Divergent Decision-Making in Context: Neighborhood Context Shapes Effects of Physical Disorder and Spatial Knowledge on Burglars' Location Choice

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ABSTRACT

Objectives Although the social disorganization tradition emphasizes the role of neighborhood context in shaping delinquent behaviors and neighborhood crime, researchers have rarely considered the influence of neighborhood context on criminals' decision of where to offend. This study explicitly examines how concentrated disadvantage in both the origin and destination neighborhoods structures burglars' preference for street physical disorder and spatial familiarity.

Methods We measure observed and perceived physical disorder from 107,858 street view images using computer vision algorithms. Geo-referenced mobile phone flows between 1,642 census units are used to approximate offenders' potential spatial knowledge about target neighborhoods. Discrete choice models are estimated separately for burglars from disadvantaged and non-disadvantaged neighborhoods (N=1,972).

Results While burglars residing in non-disadvantaged neighborhoods are not sensitive to physical disorder in non-disadvantaged target neighborhoods, they strongly avoid disadvantaged neighborhoods with disorder. Conversely, residents of neighborhoods with concentrated disadvantage swiftly act upon street disorder in better-off neighborhoods but not in disadvantaged neighborhoods. These tendencies to react to the presence of physical disorder on the street are also contingent on burglars' potential familiarity with the target environment.

Conclusions We highlight the importance of larger neighborhood structural characteristics and their interactions with spatial knowledge and environmental conditions such as visual signs of disorder, in criminal decision making. Physical disorder is not uniformly indicative of decay across neighborhoods and offenders. This divergent decision-making may also partially explain spatial heterogeneity of crime. Moreover, spatial knowledge is most effective in triggering or deterring actions in places that are categorically different from offenders' residential spaces.

Keywords: burglary, crime location choice, social context, physical disorder, mobility, concentrated disadvantage, street view images

INTRODUCTION

Understanding how criminals make location choice has been central to criminology research. Despite the extensive literature along the social disorganization tradition, the larger social context remains divorced from criminal decision-making processes (Sampson 2012; Thomas et al. 2022). Following the rational choice perspective in criminology and routine activities theory (Cornish & Clark 1986; Cohen & Felson 1979), extant literature predominantly focuses on the decision-making process of criminals at the individual level (Bernasco & Nieuwbeerta 2005; Ruiter 2017). This lack of attention to social context is also true in decision science scholarship outside of criminology. Increasingly, however, social scientists have come to acknowledge the role of social context in individual choices, including residential and activity location choices (Bruch & Feinberg 2017; Krysan & Crowder 2017). Prior criminology studies have demonstrated that structural conditions of neighborhoods such as concentrated disadvantaged shape the ways in which individuals weigh rewards, risks, and costs when making criminal decisions (Thomas et al. 2022). To date, research explicitly examining how social contextual conditions factor into *actual* criminal location choices remains scarce.

The present study explicitly considers the impact of meso-level social context on burglars' choice of target neighborhoods. In particular, we examine the concentrated disadvantage of both residential and potential target neighborhoods: depending on the residential neighborhood, burglars may assemble different decision rules; and the set of rules actually activated may also vary by the target neighborhood under consideration. We ask whether burglars' assessment of physical disorder in making burglary location choice differs by the level of neighborhood concentrated disadvantage. We additionally introduce mobility flows between neighborhoods as a proxy for burglars' spatial knowledge of or familiarity with the potential target neighborhood. We draw on a range of unique data sources, including police arrest records, mobile phone mobility big data, and massive street view images. Our findings suggest that burglars' choice preference and the potential spatial knowledge pool they can draw from are not random, but rather structured by the conditions of their residential neighborhoods. Whereas burglars residing in non-disadvantaged neighborhoods (Non-Dis) are not sensitive to physical disorder in Non-Dis target neighborhoods, they strongly avoid disadvantaged (Dis) targets with disorder, particularly as their potential spatial knowledge of the target increases. Conversely, Dis-residing burglars strongly favor Non-Dis targets with the presence of disorder. This preference grows drastically as they gain more familiarity with the target neighborhood.

BACKGROUND

Crime Location Choice: Theory and Prior Findings

Describing and explaining where offenders commit crime has a long tradition in criminology. A number of theories have been proposed to understand how criminals make location choices in space and time, including routine activity theory and crime pattern theory (Cohen and Felson 1979; Brantingham and Brantingham 1981). Routine activity theory contends that crime is likely to occur when motivated offenders converge with potential targets in the absence of capable guardianship (Cohen and Felson 1979). Combined with the rational choice perspective in criminology (Cornish and Clarke 1986), students of routine activity theory assume that the convergence of the crime triangle is a result of motivated offenders' rational mental calculation of each potential offense event. On average, individual offenders are responsive to risks, costs, and rewards in offending. Assuming criminal motivation, criminals are more likely to target routine locations where a crime can be committed with low cost, minimal risk, and high reward. Even premediated criminal offenses that do not occur during the offenders' everyday activities are nonetheless informed by spatial and nonspatial knowledge gathered during otherwise non-criminal routine activities. In the words of the original routine activity theory, "illegal activities feed upon the legal activities of everyday life" (Cohen and Felson 1979: p588). Recent work along this line suggests that the mobility pattern of the general population, irrespective of criminality, provides a "spatial template" for criminals' journey to crime (Boivin & D'Elia 2017; Song et al. 2019).

Building upon routine activity theory and rational choice perspective, Brantingham and Brantingham (2016) proposed crime pattern theory, elucidating the spatial elements in criminals' decision making. According to crime pattern theory, all people have routine activities that shape their spatial knowledge. The space of routine activities—activity space—is determined by a network of nodes, such as home, workplace, school, and third place, linked by paths between them. Within and around these nodes and paths, people develop their highly idiosyncratic spatial awareness space, defined as "the area normally within visual range of the activity space." (2016: p5), outside of which people generally have limited knowledge. People typically are more informed about the space in and around key activity nodes because of heavier and repeated routine activities therein—exhibiting nested micro movement patterns (2016). As such, the theory predicts that crime occurs at places where criminals' awareness space overlaps with crime opportunities. The distribution of crime follows a distance decay or pathway model from inside offenders' key nodes.

Crime pattern theory further posits that the urban backcloth—the arrangement of street network, land use, and urban functions—are crucial for understanding mobility and the distribution of crime. Due to the abundance of crime opportunities, certain locations are exploited more often by would-be offenders, known as *crime generators* and *crime attractors*. Crime generators are easily accessible places with large population flows and ensuing elevated crime opportunities. They result from "the summative combination of awareness and activity spaces of large numbers of people acting in the course of daily routines" (p12). Examples include shopping precincts, sports stadiums, and public transport stations. Crime attractors are places with a known reputation for crime opportunities to which motivated offenders are drawn. These emerge as a result of knowledge accumulated from prior experience and social networks. Typical crime attractors would include bars and drug markets. Places that neither create additional opportunities nor attract offenders are known as crime neutral areas.

While long articulated in criminological theories, direct tests of criminal decision-making processes were not done until 2005 when Bernasco and Nieuwbeerta applied discrete choice framework, a formal methodological approach widely employed in microeconomics to criminology. The method quickly gained popularity and has become the dominant paradigm for studying how criminals choose where to offend. Recent empirical evidence suggests that offenders are more likely to offend near former homes (Bernasco and Kooistra 2010; Lammers et al 2015), homes of family members (Menting et al. 2016), and prior offense locations (Bernasco 2010). Criminals' offending pattern generally follows a distance decay function in space, with distance indicative of time and monetary cost from home (Chamberlain et al. 2023). Further evidence indicates that they are stopped by physical barriers and facilitated by connectors (Xiao et al. 2020).

The Social Context of Criminal Decision Making

So far, most studies on crime location choice take a person-centered approach, focusing on factors internal to individual criminals (Thomas et al. 2022). Recent scholarship has begun to address variations in choice preference in criminal decision making (see Ruiter 2017 for a review). Yet, researchers have not considered social contextual factors as an influence on criminals' decision making. This is surprising given the long tradition in urban sociology and criminology that emphasizes the social and ecological contextual role of neighborhoods in various individual behaviors and outcomes, beginning with the early Chicago School (Park & Burgess [1925] 2019; Shaw & McKay 1942) and reiterated in more recent seminal work by Sampson (2012) and Matsueda (2013). Prior literature suggests that neighborhood contextual factors may factor into offenders' subjective perceptions of and preferences for risks, costs, and rewards (Matsueda 2013; Thomas et al. 2022), which in turn result in divergent decision-making patterns across criminals of different neighborhood contexts. Recent development in decision science have outlined that human decision making is characterized by biases and the frequent use of heuristics (Kahneman 2011; Thaler & Sunstein 2021; Bruch & Feinberg 2017). As we argue below, social context is one major source from which biases and heuristics are routinely developed and practiced.

Concentrated disadvantage as a social context

In particular, urban sociology and criminology scholarship has highlighted neighborhood disadvantage along multiple social and economic dimensions, i.e., concentrated disadvantage, as an encompassing social context that shape individuals' subjective perceptions and behaviors, including involvement in crime (Sampson 2012). The social context of concentrated disadvantage shapes would-be offenders' perception of risk, cost, and rewards associated with criminal offenses as well as potential choice set to target, consciously and unconsciously (Thomas et al. 2022). While there is extensive literature on how individual behaviors condition on neighborhood characteristics—including the social disorganization tradition (Shaw & McKay 1942; Bursik & Gramick 1993; Sampson et al. 1997) and broken windows theory (Wilson & Kelling 1982), the extant literature has not explicitly distinguished between social context as decision-makers' origin (i.e., as residents) or destination/target (i.e., as visitors or potential perpetrators).[1] Prior work has established that visitors, employees, and residents carry different meaning for the local social ecology and that they may behave differently depending on their relation to the neighborhood context (Jacobs 1961; Anderson 2010; Song et al. 2021). Here, we synthesize existing perspectives into two channels through which social context shapes individual decision-making: *social context as origin* and *social context as destination*.

Social context as origin

Research in the social disorganization tradition posits that the absence or weakening of local institutions associated with socio-economic disadvantage, residential turnover, and population heterogeneity—factors often overlap with concentrated disadvantage—result in a social and institutional isolation from the larger "mainstream" society (Wilson 1987), and a higher crime

[1] When offenders target their home neighborhood for criminal offense, they are subject to the same residential neighborhood social context.

rate (Shaw & McKay 1942). Criminals from disadvantaged areas thus adopt different decision rules than their counterparts from non-disadvantaged areas.

First, residential concentrated disadvantage shapes offenders' perception of and preference for *monetary and social rewards* associated with crime. Due to the scarcity of legitimate economic opportunities and the uniform social deprivation and isolation (Wilson 1996), along with the prevalence of delinquent behaviors (Shaw & McKay 1942; Kornhauser 1978) and the absence of robust local social institutions of social control (Sampson 2012) in neighborhoods of concentrated disadvantage, criminal behaviors are frequently perceived as viable or even attractive alternatives. This perception increases the likelihood that offenders will act upon criminal opportunities as they arise. This is also consistent with the subculture perspective. In disadvantaged neighborhoods where a local subculture that normalizes crime is more likely to emerge, offenders may gain respect and social status through their involvement in criminal acts (Katz 1988; Anderson 1999; Venkatesh 2006). Even for youth with a middle-class family background, constant contextual exposure to street orientations—much more likely to be the case in disadvantaged neighborhoods—make them subject to a range of choices, leaving some seduced by the criminal lifestyle (Pattillo 1999).

Second, residential concentrated disadvantage shapes offenders' *perceived arrest risk and social costs* from offense. In neighborhoods of concentrated disadvantage, the local institutions of social control are eroded (Bursik & Grasmick 1993; Sampson & Groves 1989), compromising the likelihood that informal social costs are imposed to sanction crime and deviance. As such, law-breaking carries less negative consequences in the local social network, is more tolerated and less likely to be socially stigmatized (Harding 2009). In addition, prior studies have found that residents of disadvantaged neighborhoods are less likely to intervene or report crime incidents (Sampson 2012; Baumer 2002), and that reported crimes are less likely to result in an arrest in such neighborhoods (Petersen 2017). Given that offenders strongly favor locations homophilous to their own neighborhood,[2] it follows that offenders from disadvantaged neighborhoods may, on average, perceive a lower arrest risk and associated social costs from their criminal involvement at home and beyond.

Social context as destination

While the residential social context shapes would-be offenders' baseline system of criminal decision-making, offenders may engage different evaluation rules contingent on the neighborhood under consideration. In other words, criminals' decision rules developed in their residential context may interact with the conditions of the target context. Given the often-short journey to crime (Bernasco 2010), the strong distance decay pattern of human mobility (Hipp 2016), and spatial and network spillover (Graif et al. 2019), the extant literature has not made explicit distinction between social contexts of origin and destination/target. The former concerns about the emergence of criminal motivations and criminals in the local area, while the latter focuses on the realization (or the lack thereof) of criminal acts in space. The social disorganization and collective efficacy theory (Shaw & McKay 1942; Sampson 2012) articulates theoretical pathways of both, but the distinctions are not explicitly made. The significant body of research discussing the relationship between local social ecology and crime rates primarily

[2] The same can be said to residents of concentrated disadvantage at large. A significant body of literature reveals that individuals from neighborhoods of concentrated disadvantage, particularly in segregated Black communities, commonly have a limited geographic horizon and strict mental boundaries of routine activities (Anderson 2022; Wilson 1987; Cai et al. 2024).

assumes a destination approach, including broken windows theory (Wilson & Kelling 1982) and eyes on the street perspective (Jacobs 1961).

Broken windows theory contends that neighborhood crime is often co-present with high levels of physical disorder such as litter, graffiti, and broken windows (Skogan 1990; Wilson & Kelling 1982), in part because physical disorder and crime share common origins (Sampson & Raudenbush 1999). Visual cues of physical disorder in the neighborhood often signal to the public, particularly would-be offenders, that the area is not well-maintained or surveilled, anti-social behavior is tolerated and expected, and behavioral consequences of crime and deviance are minimal. The eyes on the street perspective predicts that the informal natural surveillance produced by local shopkeepers, frequent street users and watchers strongly deters crime and incivility (Jacobs 1961). Depending on the level of commercial activities and street watching and local ability to handle strangers, streets are equipped with varying levels of “eyes on the street” to discourage crime, particularly overt and severe crimes that are observable in the public space (Browning & Jackson 2013). Social disorganization theory and collective efficacy theory also primarily concerns the capacity of local institutions and residents to create strong social cohesion, mutual trust, informal social control, and willingness to intervene on behalf of the common good to maintain social order and prevent crime (Sampson et al. 1997). As discussed above, crime pattern theory claims that the concentration of crime attractors and generators increases criminal opportunities in the local and surrounding areas (Brantingham & Brantingham 2018).

However, these broken windows, natural surveillance, social cohesion and trust, and criminal opportunities may carry different meaning depending on other dimensions of the target neighborhood context under consideration. For instance, while the presence of physical disorder in non-disadvantaged neighborhoods indicates reduced informal social control against crime, similar visual cues in disadvantaged neighborhoods may additionally represent a lack of economically viable targets. Moreover, over-policing in areas of concentrated disadvantage (Fagan et al. 2010; Kirk 2008) can make offending in these neighborhoods riskier and costlier compared to similar non-disadvantaged neighborhoods.

Less discussed in the literature is the further complication by the interaction between conditions of destination neighborhood and offenders' background (e.g., residential context). Consider the case of physical disorder: offenders from disadvantaged neighborhoods may react negatively to disorder in disadvantaged target neighborhoods but become strongly attracted to similar signs in non-disadvantaged target neighborhoods. In contrast, offenders from non-disadvantaged neighborhoods may be more likely to avoid disadvantaged neighborhoods with disorder and respond moderately to disorder in non-disadvantaged neighborhoods, as factors such as social costs and risks (e.g., the presence of mutual contact and level of surveillance) weigh in more heavily. Empirical work exploring this interaction remains scarce. One study illustrates that local burglars show a stronger preference for local-majority communities than migrant burglars in a major Chinese city (Xiao et al. 2020).

The role of spatial knowledge

While the above discussion articulates the ways in which the decision-making process varies across the combination of place of origin and place of destination, it implicitly assumes a scenario of complete information, where would-be offenders are fully aware of the conditions and nuances of all potential destinations before making a choice. Criminal location literature and decision science literature more broadly has long noted this problem (Bruch & Swait 2019;

Ruiter 2017). We argue that the interaction between residential and target neighborhood is moderated by potential spatial knowledge offenders have. In other words, would-be offenders from (non-)disadvantaged neighborhoods will exhibit a preference or avoidance for certain characteristics in target neighborhoods, more so if they are familiar with those neighborhoods. Crime pattern theory asserts that criminals search for targets within the space of which they have spatial knowledge accumulated during routine activities (i.e., awareness space, Brantingham & Brantingham 2008). Crime is likely to occur when offenders' awareness space intersects with criminal opportunities.

However, obtaining the history of criminals' activity space locations is challenging (Rossmo et al. 2012; Bernasco 2019). Prior studies following the routine activity theory approach suggest that the mobility of offenders resembles mobility of the general population (Cohen & Felson 1979) and that the mobility flows of the general population provide a spatial template for offenders' routine activity space and their offending patterns (Felson & Boivin 2015; Boivin & Felson 2018). This is true for opportunistic and premeditated crimes, both drawing heavily on prior spatial knowledge from routine activities (Song et al. 2019). Offenders residing in neighborhood *i* are more likely to develop spatial knowledge of neighborhood *j* if there exist substantial mobility flows between neighborhoods *i* and *j*. First, given the relative population homogeneity within small geographic units such as neighborhoods, residents, regardless of criminal motivation, potentially share similar routine activity locations. Prior research has long noted the strong homophily based on shared backgrounds such as identities and social class in inter-personal and inter-organizational ties (McPherson et al. 2001; Graif et al. 2017) and activity locations (Mears & Bhati 2006; Wang et al. 2018). Second, even if residents do not visit neighborhood *j* themselves, the constant flows of their neighbors commuting (e.g., family members, colleagues, next door neighbors) between the neighborhood pairs likely help them build spatial knowledge about neighborhood *j* over time due to shared networks and information channels (e.g., local newspaper, organizations). In addition to the pre-existing selection into neighborhoods, convergence of knowledge and behavior among people of shared physical space has been reported across various life domains, such as neighborhood knowledge, norms, and engagement (Jacobs 1961; Putnam 2000), health behaviors (Kobus 2003), and misinformation (Forati & Ghose 2021).

Indeed, taking this spatial template approach, prior studies show that daily mobility flows of the larger population are strongly associated with the number of local crime (Felson & Boivin 2015; Boivin & Felson 2018; Graif et al. 2017; Graif et al. 2019; Levy et al. 2020), crime trips (Boivin & D'Elia 2017) and criminal location choices (Song et al. 2019).

Summary

Despite the longstanding social disorganization tradition, criminal location choice literature has rarely considered structural influence from offenders' social context such as their residential neighborhood. Recent decision science scholarship acknowledges that human choices are characterized by heuristics and biases limitations (Thaler & Sunstein 2021; Kahneman 2011) as well as social contextual constraints (Bruch & Feinberg 2017). Offenders residing in disadvantaged neighborhoods may exhibit daily activities patterns and criminal decision rules starkly different from their counterparts from non-disadvantaged neighborhoods. This divergence likely arises from their differential evaluations of risks, costs, and rewards associated with crime, which in turn condition on their backgrounds—importantly, their residential social context. Furthermore, offenders may vary their criminal decision rules when considering different types of target neighborhoods: disadvantaged and non-disadvantaged, as the presence of certain features such as physical disorder may carry different meanings for their criminal offenses. In addition, this combination of residential and target neighborhood conditions is moderated by the spatial knowledge pool offenders have. Both criminology theories and empirical evidence suggest that mobility flows of the general population reasonably approximate offenders' spatial template and subsequent crime template.

So far, no research has explicitly examined the residential social context or the combination of residential and target context as an independent influence on criminal location choice. Using physical disorder as an example, the present study considers how burglars make location choices. It further explores how the social context of concentrated disadvantage at both residential and target neighborhoods shape such decisions, and how spatial knowledge moderates the relationship. To do so, we integrate actual burglary arrests, mobile phone mobility big data, physical disorder derived from computer vision-processed street view images, and point of interest data.

CURRENT STUDY

Data and Measures

Study Area and Unit of Analysis

The present study focuses on the city of ZG in southeast China.[3] With a total population exceeding 5 million, the subtropical city is one of the largest and most developed cities of China. We focus on the central urban area of the city where the majority of population reside and commute and where street view images are available.

[3] Access to crime data was granted by the security bureau of ZG City on the condition that the real name of the city would not be revealed in publications.

We use communities (juweihui or cunweihui) as the unit of analysis. Communities are the smallest administrative unit where population census and major survey data are collected. These communities with relatively high resident homogeneity are comparable to prior studies in terms of geographic and population sizes (Bernasco and Block 2009; Song et al. 2019). There are a total of 2,643 communities in the ZG region, with an average geographic area of 2.813km^2. After excluding communities without street view images, we have 1,652 spatially contiguous communities in the analytical sample, with an average size of 0.958km^2 and an average population of 5,957.

Data

In this study, we combine police arrest data, mobile phone mobility data, street view images, POI data, and census data. The police arrest data record the actual burglary cases between 2017 and 2018 in the city of ZG. For each arrested burglar, we have information on their residential neighborhood and the target neighborhood.

To measure the spatial knowledge between neighborhoods, we obtain mobility flows from mobile phone usage for the whole month of October 2019 from China Unicom Inc, a major telecom provider in China. The provider has a market share of 24% in the city of ZG.[4] The location information of phone users is registered when a phone call, text, or data-use request is made. During the observation period, 5,367,239 unique users made 325 million trips. On average, each user generated 2.56 trips per day. The individual level data is then aggregate to communities by China Unicom. Based on this, we construct a mobility flow matrix between all communities in the city of ZG. We then normalize the flow sizes to capture the relative strength

[4] China Unicom Inc. is one of the three largest state-owned telecom operators, alongside China Mobile and China Telecom. While detailed socio-demographic data on the users of each telecom company are not publicly available, there is no evidence to suggest that the users of China Unicom are systematically different from non-users. Like its counterparts, China Unicom offers a wide range of services for the diverse general population in China.

of connections. To do so, we calculate the relative size of each outgoing flow as a percentage of the total outgoing flows of the community of origin. Because the mobility flows are highly right-skewed, with many neighborhoods having no routine flows between one another, we take the logarithm of the flows.

We obtain point of interest data of 2016 in the city of ZG to account for common crime generators and attractors noted in the literature for burglary (Bernasco & Nieuwbeerta 2005; Xiao et al. 2020): bus stops, subway stations, parks, and entertainment venues (karaoke bars, bars, cinemas, and Internet cafes).

Community-level socio-demographic characteristics come from the 2010 sixth national census of China. Specifically, we include variables of population (log), proportion of high-rise residential buildings (9 floors or higher), and proportion of buildings built after 2000. High-rise buildings are often associated with increased security measures against burglary (Gu et al. 2016). In 1998, China abolished the social welfare housing policy. Homes built after this period thus have a higher average price (Xiao et al. 2020). To would-be burglars, newer homes are thus more lucrative.

To measure physical disorder on the street, we use street view images from Baidu Map (https://map.baidu.com), a major map service provider in mainland China. We set sampling points with 100-meter intervals on the OpenStreetMap road network of ZG City. All street view images within a 10-meter buffer around each sampling point are crawled from Baidu Map API (https://lbsyun.baidu.com/faq/api?title=viewstatic). We set the vertical angle to 20 degrees to mimic human eye perspective. Images from four horizonal angles of 0, 90, 180, and 270 degrees are collected to provide a more comprehensive picture of the street setting. For the street view images collected, we apply object detection methods (YOLOv7) to extract three most common types of physical disorder: litter, graffiti, and street encroachment (e.g., piles of debris, street vendors blocking the street) (Sampson & Raudenbush 1999). Because of the high correlation between the three both conceptually and numerically, we take the average of the three standardized disorder measures to create a composite observed physical disorder metric. In addition to these objective measures of physical disorder, we calculate the perceived disorder from the images as a more comprehensive assessment of overall physical disorder. We first have volunteer raters evaluate the overall disorder of street images and then apply image regression to train and infer perceived disorder of all street view images. Figure 1 illustrates the process of collecting and processing street view images. Full methodological details are explained in Zhang et al. (2024). Because street view images are only available in urban areas, we focus our attention on the contiguous urban areas in the city of ZG with a meaningful coverage of street view images. A total of 107,858 street view images recorded between 2015 and 2019 are used, covering 1,652 urban neighborhoods in the city of ZG.[5]

<Figure 1 about HERE>

Following prior studies (Bernasco & Nieuwbeerta 2005; Chamberlain et al. 2023), we also control for the distance between burglars' residential community and potential targets using Euclidean distance.

Neighborhood Concentrated Disadvantage

We construct neighborhood concentrated disadvantage based on the following seven neighborhood conditions: unemployment rate, low educational attainment (high school or lower), share of non-locals, overcrowding, share of renters, average rent price, and access to tap water,

[5] We use a five-year period to maximize the number of street segments covered by street view images. For segments with multiple images during the period, we calculate the average physical disorder score across all years.

bath, and kitchen. Any neighborhoods with lower-than-average values on at least five out of the seven dimensions are considered neighborhoods of concentrated disadvantage.

Discrete Choice Analysis

We model burglars' target location choice using a conditional logit specification where a burglar's decision of where to offend depends on an array of factors involving the characteristics of both the residential and potential target neighborhoods. The approach has been widely used in criminal decision making, residential choice, and activity space location choice literature (Bernasco & Nieuwbeerta 2005; Bruch & Swait 2019; Cai et al. 2024). Under this methodological framework, each burglar faces a number of potential target communities, each with a different utility. The burglar is then supposed to evaluate the utility of all alternatives. The utility of each individual community of potential choice is given by

$$U_{ij} = \beta' z_{ij} + e_{ij}$$

where z_{ij} are the attributes associated with alternative communities *j* for individual *i* and β' are the corresponding coefficients. e_{ij} is the random error term in the utility function. Specifically, this study considers the following attributes in burglars' spatial choices:

$$\beta' z_{ij} = \beta_{1g(i)} CD_j + \beta_{2g(i)} M_{ij} + \beta_{3g(i)} PD_j + \beta_{4g(i)} C_j + \beta_{5g(i)} D_{ij} + \beta_{6g(i)} I_{ij}$$

where CD_j is binary indicator of whether the potential destination *j* is a neighborhood of concentrated disadvantage. M_{ij} is the normalized mobility flow between neighborhood of origin *i* and potential destination *j*. PD_j is the level of physical disorder in neighborhood *j*. C_j includes all the control variables. D_{ij} represents the Euclidean distance between *i* and *j*. Interaction terms between neighborhood concentrated disadvantage, mobility flows, and physical disorder I_{ij} are also included.

The conditional logit model assumes that decision-makers pick the alternative with the highest utility (McFadden 1978). Specifically, the probability of a burglar *i* choosing an alternative *j* is given by

$$Prob(Y_i = j) = \frac{e^{\beta' z_{ij}}}{\sum_{j=1}^{J} e^{\beta' z_{ij}}}$$

where Y_i is the community chosen by burglar i, and z_{ij} are again the attributes of alternative communities with β' being the corresponding effect size.

All parameters are estimated separately for two groups such that parameters are free to vary across context: burglars residing in neighborhoods with concentrated disadvantage and burglar residing in non-disadvantaged neighborhoods.

FINDINGS

Descriptive Analysis

Table 1 reports the descriptive statistics. There were 1,972 burglary cases in the central city during 2017 and 2018. Figure 2 shows the relative geographic distribution of burglary incidents in the city of ZG. An equal-area cartogram is used to de-identify the specific communities and the city. During the study period, the majority of communities do not experience any burglary victimization. High concentrations of burglary cases are found in the periphery of the city. 16.59% of the 1,652 urban communities are classified as neighborhoods with concentrated disadvantage. On average, 30.40% residential buildings were built after 2000 and 17.78% are high-rises. The average numbers of subway stations, bus stops, parks, and entertainment venues are 0.07, 2.93, 0.63, and 1.27, respectively. Table 4 in Appendix report dyad level descriptive statistics and correlations.

<Table 1 about HERE>

<Figure 2 about HERE>

In the mobility flow network, we find strong descriptive evidence for network homophily in terms of neighborhood concentrated disadvantage. For an average disadvantaged neighborhood, 29.84% of the non-home neighborhoods its residents visit most frequently (i.e., the highest outdegree flow) are also disadvantaged. For an average non-disadvantaged, only 14.62% of their most frequent non-home trip locations are in disadvantaged neighborhoods.

Choice Models

Table 2 shows the choice models predicting burglars' target choice, stratified by their residential concentrated disadvantage. Three-way interactions for concentrated disadvantage, physical disorder, and mobility flows of the destination neighborhood are included, which are the key focus of the current analysis (models without mobility flow interactions are reported in Appendix Table 4). For interpretation, we summarize the marginal effects of two groups of neighborhood physical disorder—observed physical disorder and perceived disorder—on the likelihood of being targeted for burglary, conditioned on the neighborhood mobility flows (as a proxy for burglars' potential spatial knowledge) in Table 3.

<Table 2 about HERE>

Table 3 reveals a clear pattern of diverging selection criteria among burglars of different residential backgrounds. Burglars from non-disadvantaged (Non-Dis) communities favor the presence of physical disorder in Non-Dis communities of which they have no spatial knowledge (OR=1.270, p<0.001). As their potential spatial knowledge of destination communities increase to 1 (with mobility flow between the origin/residence (O) and destination/target (D) reaching

1.718% of the total flows originating from the burglar's residential community), their preference for Non-Dis destinations with visible physical disorder reduces (OR=1.184, $p<0.001$). With O-D mobility flow of over 6.389%, Non-Dis burglars are not significantly attracted to Non-Dis destinations with physical disorder. When considering disadvantaged (Dis) destinations, Non-Dis burglars exhibit a contrasting preference pattern. Specifically, as their spatial knowledge of Dis destinations increases, they strongly avoid Dis communities with physical disorder. Their odds ratio of picking such Dis communities are 0.842 (n.s.), 0.564 ($p<0.01$), and 0.378 ($p<0.01$) with 0, 1.718, and 6.389% mobility flows.

Burglars from Dis communities clearly deviate from the patterns reported above for Non-Dis burglars. Overall, they show a preference for Non-Dis destinations with physical disorder and a dislike for Dis destinations with physical disorder. At no spatial knowledge, Dis-residing burglars' odds ratio of picking Non-Dis communities is 1.372 ($p<0.001$). The odds ratios increase considerably to 1.840 ($p<0.001$) at moderate flows and to 2.467 ($p<0.001$) at significant flows. Their lack of tendency to pick Dis destinations, however, does not fluctuate meaningfully with the growth of potential spatial knowledge, with odds ratios marginally decreasing from 0.698 ($p<0.05$) to 0.662 ($p<0.01$) to 0.628 ($p<0.01$).

We observe highly similar patterns for the marginal effects of perceived disorder across both burglar groups. Non-Dis burglars are significantly attracted to Non-Dis communities with greater perceived disorder, which is indicative of burglary opportunities (OR=1.158, $p<0.001$). But as they build spatial knowledge, their tendency to pick such communities diminishes: OR=1.085 ($p<0.05$) at moderate mobility flows and OR=1.017 (n.s.) at significant flows. Non-Dis burglars avoid Dis communities with more perceived disorder for burglary, and this avoidance grows drastically as they have more potential spatial knowledge of the destination, reaching 0.524 ($p<0.001$) odds ratio at moderate flows and 0.296 ($p<0.001$) at high flows. Regarding Dis-residing burglars, they react positively to perceived disorder in Non-Dis communities, with odds ratios growing from 1.208 ($p<0.01$) at no spatial knowledge, to 1.376 ($p<0.05$) at moderate knowledge, and 1.567 ($p<0.1$) at high knowledge. On the contrary, Dis-residing burglars react negatively to perceived disorder in Dis communities, but to a much lesser extent than their Non-Dis-residing counterparts. The odds ratios of Dis burglars picking Dis communities with perceived disorder drop from 0.815 (n.s.) at no spatial knowledge, to 0.751 ($p<0.01$) at moderate knowledge, to 0.692 ($p<0.01$) at high knowledge.

<Table 3 about HERE>

<Figure 3 about HERE>

Figure 3 provides a visual illustration of the marginal effects discussed above. Specifically, panels a and b represent the effect of observed physical disorder by spatial knowledge of potential destinations, stratified by burglar's residential conditions, i.e., whether residing in a community with concentrated disadvantage or not. Estimates are based on models M1 and M2. Panels c and d show the effect of perceived disorder based on models M3 and M4. According to Figure 3-a and 3-b, both Non-Dis- and Dis-residing burglars show a preference for Non-Dis targets with disorder, particularly visual clues of physical disorder such as litter, graffiti, and road encroachment. However, as the potential spatial knowledge about target neighborhood increases, their tendency towards Non-Dis communities diverge. Non-Dis-residing burglars are generally indifferent towards disorder in Non-Dis communities with a marginal decreasing pattern as they gain greater spatial knowledge; in contrast, Dis-residing burglars react positively and strongly towards disorder in Non-Dis communities as they know the community better. Figure 3-c and 3-d show burglars' decision preference when considering Dis targets. We see divergent rules again among burglars with different residential conditions: Both dislike the presence of disorder in Dis communities, increasingly as they have greater knowledge about the target. In particular, Non-Dis-residing burglars respond more strongly by avoiding targeting Dis communities with the presence of disorder.

Regarding other covariates, we assess the role of distance, key socio-demographic characteristics, and common crime attractors and generators. The likelihood of a community being targeted for burglary reduces as its distance from burglar's home increases, more so for Non-Dis-residing burglars (reduces by a factor of 0.325 and 0.326, $p<0.001$) than Dis-residing burglars (OR ranges between 0.299 and 0.300, $p<0.001$). More populated destination communities are also more likely to be targeted, with one unit increase in the population logarithm leading to 98.6%-100.9% higher odds for Non-Dis-residing burglars ($p<0.001$) and 78.7%-82.2% higher odds for Dis-residing burglars ($p<0.001$). The presence of post-2000 newer buildings strongly predicts burglary risk for both groups of burglars with OR over 2.4 ($p<0.001$). In comparison, buildings over 9 floors are associated with lower risk of burglary, particularly for burglars from disadvantaged communities (OR=0.177, $p<0.001$). Burglars from non-disadvantaged communities also strongly dislike communities with a higher proportion of tall buildings but to a lesser extent (reduces by a factor of 0.361-0.365, $p<0.001$).

Transportation facilitations function as crime generators with one more subway station increasing the risk of being targeted by 20% among Non-Dis burglars ($p<0.05$) and over 80% among Dis burglars ($p<0.001$). Bus stops also significantly increases burglary risk by 1.2% and 1.6% among Non-Dis and Dis burglars, respectively, for each additional bus stop ($p<0.001$). This is unsurprising given that Dis-residing burglars are on average poorer and that public transportation accessibility is an important cost factor in their mental calculation. Parks are related to a marginally elevated risk of burglary only for Dis-residing burglars (OR=0.05). Entertainment venues—karaoke bars, Internet cafes, bars, and cinemas—positively predict burglary among Non-Dis-residing burglars only, with each additional venue bringing about 4% higher odds ($p<0.001$) to the local area.

CONCLUSION

In the past few decades, there has been an exponential growth of decision research across disciplines in social sciences, including Nobel-winning work on heuristics and biases (Kahneman 2011) and "nudge" (Thaler and Sunstein 2021): people are typically not aware of all the potential alternatives available and even if they do, they do not have the mental power to compare the absolute merits of each. While equally interested in decision making behaviors and their implications for collective outcomes (Coleman 1994), sociologists are largely absent in recent progress (Bruch & Feinberg 2017), in part because social context—the dimension sociologists care deeply about—is typically missing from the equation in existing decision literature. In the study of criminal location choice, whereas the rational choice framework has been extensively applied, the attention to social context as an influence on choice remains limited. In this study, we argue that a significant part of the heuristics and biases employed by offenders are developed and habitually practiced in the context of residential neighborhood; that is, offenders from different residential conditions behave systematically differently in their criminal decision-making. Furthermore, their baseline decision rules may interact with the actual neighborhood being evaluated.

In this study, we consider concentrated disadvantage of burglars' residential community as the social context shaping offending choices. Indeed, we find that burglars residing in disadvantaged neighborhoods behave differently from those from non-disadvantaged neighborhoods. Whereas burglars from non-disadvantaged neighborhoods respond negatively towards the presence of disorder, burglars from disadvantaged neighborhoods react more positively to visual signs of disorder. These confirm prior research that highlights the relevance of larger neighborhood structural characteristics in criminal decisions (Thomas et al. 2022; Matsueda 2013), through shaping offenders' assessment of risks, costs, and rewards associated with crime.

We further underline the previously overlooked interaction between the neighborhood conditions of origin/residential and destination/target in criminal location choice. Burglars from disadvantaged contexts are positive towards the presence of physical disorder only when considering non-disadvantaged target neighborhoods. They appear indifferent to disorder in disadvantaged targets. In the same vein, non-disadvantage-residing burglars strongly avoid targets with visual signs of disorder, but only in disadvantaged target neighborhoods. This highlights the nuanced multi-faceted nature of neighborhood social ecology. Physical disorder or other conditions are not uniformly indicative of the same level of decay across neighborhoods. This is in line with Sampson and Raudenbush's (1999) finding that disorder is only moderated associated with crime, a pattern they attribute to disorder and crime sharing "the same explanatory process" from structural conditions of concentrated disadvantage and collective efficacy (p608). While we do not have measures of collective efficacy, our results suggest that local concentrated disadvantage alone is not sufficient in explaining criminal offending choices. The combination of offenders' residential and target neighborhood conditions shapes how interpretations of visual signs of disorder unfold in criminal location choices. These observed diverging decision-making patterns may also additionally explain the widely noted spatial heterogeneity of crime in urban spaces since the early Chicago School. Moreover, we argue that physical disorder may be evaluated relative to other alternatives in the choice set, a direction we hope future research can take.

Our results also show that spatial knowledge moderates the above relationship between social contexts and physical disorder with its role most effective in triggering or deterring actions in places that are categorically different from their residential space. As spatial knowledge increases, whereas non-disadvantage-residing burglars react strongly to the presence of disorder in disadvantaged communities by avoiding them, disadvantage-residing burglars instead react strongly to disorder in non-disadvantaged communities by acting upon potential opportunities. This finding is in line with predictions from crime opportunity theories (Cohen & Felson 1979; Brantingham & Brantingham 2008) as well as other commonly observed human behavioral patterns (Thaler & Sunstein 2021). For places that offenders are used to, such as neighborhoods similar to their own, they may be able to draw on their prior knowledge and infer the meaning of disorder more accurately, thus the limited effect of spatial knowledge. This could also be related to the strong network homophily and co-offending patterns among offenders with similar backgrounds (Graif et al. 2019; Papachristos & Bastomski 2018). Conversely, for places categorically different from their routine activity locations and awareness spaces, offenders may rely more heavily on stereotypes and guess the implications of certain environmental features (Krysan & Crowder 2017). In the latter case, greater spatial knowledge from routine activities and social networks may be more effective guiding their criminal choices.

Our study has several limitations that deserve future inquiries. First, although this study illustrates neighborhood concentrated disadvantage as an encompassing social context, there are other key neighborhood structural conditions that shape offenders' decision-making process.

Characteristics such as social cohesion, ecological networks, and collective efficacy may also affect ways in which of residents conduct daily social interactions and develop behavioral patterns (Sampson et al. 1997; Browning et al. 2017). These could be the potential mechanisms behind the divergent decisions by neighborhood concentrated disadvantage observed in this study. We hope future studies can explicitly test these mechanisms. Relatedly, we suspect that individual-level disadvantage may further interact with neighborhood contextual disadvantage to affect individual perceptions of risks, costs, and rewards. Due to data restrictions, we are not able to get individual demographics of the offenders. We encourage future studies to consider other dimensions of structural conditions as well as potential ways contextual factors interact with individual characteristics.

Second, we approximate criminals' spatial knowledge of other neighborhoods based on routine mobility flows between neighborhoods, assuming that the mobility patterns of the general population provide a spatial template for criminals. However, they are not direct measures of offenders' true underlying spatial knowledge and choice set they can draw from. This assumption thus runs the risk of ecological fallacy (Robinson 1950). Given the challenge of measuring offenders' travel history (Rossmo et al. 2012; Bernasco 2019), the mobility of the general population as a spatial template approach still offers important insights to the crime location choice literature with its strong theoretical underpinnings (Cohen & Felson 1979; Brantingham & Brantingham 2016) and empirical support (Boivin & Felson 2018; Song et al. 2019; Bernasco 2019). Future research should examine the extent to which criminals' behavioral patterns deviate from those of the public and whether specific mobility patterns by age and class provide more accurate spatial templates for respective offender groups.

Third, physical disorder from street view images is aggregated to communities in this study. However, disaggregating the unit of analysis to smaller units is not computationally viable. Further analysis decomposing the variance in physical disorder into image-level and community-level components reveals that up to 0.283 of the variance lies at the community level. Combined with the relatively high homogeneity in population composition and built environment, we argue that the risk of modifiable geographic unit area problem is limited.

Last, by focusing on arrested burglars, the present study cannot make inference about location choices of burglars who were not arrested and offenders of other types of crime. It is possible that their offenses involve different mental calculations. But we believe that their location choices are also subject to similar social contextual processes. We leave this task of result generalizability to future studies.

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Tables

Table 1. Descriptive Statistics

Variables	Mean (Percentage)	SD
Outcome		
Burglary Cases	1972	-
Neighborhood Conditions (N=1652)		
Concentrated Disadvantage	16.586%	-
Physical Disorder Sub-indicators		
Litter (%Area)	0.164	0.209
Graffiti (%Area)	0.369	0.472
Road Encroachment (%Area)	1.021	1.060
Observed Physical Disorder[1]	0	0.670
Perceived Disorder	3.391	0.855
Controls (N=1,652)		
Socio-Economic		
Population (log)	8.467	0.703
%Bldgs Post-2000	30.397%	-
%Bldgs 9 Floors or Higher	17.782%	-
POIs		
#Subway Stations	0.071	0.279
#Bus Stops	2.931	4.571
#Parks	0.633	4.074
#Entertainment Venues	1.274	2.293

Note: [1] Sum of standardized scores of sub-indicators.

Table 2. Conditional Logit Models Predicting Burglary Choice

	Observed Physical Disorder		Perceived Disorder	
	M1	M2	M3	M4
Residential Context	Non-Disadvantaged	Disadvantaged	Non-Disadvantaged	Disadvantaged
Target Context (ref. = Non-Disadvantaged)				
Disadvantaged	1.003	1.119	0.986	1.100
	(0.096)	(0.181)	(0.096)	(0.181)
Spatial Knowledge (Flow, log)	1.992***	2.508***	2.002***	2.510***
	(0.077)	(0.411)	(0.077)	(0.417)
Disorder				
Observed Physical Disorder	1.270***	1.372***		
	(0.056)	(0.114)		
Perceived Disorder			1.158***	1.208**
			(0.044)	(0.088)
Two-Way Interactions				
Disadvantaged × Flow	1.634***	0.737*	1.943***	0.766†
	(0.204)	(0.108)	(0.270)	(0.115)
Disadvantaged × Observed Physical Disorder	0.663***	0.508***		
	(0.077)	(0.099)		
Disadvantaged × Perceived Disorder			0.801*	0.674**
			(0.071)	(0.098)
Flow × Observed Physical Disorder	0.933*	1.341†		
	(0.032)	(0.232)		
Flow × Perceived Disorder			0.937**	1.139
			(0.023)	(0.146)
Three-Way Interactions				
Disadvantaged × Flow × Observed Physical Disorder	0.718	0.707†		
	(0.146)	(0.143)		
Disadvantaged × Flow × Perceived Disorder			0.603***	0.809
			(0.082)	(0.113)
Controls				
Distance (log)	0.326***	0.300***	0.325***	0.299***
	(0.010)	(0.021)	(0.010)	(0.020)
Population (log)	1.986***	1.787***	2.009***	1.822***
	(0.086)	(0.163)	(0.088)	(0.166)
Prop. Post-2000 Bldgs	2.400***	2.407***	2.412***	2.409***
	(0.241)	(0.489)	(0.243)	(0.496)
Prop. Bldgs 9 floors or higher	0.361***	0.177***	0.365***	0.177***
	(0.047)	(0.054)	(0.050)	(0.057)
POIs				
#Subway Stations	1.211*	1.843***	1.207*	1.904***
	(0.099)	(0.275)	(0.101)	(0.288)
#Bus Stops	1.012***	1.016***	1.012***	1.016**
	(0.002)	(0.005)	(0.002)	(0.006)
#Parks	1.005	1.011*	1.005†	1.011*
	(0.003)	(0.005)	(0.003)	(0.005)
#Entertainment Venues	1.040***	0.952†	1.040***	0.950†
	(0.007)	(0.028)	(0.007)	(0.027)
N	1600	372	1600	372
McFadden Pseudo R^2	0.247	0.231	0.248	0.230
AIC	17884.101	4268.796	17868.841	4276.985
BIC	17964.767	4327.579	17949.507	4335.769

Note: P-values from two-tailed hypothesis tests: †p<0.1; *p<0.05; **p<0.01; ***p<0.001. Robust standard errors in paratheses.

Table 3. Marginal Effects of Physical Disorder by Neighborhood Context and Spatial Knowledge/Mobility Flows

	Residential: ND Target: ND	**Residential: ND Target: D**	**Residential: D Target: ND**	**Residential: D Target: D**
Effect of Observed Physical Disorder				
Mobility Flow = 0	1.270***	0.842	1.372***	0.698*
Mobility Flow = 1	1.184***	0.564**	1.840***	0.662**
Mobility Flow = 2	1.105	0.378**	2.467**	0.628*
Effect of Perceived Disorder				
Mobility Flow = 0	1.158***	0.928	1.208**	0.815
Mobility Flow = 1	1.085*	0.524***	1.376*	0.751**
Mobility Flow = 2	1.017	0.296***	1.567†	0.692**

Note:

The marginal effects hold log(mobility flow+1) at 0, 1, 2 (i.e., flow = 0, e-1, e^2-1).
P-values are based on two-tailed hypothesis tests: †p<0.1; *p<0.05; **p<0.01; ***p<0.001.
Confidence interval calculated based on robust standard errors.

Figures

Figure 1. Measurement framework for mean level of objective and perceived physical disorder

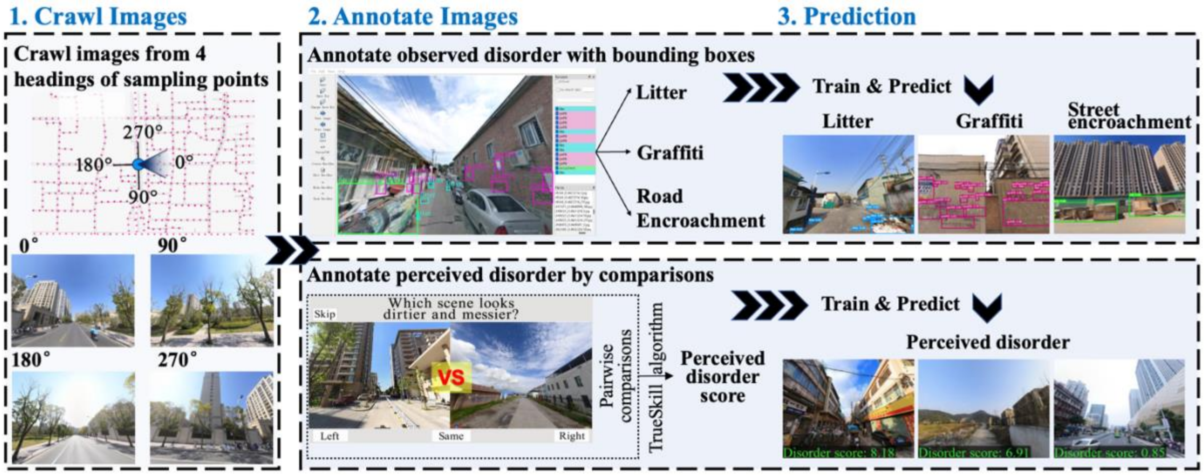


Figure 2. Cartogram of Burglary Cases in the City of ZG

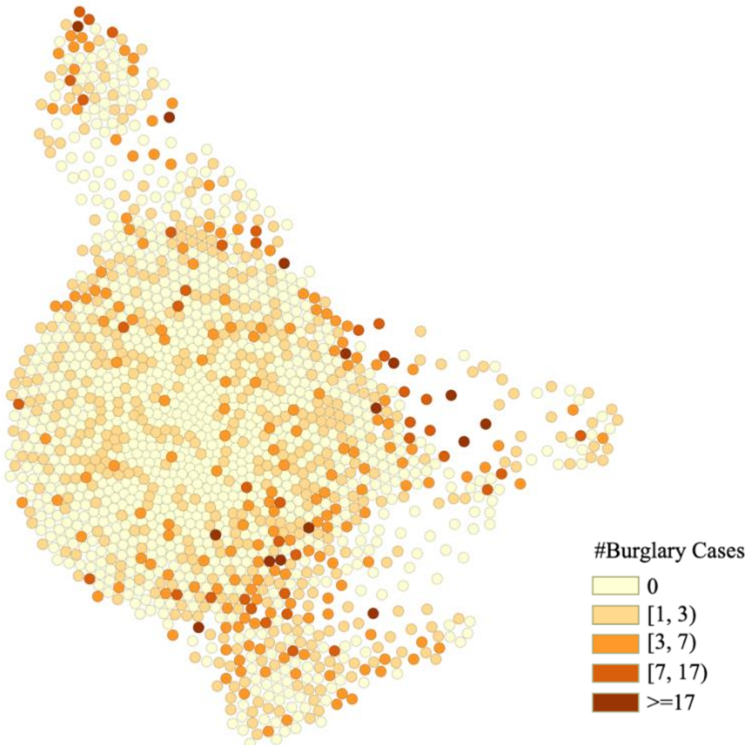
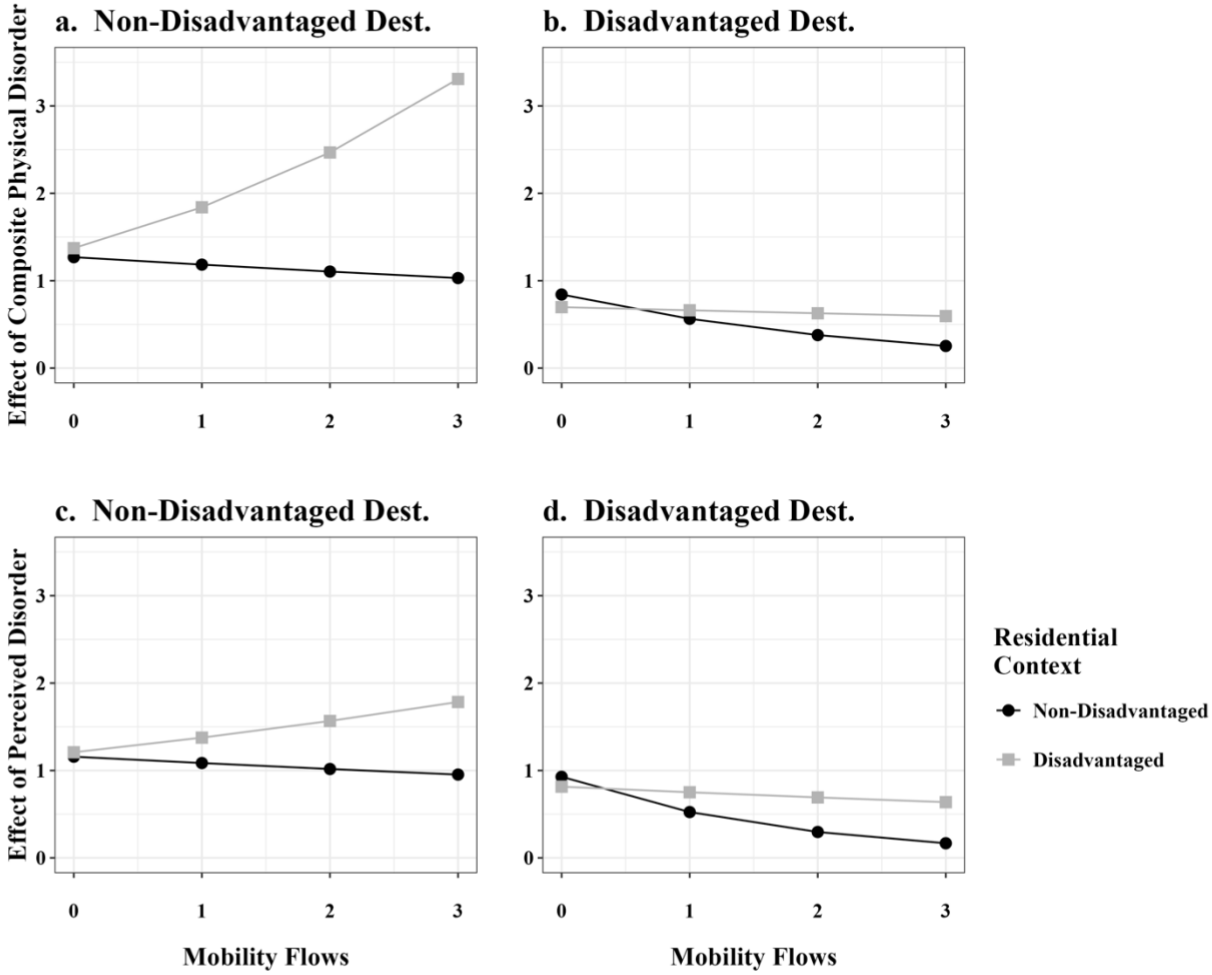


Figure 3. Marginal Effects of Objective and Perceived Physical Disorder by Destination Type and Spatial Knowledge/Mobility Flow Strength, Odds Ratios



Appendix

Table 4. Dyad level descriptive statistics and correlations (1,972*1,652)

	Variables	Mean (SD)	1	2	3	4	5	6	7	8	9	10	11
1	Distance (log)	2.729 (0.738)											
2	Population (log)	8.467 (0.702)	-0.001										
3	%Bldgs Post 2000	0.304 (0.294)	0.057	0.202									
4	%Bldgs 9 Floors or Higher	0.178 (0.269)	-0.092	0.024	0.427								
5	#Subway Stations	0.071 (0.279)	-0.034	0.004	0.037	0.087							
6	#Bus Stops	2.931 (4.570)	0.107	0.344	0.246	-0.123	0.152						
7	#Parks	0.633 (4.073)	0.004	0.068	0.026	-0.032	0.038	0.077					
8	#Entertainment Venues	1.274 (2.292)	0.036	0.268	0.082	-0.015	0.170	0.312	0.027				
9	Concentrated Disadvantage (Yes=1)	0.166 (0.372)	0.010	-0.097	-0.066	-0.226	-0.020	-0.010	0.004	-0.067			
10	Observed Physical Disorder[1]	0.000 (0.669)	0.011	0.115	-0.022	-0.224	-0.070	-0.008	0.023	0.012	0.161		
11	Perceived Disorder[2]	3.391 (0.854)	0.062	0.088	-0.045	-0.332	-0.138	0.017	-0.011	-0.014	0.175	0.669	
12	Mobility Flows (log)	0.038 (0.138)	-0.407	0.114	0.083	-0.030	0.097	0.181	0.042	0.120	-0.001	0.019	0.002

Note: [1] Sum of standardized scores of sub-indicators.

Table 5. Conditional Logit Models Predicting Burglary Choice without Mobility Flow Interactions

	Observed Physical Disorder		Perceived Disorder	
	M1	M2	M3	M4
Residential Context	Non-Disadvantaged	Disadvantaged	Non-Disadvantaged	Disadvantaged
Target Context (ref. = Non-Disadvantaged)				
Disadvantaged	1.182*	0.912	1.213*	0.931
	(0.096)	(0.143)	(0.100)	(0.145)
Spatial Knowledge (Mobility Flow, log)	1.952***	1.868***	1.949***	1.880***
	(0.072)	(0.167)	(0.072)	(0.168)
Disorder				
Observed Physical Disorder	1.216***	1.480***		
	(0.052)	(0.112)		
Perceived Disorder			1.108**	1.268***
			(0.038)	(0.087)
Two-Way Interactions				
Disadvantaged × Observed Physical Disorder	0.627***	0.412***		
	(0.069)	(0.078)		
Disadvantaged × Perceived Disorder			0.713***	0.559***
			(0.058)	(0.067)
Controls				
Distance (log)	0.321***	0.282***	0.320***	0.282***
	(0.010)	(0.018)	(0.010)	(0.018)
Population (log)	2.006***	1.806***	2.026***	1.828***
	(0.086)	(0.162)	(0.087)	(0.163)
%Bldgs Post-2000	2.439***	2.534***	2.471***	2.545***
	(0.245)	(0.506)	(0.252)	(0.516)
%Bldgs 9 Floors or Higher	0.361***	0.156***	0.359***	0.165***
	(0.047)	(0.048)	(0.049)	(0.053)
POIs				
#Subway Stations	1.221*	1.890***	1.233*	1.935***
	(0.099)	(0.283)	(0.101)	(0.291)
#Bus Stops	1.013***	1.018***	1.013***	1.018***
	(0.002)	(0.004)	(0.002)	(0.004)
#Parks	1.005	1.012*	1.005	1.012*
	(0.003)	(0.005)	(0.003)	(0.005)
#Entertainment Venues	1.038***	0.955	1.038***	0.955
	(0.007)	(0.027)	(0.007)	(0.027)
N	1600	372	1600	372
McFadden Pseudo R^2	0.246	0.229	0.246	0.228
AIC	17895.88	4272.091	17900.728	4279.024
BIC	17960.413	4319.117	17965.261	4326.051

Note: P-values from two-tailed hypothesis tests: †p<0.1; *p<0.05; **p<0.01; ***p<0.001. Robust standard errors in paratheses.