtis-Ham et al. 2022). The fact that this study used data routinely (though not comprehensively) collected by police for operational purposes additionally highlights how much activity location data is likely available to police within their own data systems that could be used for these geographic profiling purposes.

**Supplementary Information** The online version contains supplementary material available at <https://doi.org/10.1007/s11896-022-09540-8>.

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<sup>13</sup> This disaggregation could also explore whether prior crimes are more likely to be of the same type as the reference offence than victim/witness experiences: an additional potential explanation for the present findings.

**Data Availability** The data used in this research study are not publicly available and were obtained with approval from the New Zealand Police Research Panel (reference EV-12-462). The results presented in this paper are the work of the authors and do not represent the views of New Zealand Police.

## Declarations

**Ethics Approval** This research study was conducted retrospectively from data obtained for operational purposes. Ethics approval was obtained from the Psychology Research and Ethics Committee of the University of Waikato (reference #19:13).

**Conflict of Interest** The first author is employed as a researcher at New Zealand Police. This study was not conducted as a part of that employment.

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