Received: 8 April 2023 | Revised: 29 April 2024 | Accepted: 2 May 2024

DOI: 10.1111/1745-9125.12381

ORIGINAL ARTICLE

CRIMINOLOGY

Understanding the role of street network configurations in the placement of illegitimately operating facilities

Ieke de Vries[1] | **Toby Davies**[2]

[1]Institute of Criminal Law and Criminology, Leiden University, Leiden, The Netherlands

[2]School of Law, University of Leeds, Leeds, UK

Correspondence
Ieke de Vries, Institute of Criminal Law and Criminology, Leiden University, Steenschuur 25, 2311 ES, Leiden, The Netherlands.
Email: i.de.vries@law.leidenuniv.nl

Additional supporting information can be found in the full text tab for this article in the Wiley Online Library at https://onlinelibrary.wiley.com/doi/full/10.1111/1745-9125.12381.

Replication Data and Code
The code for this manuscript is publicly available at https://osf.io/kqu39/

Funding was provided by the U.S. Department of Justice, Office of Justice Programs, National Institute of Justice 2018-R2-CS-0005. The authors would like to thank the audiences at a panel hosted by the Environmental Criminology and Crime Analysis Conference (2022), a seminar hosted by the Leiden Institute of Advanced Computer Science (2022), and a panel hosted by the American Society of Criminology Conference in Atlanta (2022), for their invaluable feedback.

Abstract
The role of street networks in shaping the spatial distribution of crime has become a foundational component within environmental criminology. Most studies, however, have focused on opportunistic crime types, such as property offenses. In this study, we instead research a theoretically distinct phenomenon by examining the placement of venues that host criminal activity. In particular, we study the relationship between network structure and the placement of illicit massage businesses, which operate on the intersections of illicit and legitimate activity by hosting illicit commercial sex under the guise of legitimate massage. We model their placement as a function of two network metrics: betweenness, which measures a street's usage potential, and a variant called "local betweenness," which measures the potential of nearby streets. Multilevel models are used to examine the importance of these street-level metrics while accounting for tract-level covariates. Our findings demonstrate that, unlike property crimes, illicit massage businesses tend to be located on streets that are themselves quiet but that are close to areas of high activity. Such locations seem to combine accessibility and discretion, and therefore, represent ideal conditions

Funding information
National Institute of Justice, Grant/Award Number: 2018-R2-CS-0005

for such businesses to thrive. Our findings can inform problem-oriented approaches to prevent the harms associated with illegitimately operating businesses.

KEYWORDS
crime, illicit massage businesses, multilevel model, street networks

1 | INTRODUCTION

An extensive body of criminological research has consistently demonstrated that the spatial distribution of crime in cities is influenced by their physical configuration (Bernasco & Block, 2011; Brantingham & Brantingham, 1993a; Taylor & Gottfredson, 1986). In particular, several recent studies have focused on the role of street networks in shaping patterns of crime (Davies & Johnson, 2015; Kim & Hipp, 2020). Street networks are the primary structures around which cities are arranged, and as such, they are a key determinant of the interactions between people and places. One implication of this, based on principles of environmental criminology, is that the risk of crime should be associated with structural features of the network, and indeed, this has been demonstrated empirically: In general, streets that are more connected and have higher usage potential experience higher levels of crime (e.g., Beavon et al., 1994; Davies & Johnson, 2015; Kim & Hipp, 2020). These studies, however, have been concerned almost exclusively with property crimes, and most are grounded in opportunity theories of crime. Much less is known about whether such relationships can also be observed for other contexts, such as where particular venues play host to distinctive and persistent illicit behaviors. Examples of these venues include drug-dealing premises, illegal car-washes, and—as we focus on here—massage businesses offering illicit commercial sex. Our aim in this study is to examine the placement of these crime-hosting venues (and thus the illicit activities occurring therein) to provide insight into the kind of urban infrastructure that creates structural opportunities for illegitimately operating facilities.

From a theoretical perspective, the placement of crime-hosting venues involves different principles to those that apply to property crime. Since property crime can occur almost anywhere, its spatial distribution is typically considered to be a function of opportunity, and most theoretical perspectives focus on explaining where, and how, offenders tend to encounter targets. In particular, theories based on the routine activities approach (Cohen & Felson, 1979) are concerned with the way in which the daily lives and routine movements of individuals can give rise to such encounters, and therefore shape their distribution. For crime-hosting venues, on the other hand, the fact that the activity takes place at fixed locations means that the distribution of crime is determined by the placement of those locations, which in turn is decided by their proprietors. Furthermore, this placement has a strategic element: Such venues require locations beneficial to their (criminal) function (Eck, 1995). As such, arguments based on routine activities principles will be of only limited relevance in this context, requiring an alternative perspective.

Crime-hosting venues can take many forms, but one prominent example is that of illegitimately operating businesses, that is, businesses concerned with the sale of illegal goods or services. The nature of such businesses means that their placement is likely to be subject to contrasting influences, with diverging implications for the role of the street network. On the one hand, the same principles that guide the placement of *legitimate* businesses might also be expected to apply to crime-hosting venues, with locations that are accessible and offer exposure to potential customers being favored. Previous research has shown that retail premises, for example, tend to be located on streets that are well connected and likely to experience high levels of traffic (Ozuduru et al., 2021; Porta et al., 2012; Zhang et al., 2019). On the other hand, however, the illicit nature of the activities means that both the businesses themselves and their clientele need to be inconspicuous (Cohen & Felson, 1979; Felson, 1987). This would imply that more prominent streets are undesirable, and these businesses' proprietors may prefer places that offer a greater level of concealment. The tension between these influences means that it is far from clear which kinds of streets are most likely to host such venues.

To understand which type of street network configurations are associated with the placement of illegitimately operating facilities, this study focuses on the case of illicit massage businesses (IMBs) in the United States, examining data from one particular city. IMBs are storefronts that host illicit commercial sex under the guise of legitimate massage (Bouché & Crotty, 2018; de Vries, 2020; de Vries & Radford, 2022) and, therefore, represent clear examples of (seemingly) legitimate venues that host illicit activities. Although soliciting commercial sex is not universally criminalized, it is illicit according to federal and state laws in the United States (except for some counties in Nevada), which is likely to affect the locational strategies of IMBs. To illustrate, research has suggested that IMBs are more likely to thrive in areas that are discreet, and therefore less likely to be monitored by police, since police presence can deter buyers of commercial sex who fear getting caught (see, e.g., de Vries, 2023b; de Vries & Farrell, 2023; Holt et al., 2008, 2014). In addition, the detection of illicit commercial sex in IMBs has repeatedly led to shutdowns of these venues (see, e.g., de Vries & Farrell, 2023). Conversely, however, the literature has also suggested that the seemingly legitimate provision of massage allows IMBs to be located in more visible, accessible, and busier areas, which are frequented by a larger pool of potential clientele and where illicit behaviors blend into legitimate contexts (e.g., in retail areas, see Chin et al., 2023; Crotty & Bouché, 2018; de Vries, 2020, 2023a). To be clear, the illicit activities we are concerned with in this study are those that occur within, or are directly associated with, IMBs; even though such facilities may influence (e.g., attract) crime more generally in their vicinities, that is not our focus here.

Although we focus on IMBs because they host illicit commercial sex, such businesses have received considerable public and policy attention due to growing concerns about their association with human trafficking (Polaris, 2018), which involves forced sexual services and forced labor (Trafficking and Violence Prevention Act, "TVPA"). In fact, IMBs are one of the venue types where human trafficking victimizations are most commonly being reported in the United States (Polaris, 2018, 2021), although the true scale of human trafficking is hard to quantify (de Vries & Radford, 2022; Farrell & de Vries, 2020). Growing concerns about this issue have prompted police, municipalities, and other stakeholders to initiate interventions aimed at identifying human trafficking in IMBs (de Vries, 2020; de Vries & Farrell, 2023). Many of these traditional policing strategies, however, have proven to be ineffective in preventing future IMB placement and do not seem to address human trafficking victimizations effectively (de Vries, 2020; de Vries & Farrell, 2023) in part because of the lack of knowledge of why IMBs thrive in specific places. Besides the need to foreground victim-oriented responses, more effective prevention strategies are problem oriented and require the identification of conditions in which IMBs thrive.

Although studies on the urban geography of commercial sex and human trafficking are often challenged by scarcity, uncertainty, and inaccuracy of data (see Cockbain et al., 2022), the increased availability of digitized data, along with new data mining and analytic techniques, have allowed recent studies to begin examining the geography of commercial sex, human trafficking, and relating facets, mostly at the level of census tracts (e.g., Chin et al., 2023; Crotty & Bouché, 2018; de Vries, 2023a; Huff et al., 2018; Lopez et al., 2020; Mletzko et al., 2018). Until now, the locations of IMBs have not been investigated by examining the urban infrastructure at the level of street segments. To do so, we obtained point location data about IMBs hosting illicit commercial sex in a large city in the U.S. South (Houston, TX) from a popular online review board. For comparison, we also collected point location data from Yelp about online-reviewed retail businesses with no apparent association with illicit activity (i.e., no evidence that they were crime-hosting venues). In both cases, the locations of these businesses were matched with their street segments. We modeled the city's street segments as a complex network to calculate metrics that reflect their position and likely levels of usage during routine movements. Using these data, we test the hypothesis that illegitimately operating businesses are located on street segments that are both accessible and discreet.

This study proceeds as follows. In the next two sections, we describe the theoretical and empirical research on the influence of street configurations on crime and legitimate retail markets. In a current study section, we outline how our research contributes to prior work and explicate the hypothesis that guided our analyses. In subsequent sections, we present our data and methods, followed by our findings. We conclude with a discussion on how our findings advance prior work on the street network configurations of crime and how they can guide targeted crime prevention and crime control measures.

2 | BACKGROUND

The placement of illegitimately operating businesses is the outcome of a complex process, involving many actors, that can give rise to patterns across a range of spatial scales. There are a number of reasons why such businesses might locate in some neighborhoods and not others, for example. From an economic perspective, illegitimately operating businesses would be expected to act like any other commercial entity, locating themselves to optimize the trade-off between their operating costs and the size of their custom (Jensen, 2009; Marcus, 2010). This approach is likely to result in some areas being favored, such as those representing larger potential markets. Economic factors are not the only forces at play, however. Businesses are also constrained in where they establish, most immediately, by planning decisions and regulations (Levy, 2016). One role of urban planning is to moderate the free market to ensure that towns and cities are configured to promote overall social and economic well-being. Often this means placing constraints on where certain types of economic activity can be located, which is particularly relevant for businesses with perceived negative effects: Governments and local communities can seek to deter their presence, either by making conditions unappealing or by formal means (e.g., zoning; see Dear, 1992; Schively, 2007). In practice, the process of planning reflects the extent to which communities can exert power, at both local and national levels (see Logan & Molotch, 2007). Less powerful communities tend to have less political capital and are therefore less able to resist the influx of "undesirable" businesses. Therefore, the distribution of such businesses may reflect—and reinforce—existing inequalities (Schneider, 1989). In short, the locations of illegitimately operating businesses are a product of where they *want* to be and where they are *allowed* to be, which is likely to reflect the socioeconomic makeup of neighborhoods.

Although the placement of illegitimately operating facilities is clearly influenced by a complex set of social, economic, and political processes, it is also expected that environmental factors will play a role. These factors are particularly pertinent at microscales of geography: Even if a neighborhood is favorable for such a facility, it still has to locate at a specific place within the area, and some potential settings will be more conducive than others. The differences between streets may substantially affect where such facilities ultimately locate, and, if environmental conditions are not favorable, such venues may not establish at all. Previous work has demonstrated how environmental factors can complement the role of social processes (e.g., collective efficacy) in understanding where crime happens (Bernasco & Block, 2011; Perkins et al., 1993). Moreover, understanding the role of environmental factors may offer useful guidelines for integrating urban planning efforts in crime prevention and crime control strategies at microscales (e.g., via new planning guidelines for new cities, focused enforcement of city codes, or zoning adjustments; see Bichler et al., 2013; Cozens, 2008; Dear, 1992; Schively, 2007).

In this section, we will outline the theoretical context for the relationship between street network structure and crime risk before summarizing prior research on the topic. We will then discuss gaps in the present understanding, as well as the distinct issues raised when considering crime associated with illegitimately operating businesses rather than the property crimes that have typically been studied. In motivating our hypotheses for this study, we will also draw on research concerned with retail businesses and consider how these principles may be adapted in the illicit case.

2.1 | Theoretical context—Street networks and crime

Environmental criminology is concerned with understanding the circumstances under which crime takes place, and the way in which crime can result from the interactions of individuals with each other and with their surroundings (Wilcox & Cullen, 2018). Opportunity theories in particular argue that recognizing where, when, and how these interactions give rise to opportunities for crime is crucial to understanding the distribution of crime. Since all crimes require opportunity, and situational factors will influence whether a given opportunity is taken, it is the crucial limiting factor for crime and therefore a natural lens through which to examine it. At the core of many opportunity theories is the routine activity framework (Cohen & Felson, 1979; Felson, 1987), which sets out the fundamental observation that, for a crime requiring direct contact to occur, three elements must converge in space and time: a suitable target, a motivated offender, and the absence of a capable guardian. One implication of this framework is that the spatiotemporal characteristics of crime can be understood in terms of the movements and behaviors of these three elements.

Crime pattern theory (Brantingham & Brantingham, 1993a) extends this idea by offering a mechanistic explanation for why and where these criminogenic convergences occur. In particular, it describes how routine activities are shaped by the features of cities and their layout, which together constitute the “urban backcloth” upon which human activities take place. A central principle of the theory is that individuals’ activity spaces are centered on a few key “activity nodes” (such as homes, workplaces, and leisure facilities), which act as anchors for movement. As individuals move around and between these places, they construct “awareness spaces” representing those locations with which they are familiar. According to the theory, it is where these spaces intersect with criminal opportunities that crime is likely to occur. When the population of potential offenders is large, this implies that places featuring in the awareness spaces of more people will—all else equal—be at greater risk of crime. Crime pattern theory highlights two types of place as examples of this: *crime generators*, which draw large numbers of potential offenders and targets and therefore give rise to many criminogenic interactions (e.g., transport hubs), and *crime attrac-*

tors, to which offenders are drawn because of the criminal opportunities known to be available (e.g., drug markets).

The mechanisms proposed by the routine activity framework and crime pattern theory have natural implications for the relationship between street network structure and crime risk. Not only do street networks determine the configurations of cities, but they are also the primary means by which people travel between places. Therefore, rather than conceptualizing awareness spaces as amorphous forms, they can be thought of more concretely in terms of the routes and streets that they comprise. Although the relationship between the structural properties of streets and their usage is not straightforward, the general implication of this argument is that streets that are more *central*, in the sense of being used more often, will give rise to more opportunities for crime (see Davies & Bowers, 2018).

Whether this implication translates into higher levels of crime, however, partly depends on the third element of the crime triangle: guardianship. Streets that feature prominently in activity spaces would also be expected to have a greater supply of potential guardians, who could deter or interrupt crime (Hollis et al., 2013). Thus, the greater exposure of such streets could be offset, as captured in Jacobs's 1961 notion of natural surveillance, through "eyes on the street." Elsewhere, however, the opposite is suggested: The principle of "defensible space" proposed by Newman (1972) argues that places where through traffic is discouraged, and where a sense of territoriality exists, will be safer. At the core of this principle is the idea that guardianship is variable and situation dependent (see Reynald & Elffers, 2009): The transient nature of through traffic means that passers-by will be inattentive and may even provide cover for crime, whereas outsiders will be more likely to "stand out" and be challenged in less permeable places. According to this argument, therefore, any guardianship effect is secondary, and the risk of crime in places is best reduced by limiting their exposure to potential offenders. The diverging implications of these theories mean that the relationship between street network structure and crime is not straightforward and may be context dependent.

2.2 | Prior research on the street network configurations of crime locations

The earliest studies investigating street configurations associated with crime did so on aggregate levels, such as blocks and census tracts. For example, research by Bevis and Nutter (1977) identified that through-streets and "T-type" streets, which offer greater accessibility relative to dead end, cul-de-sac, or "L-type" streets, were associated with opportunities for residential burglaries. Similarly, the ratio of street segments to junctions within census tracts—reflecting the "density" of the networks—was associated with more residential burglaries. In a later study, White (1990) identified higher burglary rates in neighborhoods that had more direct connections to major roads, which might therefore feature in the awareness space of offenders. The first study to perform analysis at the more granular street segment level was that by Beavon et al. (1994), who measured each segment's accessibility as the number of other segments to which it was adjacent. Examining data on property crimes across 1,575 street segments in two municipalities in British Columbia (Canada), they found that more accessible roads experienced greater levels of risk.

In recent years, researchers have begun to measure the structural properties of street networks in more formal terms, which is in line with developments within urban studies more generally. Much of this movement has been inspired by the "space syntax" approach (Hillier & Hanson, 1984), in which the configuration of urban space is represented as a mathematical graph. In space syntax, graphs are constructed by finding the intersections between “axial lines”—lines that represent lines of sight in urban environments—and their properties are measured using several metrics. The approach has been applied in several studies of crime, with mixed findings: Although some observed that more accessible streets were at higher risk of crime (Baran et al., 2006, 2007), others have found the opposite (Hillier & Sahbaz, 2005).

Space syntax does have several shortcomings—such as its reliance on axial lines and emphasis on topological (rather than metric) distance—and later work has sought to address these while retaining the principles of the approach (Porta et al., 2006a). As well as adapting the street network representation itself, this strand of work has drawn on several metrics from the network science literature. One such metric is *betweenness*, which is widely studied for networks, having originally been proposed as a measure of “brokerage” in social networks (Freeman, 1977). Betweenness measures the frequency with which elements of the network lie on the shortest paths between other elements; features with high betweenness are therefore those that act as intermediaries for communication through the network.[1]

For street networks, betweenness measures how often street segments feature in routes through the network and, therefore, provides an estimate of how often they are likely to be used in the course of routine travel. As such, it has an intuitive appeal when studying crime as it reflects the extent to which streets may feature in the “awareness spaces” proposed by crime pattern theory (Brantingham & Brantingham, 1993b). A study analyzing the locations of burglaries in Birmingham (U.K.) found that street segments with higher betweenness experienced higher rates of burglary (Davies & Johnson, 2015), and a similar relationship was found for robbery in Cincinnati (U.S.; Kelsay & Haberman, 2021). Other studies have also corroborated a positive relationship between betweenness and violent crimes, such as assault (Davies & Bowers, 2018) and serious violence (Summers & Johnson, 2017). The role of betweenness centrality in shaping crime opportunities may not, however, be as straightforward as these findings seem to suggest. For example, recent work has indicated that betweenness centrality may have a curvilinear relationship with violent and property crimes: Increasing betweenness is associated with higher levels of crime up to a certain threshold, after which the level of crime begins to fall (Kim & Hipp, 2020). The initial increase is likely due to increased exposure to offender awareness spaces, which may be outweighed by guardianship and social control effects once levels of natural surveillance are sufficiently high. Furthermore, other research has suggested that alternative centrality metrics may have more explanatory value than betweenness. One such metric is *closeness*, which measures the average distance from a given segment to all others. Unlike betweenness, which identifies streets that lie on the routes between locations, closeness simply reflects proximity and therefore tends to be higher for streets that lie in densely built areas. A recent study suggested that closeness can be a stronger predictor than betweenness centrality for burglaries in Amsterdam (Mahfoud et al., 2021), indicating that movement patterns may be less important than physical layout. Aside from these inconsistencies, research has yet to unravel the interplay between segments and their local contexts: whether, for example, low betweenness streets might attract crime when neighboring streets have high betweenness, which might be the ideal formula for greater accessibility while avoiding visibility.

Besides the street network configuration of a city, research has identified several physical features of street segments that make them attractive crime locations by signaling opportunity and featuring in the awareness space of offenders. For example, streets can serve as, or be connected to, a busy or major road (Johnson & Bowers, 2010; Kim & Hipp, 2020; Summers & Johnson, 2017)

[1] We provide a formal definition of betweenness in Section 4.3.2.

or may attract a greater population when they contain crime attractors such as bars, restaurants, or other types of retail land use (Kim & Hipp, 2020; Mahfoud et al., 2021; Summers & Johnson, 2017). More generally, extant literature has established significant associations between a variety of land use measures and crime rates, depending on the types of crime (see, e.g., Boessen & Hipp, 2015; Kubrin et al., 2018; Wo, 2019). Streets and their surrounding areas may also have certain socioeconomic characteristics—such as disadvantage, population heterogeneity, or other factors—that can diminish informal social control through reduced interaction and community investment (e.g. Johnson & Bowers, 2010; White, 1990).

Although the evidence base outlined above presents a compelling case that more central streets are subject to greater risk of crime, research to date has been restricted to property and violent crimes. An alternative context that has not been considered is that of crimes associated with particular fixed locations, that is, crime-hosting venues. The placement of such venues is an important issue: Such venues can have significant negative effects, and understanding where they locate provides an opportunity to address the environmental conditions under which they thrive. The theoretical principles in the context of crime-hosting venues differ from those relating to property crime. In particular, the nature of the target—used here in the sense of "location" rather than necessarily "victim"—means that the spatial distribution of crime is not shaped by the confluence of actors in the same way. For property crimes, targets are typically abundant and widely distributed, and where crime occurs therefore depends on which ones are encountered by motivated offenders. Crime-hosting venues, on the other hand, are few in number and static, and, thus, crime can only take place in a fixed number of places. The spatial distribution of the associated offending is not determined by the extent to which targets are encountered but by the placement of businesses themselves.

To be clear, we draw a distinction between the type of location being considered here and the concept of "crime attractors" as outlined in crime pattern theory (Kinney et al., 2008). Crime attractors draw offenders because they present rich opportunities for crime; however, the crimes in question (e.g., theft) are not uniquely linked to those places. Rather, attractors offer distinctive levels and forms of opportunity within a wider landscape. For crime-hosting venues, on the other hand, the crimes they host are intrinsically tied to the locations, particularly when the activities taking place are explicitly advertised or promoted. Such venues are not just rich in opportunity; they are the only opportunities.

Understanding the spatial distribution of incidents linked to crime-hosting venues, therefore, means understanding the locational preferences of their proprietors. These preferences are likely to have a strategic element because they will choose places beneficial to their function, such as those that offer a greater supply of potential customers (see also Eck, 1995). As a result, the routine activities perspective would remain relevant, albeit in a different way to that which is hypothesized for property crime. Rather than "producing" crime themselves (by bringing together offenders and targets), in this case, the routine activities attract the criminal enterprise since they represent a potential market. Put simply, one would still expect more prominent places to be preferred—but because of the decisions of proprietors rather than the behavior of offenders.

The extent to which such businesses seek exposure to potential customers, however, is likely to depend on the kind of activity being hosted. Although some forms of activity are reliant on passing trade, others—including IMBs—draw purposive travel, making their location irrelevant. This will particularly be the case for those that are promoted by other means, such as via word of mouth or online, which may remove the need for physical visibility. Furthermore, the illicit nature of activities such as commercial sex means that exposure may be a negative feature in itself: Not only might it draw the attention of law enforcement, but visibility may also deter potential clientele.

In this context, guardianship relates less to the risk of interruption and more to the social stigma of the activities themselves. This line of reasoning implies that the placement of such venues may involve a balance between competing forces: the need for access to potential clientele, but also the desire for discretion. The clear parallels with legitimate businesses mean that the literature on the relationship between street network configurations and legal commercial activity may offer further guidance.

2.3 | Prior research on the street network configurations of retail markets

In contrast to crime locations, legitimate retail places have no reason to conceal their activities from law enforcement or other capable guardians, which can result in different locational strategies. When examining the street network configurations of retail markets, studies have overall found that premises such as restaurants, bars, and grocery stores tend to be located on central streets (Ozuduru et al., 2021; Porta et al., 2009, 2012; Zhang et al., 2019). The number of retail businesses tends to be particularly profound in areas with high betweenness (Lin et al., 2018; Porta et al., 2009; Wang et al., 2011; Zhang et al., 2019) and closeness (Cui & Han, 2015; Porta et al., 2012; Zhang et al., 2019). Notable differences, however, exist based on type of retail activity.

For example, Porta et al. (2012) demonstrated that retail businesses linked with the movement economy (i.e., those relying on passers-by, which is also true for IMBs) need to be as central as possible. This requirement is less important for primary economic activities (e.g., health and transport activities) that draw people through their function rather than through their location and are, therefore, less dependent on street centrality indices. In addition, various studies have identified that the specific centrality orientations can differ across store types. As an illustration, Wang et al. (2014) noted that specialty stores were more frequently located on streets with higher closeness, whereas supermarkets and department stores were placed on streets with higher betweenness and consumer product stores on streets with higher straightness. In addition, Lin et al. (2018) examined the street centrality of various retail stores in Guangzhou, China, and found that shopping malls and nontraditional convenience stores were placed on streets with higher closeness indices, whereas other retail store types such as specialty stores, textile and clothing stores, and supermarkets were more frequently identified on streets with higher betweenness. Some of these differences in the relationship between certain centrality indices and store placement may also be due to differences in urban growth and planning approaches across cities (see Omer & Goldblatt, 2016, for a comparative approach across eight Israeli cities).

In addition to their structural features, streets also provide "spatial capital" in the form of the activities, facilities, and landmarks that they host (Marcus, 2010). Some streets might represent more profitable locations for retail stores than others as a result of these features (Scoppa & Peponis, 2015), and this has been demonstrated in several studies. A study by Wang et al. (2014), for example, examined the locations of retail stores in Schichahai, Beijing, and found that store location was not only influenced by street centrality indices such as betweenness and closeness but also by clustering near other retail stores or the proximity to central business districts and nearby landmarks (see also Han et al., 2019; Zhang et al., 2019). In particular, specialty stores, construction material markets, and consumer product stores were more likely to cluster near other stores, where they benefit from a collective pool of customers, whereas other stores such as supermarkets were found to be more dispersed as a strategy to reduce competition. On the whole, the optimal placement for retail stores seems to depend on a combination of street centrality and spatial capital associated with traffic-generating activities (Jensen, 2006, 2009; Karamshuk et al., 2013).

2.4 | Accessibility at the cost of visibility?

Given the above literature on crime and legitimate retail markets, it is clear that street configurations matter and that betweenness centrality is an important parameter for the locations of property crime and legitimate retail businesses. Higher betweenness centrality can attract more crime and more retail businesses through increased accessibility and traffic (though its relationship with crime may be curvilinear, for the reasons stated above; see also Kim & Hipp, 2020). The role of betweenness in shaping opportunities for illegitimately operating businesses such as IMBs, however, requires further research. The traffic-generating features of accessible and prominent streets are important in providing businesses with sufficient custom to be sustainable, and many IMBs may rely on passing traffic to provide clientele. Accessibility may come at the cost of increased visibility, however, which may deter potential clients or raise law enforcement suspicion, in turn resulting in their shutdowns. Identifying which streets are accessible, yet also hidden from plain sight, requires street network metrics that capture those areas that are discreet, yet reap the traffic-generating benefits of accessible streets.

3 | CURRENT STUDY

The current study seeks to extend the prior literature on crime and retail businesses by examining if and how the locations of illegitimately operating businesses are associated with specific street network configurations. We examine the relationship between street network characteristics and the placement of IMBs as a compelling case study on illegitimately operating businesses that require both accessibility—to generate and maintain a market of buyers of commercial sex—and discretion—to operate and remain under the radar of law enforcement detection. In doing so, we seek to advance our understanding of the relationship between urban morphology and crime in three important ways.

First, our focus on venues that host illicit commercial sex extends street network analyses that have mostly been limited to the context of property and violent crimes. To be clear, our work is not concerned with the level of (violent or property) crimes near IMBs and we do not assume that IMBs attract or generate more crime (for that, see, e.g., Huff et al., 2018). Rather, we focus on IMBs because of the particular illicit activities (e.g., commercial sex) that they host, or which are directly associated with them. Other research has already begun to demonstrate that certain geographic features that signal accessibility at the level of census tracts, such as proximity to business districts and retail centers, are important correlates for the placement of IMBs (e.g., Chin et al., 2023; Crotty & Bouché, 2018; de Vries, 2023a). At the same time, some studies have also suggested how social stigma and police monitoring may draw IMBs away from the busier areas (de Vries, 2020, 2023a; de Vries & Farrell, 2023). Here, we seek to unpack accessibility versus invisibility by examining street network configurations, anticipating a segment's network centrality to play an important role in determining whether it represents a favorable location for IMBs.

Second, we seek to deepen our understanding of the influence of one particular network feature, betweenness, in shaping patterns of criminal behavior. Intuitively, betweenness measures the frequency with which features of the network are likely to be used in the course of travel through the network and, thus, has a natural application in criminological studies that draw on the routine activities perspective and crime pattern theory. In previous studies, betweenness has been shown to be strongly associated with the risk of both property and violent crimes (Davies & Johnson, 2015; Kelsay & Haberman, 2021; Summers & Johnson, 2017). Here we examine its role in the placement of IMBs and further contrast this with its relationship with the placement of online-promoted retail facilities without substantiated concerns of illegitimate activities.

Third, we introduce a new variant of betweenness—hereafter referred to as "local betweenness"—that, for any given segment, measures the average betweenness of other nearby segments. The motivation for this measure is to capture the level of activity in the vicinity of a segment, independently of that of the segment itself. In particular, it allows us to identify cases in which a street segment does not itself have high movement potential but is near to those that do, that is, segments that have low betweenness but are close to those with high betweenness. A real-world example might be an alley or side road adjacent to a primary thoroughfare.

By using these two measures of betweenness centrality, we test the hypothesis that IMBs are located on street segments that have low segment betweenness, to maintain a low profile and reduce the risk of detection, but high local betweenness, to benefit from the traffic-generating features of nearby streets. In contrast, we anticipate that legitimately operating businesses—which have no reason to conceal their activities—would have high segment betweenness and high local betweenness.

4 | DATA AND METHODOLOGY

4.1 | Study area

Data were obtained for the city of Houston, Texas. Previous research has referred to the city as a major hub for IMBs and for commercial sex and sex trafficking more generally (Bouché & Crotty, 2018; Crotty & Bouché, 2018; de Vries, 2023b). According to the Texas Penal Code, buying commercial sex classifies as a state jail felony; selling sex is considered a misdemeanor (Texas Penal Code, §43.021). To date, city officials and police have responded to commercial sex and potential sex trafficking victimization in IMBs mostly by updating local ordinances and through police interventions such as IMB shutdowns, crackdowns, and sting operations, despite widespread concerns about the ineffectiveness and potential harm to IMB staff (including victims) associated with these types of police responses (see de Vries & Farrell, 2023). Problem-oriented and prevention models are infrequently applied, partly because few studies have examined the conditions in which IMBs can thrive.

4.2 | Data

4.2.1 | Online location data

We obtained the addresses of IMBs from a publicly accessible and popular national review board that provides a comprehensive overview of the locations of IMBs by state and city.[2] The review

[2] We decided not to include the name of the website to not promote its use and preserve the confidentiality of users, IMB staff, and locations where illicit events and potential victimization have been identified.

board is used by buyers of commercial sex to search for the addresses of IMBs and leave and/or read reviews about sexual services in these places. Websites like the one we used for this study have also been used in prior research on the geography of IMBs (Chin et al., 2023; Crotty & Bouché, 2018; de Vries, 2020, 2023a; Huff et al., 2018). Furthermore, online samples have been increasingly used in the social sciences and criminological research and offer an alternative source of information to identify otherwise hard-to-observe problems (see also de Vries & Radford, 2022; Holt et al., 2008, 2014). Although the current sample may not be exhaustive of all IMBs as only those IMBs reviewed by buyers of commercial sex are listed, the advantage of using online review data is the opportunity to work with a unique and theoretically relevant pool of IMBs where the presence of illicit commercial sex was confirmed in buyer reviews. The disadvantage is that the current sample may be biased when nonreviewed locations are in substantially different areas. Therefore, the conclusions of our analyses must be restricted to the context of online-promoted IMBs. We obtained the locations for IMBs that had at least one buyer review between January 1, 2015, and December 31, 2017, which we used as an indication that they were actively operating within this timeframe. A total of 395 IMBs were identified in the city of Houston, which were geocoded to coordinates using Google's Place API.

Rather than obtaining an exhaustive list of retail facilities as comparison groups, we purposefully collected the addresses of several retail businesses that had received online reviews on Yelp. The addresses and coordinates of 942 bars, 326 grocery stores, 427 laundromats, and 666 nail salons were collected via the Yelp Fusion API and matched onto their street segments.[3] These Yelp-listed retail businesses are a comparable and similarly-sized control group for the online-promoted IMBs in our analyses: Their online promotion did not signal any illegitimate events, and no specific indications suggested that any of these facilities structurally hosted or promoted illegitimate events. Although some facilities within the comparison groups may have hosted illicit activity, a key difference between IMBs and the Yelp-listed facilities concerns the presence versus absence of online promotion of illicit events, which may account for different location strategies to reach clientele.

4.2.2 | Street network data

The street network data used for this study was obtained from OpenStreetMap (OSM) via the OSMnx Python library (Boeing, 2017). OSM is a large-scale collaborative mapping project, via which open-source geospatial data can be obtained for most regions of the world. The data set used here contains all streets within the greater Houston area ($N = 695{,}451$ street segments). In each case, the geometry of the street is provided, along with contextual information such as street name and routing restrictions (e.g., one-way). One feature of OSM that distinguishes it from other sources of network data is that it includes some types of streets that others do not, such as footpaths or cycle ways. Since our analysis is concerned with accessibility in a broad sense, we include all street types in our network definition. Notably, then, service roads—upon which the point of access for some IMBs may be located—will be included in the network.

To quantify the structural properties of the street network, it must first be expressed mathematically, and this is typically done by representing it as a *graph*. Formally, a graph $G = (V, E)$ is a set of vertices, V, together with a set of edges, E, which represent links between pairs of vertices. In simple terms, a graph is a collection of objects, some pairs of which are connected: Vertices connected by an edge are said to be *adjacent*.

[3] The Yelp Fusion API only allows for including businesses open on the day of the search (here September 7, 2021).

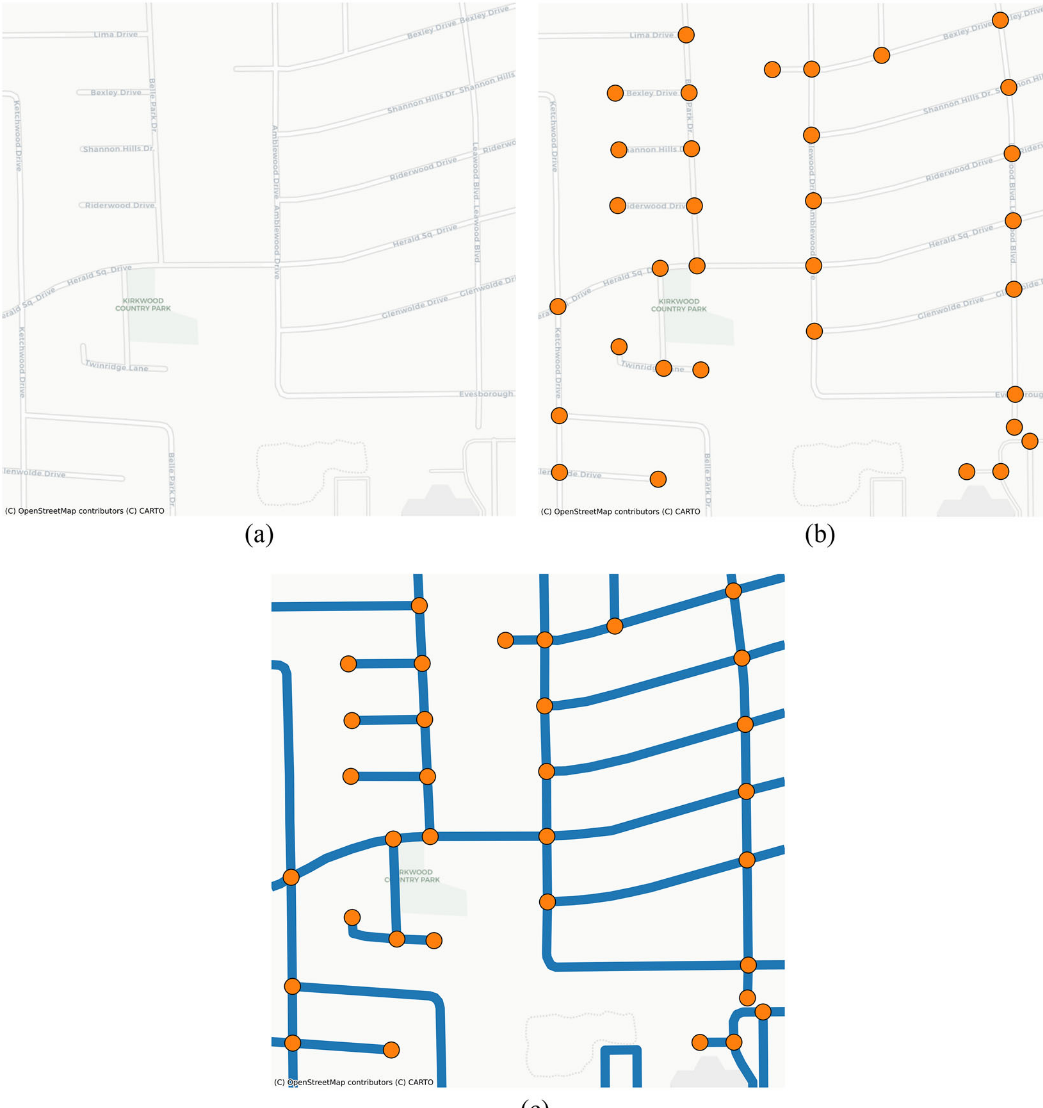


FIGURE 1 Construction of the primal representation of a street network.
[Color figure can be viewed at wileyonlinelibrary.com]

Note. (a) The original map, (b) vertices placed at intersections, and (c) edges placed between any pair of intersections that are directly connected.

Street networks can be represented as graphs in several ways. The most intuitive of these is the “primal” representation, in which each intersection is represented by a vertex, and an edge is added between any two vertices connected by a road (Porta et al., 2006a). In this representation, edges correspond directly to street segments, and the graph can be straightforwardly visualized as a map (see figure 1).

The primal representation is not the only way to encode a street network, and several alternative network representations have also been employed in empirical studies (Jiang, 2007; Kalapala et al., 2006; Masucci et al., 2009). These representations typically employ some variant of the "dual" approach (Porta et al., 2006b), in which the roles of vertices and edges are interchanged: Vertices represent streets, and these are connected if the streets intersect. Although these other representations have advantages, they come at a cost: Most immediately, metric distances are not well defined in such networks. For this reason, we use the primal representation in this study.

4.2.3 | Census tract data

We accounted for several ecological and situational covariates on the broader level of census tracts (discussed below), using data from the 2013–2017 American Community Survey, which was downloaded from the National Historic Geographic Information System (Manson et al., 2018), and geospatial data obtained from OSM. We chose to control for tract-level characteristics to account for area characteristics that previous studies on IMBs had included using tract-based analyses (Chin et al., 2015, 2023; Crotty & Bouché, 2018; de Vries, 2023a), which also enables us to account for features of areas that occupy more and different space than our betweenness and local betweenness measures represent.

As one street segment can run through multiple census tracts, we linked each segment to the census tract with which it had the largest intersection. Missing information on several relevant census tract covariates (discussed below) reduced the total sample of $N = 763$ census tracts (and $N = 695{,}451$ street segments) to our analytical sample of $N = 754$ census tracts (and $N = 686{,}718$ street segments, which approximates 98.7 percent of all street segments).

4.3 | Measures

4.3.1 | Outcome measures: The presence or absence of a business

Our primary outcome for each street segment is whether the segment contains an IMB (1 = "Yes"; 0 = "No"). To establish this, it was first necessary to associate each IMB with the street segment on which it is located. Doing so accurately is not straightforward since the coordinates of IMBs do not always reflect the precise locations of their storefronts: In many cases, the closest segment does not match the address of the business. We sought to match locations to their named addresses as closely as possible, on the basis that 1) the address is likely to be the most reliable indicator of the entrance of the business, and 2) it is where customers are directed by businesses' online promotions. We therefore used a method based on a combination of address-based and geospatial matching. Specifically, for each IMB, we examined the nine closest segments: If any of these matched the street name in the IMB's address, we associated the IMB with the closest of these. If no name matches were found, the IMB was simply associated with the segment that was closest in a geospatial sense. Of the 395 IMBs that were included in our study, 215 were name matched, and the remaining 180 were distance matched. We then identified all segments with at least one IMB, of which there were 359: 3 segments contained 3 IMBs, 30 contained 2, and the remainder only 1.[4] Due to exclusion of nine census tracts (see earlier), our final analytical sample includes 394 IMBs, distributed across 358 unique street segments.[5]

[4] For robustness, we repeated our analysis using a matching approach based purely on distance (i.e., ignoring street names). Detailed findings can be found in appendix C.

[5] Only one IMB was excluded from the final analytical sample due to missing information on census tract characteristics.

To facilitate our comparative analysis of businesses without concerns of illegitimate activities, we repeated this procedure for the four categories of business for which we obtained locations from Yelp. Our final analytical sample includes 805 segments containing bars, 403 containing laundromats, 325 containing grocery stores, and 644 containing nail salons.[6] Indicator variables based on these (1 = "Yes"; 0 = "No") acted as the dependent variables for our comparative models.

4.3.2 | Street network independent variables

Our hypotheses for this study are concerned with the relationship between the usage level of streets and the presence of IMBs; in particular, we hypothesize that IMBs will tend to be located on streets that receive less exposure to traffic, but that are close to streets that are likely to be busy. As noted, one metric that has frequently been used in previous studies as an estimate of the likely usage level of a street is *betweenness*, and we use this as our primary measure here. In addition, we derive an additional measure—*local betweenness*—which reflects the usage level of nearby streets.

Betweenness

To formally define segment betweenness, we need to introduce the concept of a network *path*. A path is a route through the network between two vertices, that is, a sequence of vertices that can be traversed by following edges. For street networks, such a path corresponds to a sequence of street segments between any pair of junctions. The length of such a path can be measured as the total length of its constituent segments.

For any pair of vertices between which a path exists (for street networks, this will typically be the case for all pairs), the *shortest path* is defined as the path of minimal length. More than one shortest path may exist for a given pair of vertices: If two distinct paths of equal length exist, then both are the shortest paths. The betweenness of a given edge e is defined as follows:

$$B_e = \sum_{v,w \in V, v \sim w} \frac{\sigma_{vw}(e)}{\sigma_{vw}} \tag{1}$$

where σ_{vw} is the total number of shortest paths between a given pair of vertices v and w, and $\sigma_{vw}(e)$ is the number of such paths that pass through edge e (i.e., the number of times that e occurs on shortest paths between v and w). The relation $\sim$ refers to the existence of a path between two vertices, so the summation is over all pairs of junctions reachable from each other.[7] Beyond the formal definition, the calculation of betweenness can be expressed more intuitively as a sequence of steps:

1. For all edges, initialize $B_e = 0$.
2. Consider all pairs of vertices, v and w.
3. In each case, find the shortest path(s) through the network between v and w.

[6] The original sample sizes included 942 bars across 808 segments, 326 grocery stores across 325 segments, 427 laundromats across 403 segments, and 666 nail salons across 645 segments. Given minimal reductions in sample sizes (<1 percent), their exclusion unlikely substantially affects the results.

[7] To be clear, the form of betweenness we describe here is *edge betweenness* rather than *vertex betweenness*. The latter is defined analogously but is measured at the vertex (intersection) level, which means it is not applicable when the units of analysis are segments.

4. For each edge that appears on one of these paths, increment its B_e by $\frac{1}{m}$, where m is the number of shortest paths between v and w (m will only be greater than 1 when multiple distinct paths have the same length).

Betweenness is therefore an estimate of the frequency with which each edge will be used during travel through the network, under the simple assumption that exactly one journey occurs between every pair of junctions. Although this assumption clearly does not reflect the complexity of real-world travel patterns, it provides a convenient (and objective) first-order heuristic for the spatial distribution of routine movements. In a criminological context, it has a particular appeal because it reflects the extent to which places will be exposed to potential offenders: In the language of crime pattern theory, streets with high betweenness are those likely to lie in the overlapping activity spaces of many individuals. In this study, betweenness also acts as a proxy for other phenomena of interest: Streets with low betweenness are likely to be those with few potential guardians, whereas high betweenness streets would be expected to have a greater supply of potential customers for businesses. These extremes reflect the tension between the needs for exposure and discretion that we anticipate for IMBs.

One refinement can be made to the definition of betweenness to better reflect human movement. Rather than considering all pairs of vertices within the calculation—which would mean that some of the journeys included might be unrealistically long—a constraint can be imposed such that only trips up to a certain maximum length will be considered. For a given length, l, the length-constrained betweenness B_e^1 can be defined by modifying the original form in equation 1 so that the $\sim$ relation represents "there exists a path *of length at most* l between v and w."[8]

When calculating this form of betweenness, the choice of l depends to some extent on the form of movement being considered: l corresponds to a typical scale for trip lengths, and different values might be used when considering foot or vehicular travel, for example. Little empirical basis exists upon which to select this value: Few criminological studies have directly examined the activity spaces of offenders, and those that have (Bernasco, 2019; Curtis-Ham et al., 2021; Menting et al., 2020) did not characterize trip lengths in these terms. Perhaps the best evidence comes from a recent large-scale study of (noncriminal) mobility by Alessandretti et al. (2020), who found that local travel had a characteristic scale of approximately 3 km. In our analysis, we ran models for a range of possible values, all of which gave qualitatively similar findings. In this article, we show results for $l = 2.5$ km.

Local betweenness

In addition to betweenness, we also define an additional segment-level metric, which we refer to as *local betweenness*, as a proxy measure for the level of activity in a segment's vicinity. For any given edge e, the local betweenness is the average betweenness of nearby segments, that is, those within some vicinity of e. To calculate local betweenness, we must define what we mean by the *vicinity* of a street segment e. In principle, we seek to identify all segments within some radius R of e; however, this can be done in several ways. On the one hand, R can be defined in terms of either topological or metric distance. In the former case, a segment can be considered to be within R of e if a traveler would need to cross R junctions to travel between them. This approach can lead to a large degree of variation in the size of neighborhoods, however, because it does not take into account the lengths of segments.

[8] This length-constrained form of betweenness is sometimes referred to elsewhere in the literature as "local betweenness" (e.g., Yamaoka et al., 2021). In this article, "local" is used in a different sense, as explained in subsequent sections.

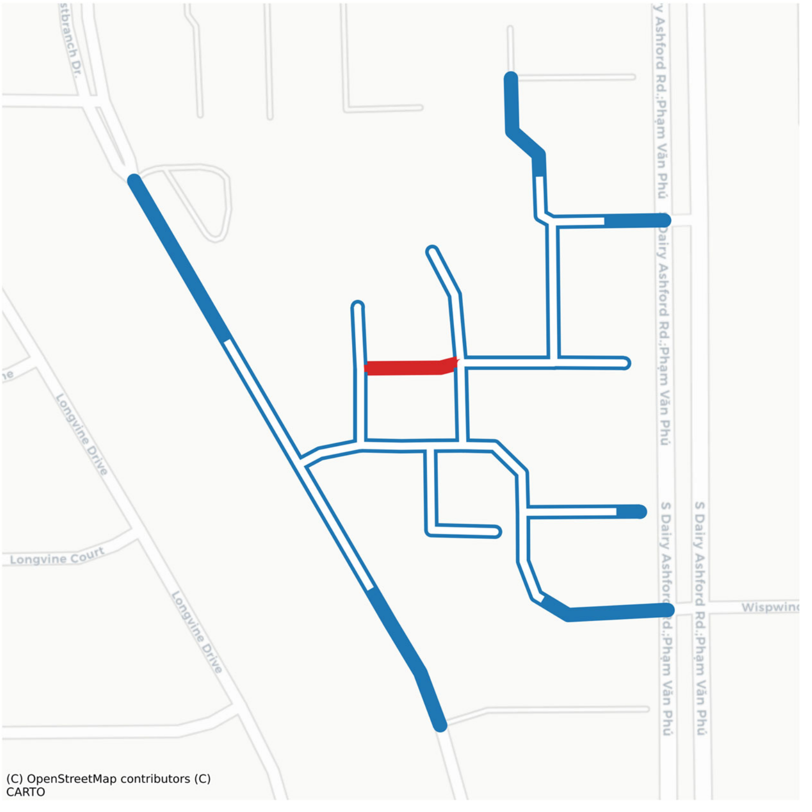


FIGURE 2 Construction of the *vicinity* of a given segment, used in the calculation of local betweenness. [Color figure can be viewed at wileyonlinelibrary.com]

Note. For a given segment, colored red, the white region shows the extent of the network within R meters of the central segment. All segments that intersect with this region (colored blue) are included in the vicinity.

On the other hand, R can be defined in metric terms, so that the region is determined by what can be reached within a certain distance. This approach also presents problems, however, because the distance between two segments is not well defined. Because segments are linear features, the distance between them cannot be measured uniquely, and so it is necessary to adopt a convention. In this study, we consider two segments to be within R meters of each other if any part of one segment lies within R of any part of the other. An example is shown in figure 2: Segments are included in the R vicinity if any part of them can be reached by a path of length R from one of the ends of e. Trivially, e itself is not included in its own vicinity, which ensures that the local betweenness of e is independent of its betweenness. In this article, we present results with R equal to 100 m; however, we have replicated our analysis for other values of R and find qualitatively similar results.

Once the vicinity of e has been constructed, its local betweenness is simply the mean betweenness of all constituent segments. Segments with high local betweenness are, therefore, those for which the streets nearby are likely to have high levels of usage—again, this is intended to act as a proxy for the levels of guardianship and supply of potential clientele. Using this metric to complement betweenness itself allows us to disentangle the characteristics of streets themselves and their vicinity, reflecting our hypothesis that IMBs might locate nearby busy streets, while not directly on them. Figure 3 shows a section of the network with values colored according to both

(a) Betweenness

(b) Local betweenness

FIGURE 3 Discriminatory value of local betweenness.
[Color figure can be viewed at wileyonlinelibrary.com]
Note. Segments A and B both have similar low betweenness, but B's local betweenness is high, thanks to its proximity to high-betweenness segments.

betweenness and local betweenness. The two highlighted segments exemplify the kinds of cases that local betweenness is intended to discriminate between: Both segments have low betweenness, but B's proximity to high-betweenness thoroughfares means that it has a much higher value of local betweenness than A, which is further removed. Equivalent pairs of contrasting high-betweenness segments can also be found.

4.3.3 | Census tract covariates

Motivated by an environmental criminology approach and previous research on the geography of IMBs, we accounted for several covariates at the census-tract level (see table 1 for an overview of all summary statistics). Besides accounting for the *population size (logged)*, we included two socioeconomic indices through principal component analysis with orthogonal rotation: 1) *concentrated disadvantage*, based on the proportions of the population with an income below the poverty line, proportions of the population age 25 and older being unemployed, and female-headed households as a percentage of all households (Cronbach's alpha = .797, 95 percent confidence interval [CI] [.761; .830]); and 2) *residential instability*, based on the proportion of renter-occupied housing and the proportion of the population with a different house in the United States a year earlier (Cronbach's alpha = .758, 95 percent CI [.726; .788]). Furthermore, *racial and ethnic heterogeneity* was included as an index via $1 - \sum \pi^2$, where π refers to the proportion of each racial or ethnic group (Blau, 1977). Racial and ethnic heterogeneity ranged from .054 (tracts with little heterogeneity) to .761 (substantive heterogeneity). *Income inequality* was included as the standard deviation of the household income in the past year, which was calculated using the log-transformed midpoints of each census-provided income bin, which were multiplied by the number of observations in each

TABLE 1 Summary statistics.

Variable	Mean / *N*	SD / %	Min	Max
Outcome				
IMB (1 = Yes)	358	.052	0	1
Level 1 (*N* = 686,718)				
Betweenness (log)	8.693	2.772	0	14.273
Local betweenness (log)	8.239	1.406	0	14.288
Level 2 (*N* = 754)				
Population (log)	8.565	.558	6.207	11.090
Concentrated disadvantage (index)	0	1	−1.819	6.943
Residential instability (index)	0	1	−1.732	5.004
Racial and ethnic heterogeneity (index)	.511	.164	.054	.761
Income inequality	1.044	.222	.399	2.115
Commercial land use (%)	6.564	19.817	0	100
Retail land use (%)	10.550	26.191	0	100
Industrial land use (%)	9.030	24.492	0	100
Residential land use (%)	35.082	43.796	0	100
Primary road (1 = Yes)	246	32.626	0	1
Police within mile distance (1 = Yes)	142	18.833	0	1
Violent crime incidents (per 1,000)	6.856	9.812	0	141.129

bin (to calculate means and standard deviations). A higher value on this measure represents larger income inequalities within census tracts ($\bar{x}$ = 1.044, standard deviation [SD] = .222).

Furthermore, we also accounted for several opportunity structures at the tract level. Specifically, we accounted for specific *land use activity*, following previous literature demonstrating significant relationships between a variety of land use measures and crime rates (see, e.g., Boessen & Hipp, 2015; Kubrin et al., 2018; Wo, 2019). OSM data were used to construct four variables that represent the percentage land use devoted to commercial ($\bar{x}$ = 6.564, SD = 19.817), retail ($\bar{x}$ = 10.550, SD = 26.191), industrial ($\bar{x}$ = 9.030, SD = 24.492), and residential ($\bar{x}$ = 35.082, SD = 43.796) activity. Other land use activity (e.g., allotments, cemetery, farm, forest, orchards, and parks) was combined into the reference category. Moreover, we accounted for another measure of accessibility by including a variable representing whether a *primary road* intersected with a tract (1 = "Yes", n = 246, 32.63 percent). Lastly, we account for potential or anticipated increased police monitoring by including a variable representing whether a tract's centroid was within a mile distance of a police station (1 = "Yes", n = 142, 18.83 percent), and the extent to which an area attracted violent crimes by including a variable representing the number of *violent crime incidents* (murder, manslaughter, rape, robbery, and assault) per capita using the Houston Police Department's crime reports ($\bar{x}$ = 6.856, SD = 9.812).

4.4 | Analytical strategies

To test our hypotheses, we sought to model our key binary outcome of interest: the presence or absence of a business on each street segment. In doing so, however, an immediate statistical challenge was presented by the extremely high level of class imbalance in our data: Of 686,718 street segments, only 358 (.05 percent) contained IMBs, and the same was also true for bars (.12 percent), laundromats (.06 percent), grocery stores (.05 percent), and nail salons (.09 percent). Such imbalances are likely to lead to unreliable estimates of the associations between independent and dependent variables if models are fitted to the data as a whole.

To address this sample imbalance, therefore, we applied a form of stratified downsampling of the majority class for each business type to generate balanced samples in each case. For each business type, the segments with businesses present were supplemented with a proportionate set of street segments without such a business, equally divided across census tracts with and without the business (although the total number of census tracts may slightly differ between analytical samples, e.g., in the few instances when a tract had multiple IMBs and multiple segments within one tract were randomly included in one sample but not in another). The rationale for stratifying in this way was to account for the overall propensity of areas to contain such businesses. More specifically, the sample of 358 segments with IMBs was supplemented with 1) 358 segments without IMBs, randomly drawn from within census tracts that had at least one IMB; and 2) 358 × 2 segments without IMBs, randomly drawn from census tracts that had no IMBs. We repeated this procedure 100 times for each business type and estimated the coefficients separately for each sample. As such, each of the 100 samples for IMBs contained 1,432 segments, 25 percent of which had IMBs. Using the same procedures, we constructed 100 balanced samples each for bars, laundromats, grocery stores, and nail salons. We favored this procedure over alternative downsampling strategies (e.g., matching street segments with IMBs to a set of control segments without IMBs) because it did not require any segment-level information to create control groups and allowed us to verify the results across varying samples.

To examine the impact of both street-level and census-tract level covariates on the placement of IMBs, we conducted hierarchical generalized linear modeling for binary outcomes. Multilevel techniques are appropriate in this context as they do not violate the assumption of independent error terms (Raudenbush & Bryk, 2002). Although we are primarily interested in examining the impact of street-level factors, we preferred multilevel techniques instead of fixed-effects models in order to account for specific tract covariates that other studies have found to be associated with the placement of IMBs.

Using this approach, we modeled the log odds that an IMB is present on a particular segment: This is denoted Y_{ij}, where i indexes the street segments (level 1) and j indexes the census tracts in which they lie (level 2). We began by estimating an unconditional model, without the independent variables, to identify the extent to which the placement of IMBs on a specific street segment varies by census tracts, through the following equations:

$$\text{Level 1}: \; Y_{ij} = \beta_{0j} + r_{ij} \tag{2}$$

$$\text{Level 2}: \; \beta_{0j} = \gamma_{00} + \mu_{0j} \tag{3}$$

$$\text{Combined}: \; Y_{ij} = \gamma_{00} + \mu_{0j} + r_{ij} \tag{4}$$

Here, the error terms are denoted with r for the street segments and with μ for the census tracts. In addition, β_{0j} is the intercept corresponding to census tract j and γ_{00} is the overall intercept. A likelihood ratio test comparing the unconditional model with an intercept-only model confirmed that the unconditional model was a significantly improved fit to the data ($p < .001$) for all 100 input samples. Using the between-tract variance from each sample, the intraclass correlation coefficient (ICC) was calculated as follows: $\frac{variance}{variance+\frac{\pi^2}{3}}$ and ranged from .359 to .469. This indicates that between 35.9 percent and 46.9 percent of the variation in the outcome measure can be attributed to tract-level variation, which underscores the need for a multilevel approach.

Next, the impact of level 1 (X) and level 2 (Z) variables were estimated by adding those covariates to the model. We used a model with fixed effects at both levels, and random intercepts (so that the level 1 intercept, for example, is a combination of the overall intercept, the level 2 covariates and a level 2 random intercept). The model was defined as follows:

$$\text{Level 1}: Y_{ij} = \beta_{0j} + \sum_{s=1}^{S} \beta_{sj} X_{sij} + r_{ij} \tag{5}$$

$$\text{Level 2}: \beta_{0j} = \gamma_{00} + \sum_{t=1}^{T} \gamma_{0t} Z_{tj} + \mu_{0j} \tag{6}$$

$$\beta_{sj} = \gamma_{s0} \tag{7}$$

$$\text{Combined}: Y_{ij} = \gamma_{00} + \sum_{s=1}^{S} \gamma_{s0} X_{sij} + \sum_{t=1}^{T} \gamma_{0t} Z_{tj} + \mu_{0j} + r_{ij} \tag{8}$$

Here, s indexes the independent variables X defined at level 1 (of which there are S in total), and t indexes the level 2 variables Z (of which there are T). Continuous variables were mean centered to avoid multicollinearity between the independent variables and the intercept, as well as to facilitate interpretation. Each main effect can be interpreted as the effect of a variable when other variables were at their means of zero.

To examine the results of our model across all 100 of our samples, we use an approach inspired by "specification curve analysis" (Simonsohn et al., 2020), which is a means of examining the consistency of findings across possible model specifications. Having run all models, the set of coefficients corresponding to a particular effect can be depicted via a curve plot, in which effect sizes are shown in increasing order, alongside their standard errors and significance. As well as showing the extent to which estimates vary, the proportion for which effects are significant can also be seen. In this case, the "specification" corresponds to the particular sample: If findings are consistent across samples, then this implies that the effects are robust to our sampling procedure. Analyses were conducted using the programming language *R* (R Core Team, 2021), specifically through the *lme4* package for multilevel modeling (Bates et al., 2015) and the *specr* package for specification curve analyses (Masur & Scharkow, 2020). Multicollinearity was not an issue in any of our models.[9]

5 | FINDINGS

We begin by examining the effects of betweenness and local betweenness on the placement of IMBs in street segments. Figure 4 shows specification curves for the coefficients associated

[9] The code for our analyses is available at https://osf.io/kqu39/.

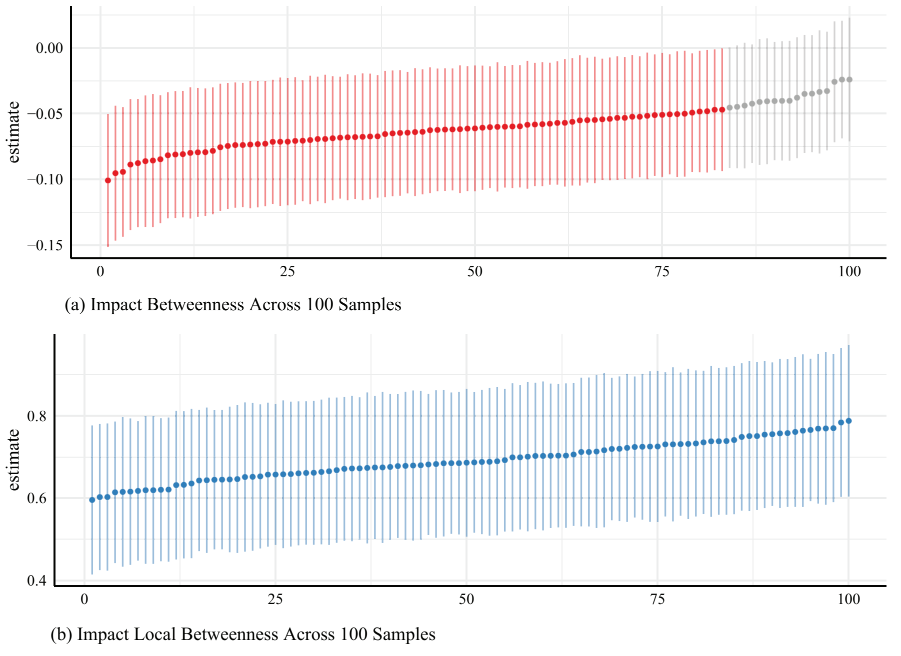


FIGURE 4 Specificity curves for estimated logit coefficients.
[Color figure can be viewed at wileyonlinelibrary.com]
Note. Each point represents the coefficient for one of our 100 samples, and these are plotted in increasing order. Vertical lines represent standard errors, and the lines are colored according to significance at $p < .05$ level (colored if significant with red indicating a negative relationship and blue indicating a positive relationship; gray otherwise).

with these variables, summarizing the results across our 100 samples. In both cases, results are consistent across samples, with the directionality of the effects being the same in all cases. Overall, betweenness centrality is negatively associated with a street's likelihood to have an IMB, with logit coefficients ranging from $\beta = -.101$ to $-.024$ (median $\beta = -.061$), and the effect is significant ($p < .05$) for a clear majority of the samples. Findings from the model with optimal Akaike information criterion (AIC) values (see table 2) indicate that an increase in betweenness centrality decreases the likelihood for a street to have an IMB. Local betweenness, however, has the opposite effect: Segments with higher local betweenness are more likely to have IMBs, with logit coefficients ranging from $\beta = .596$ to $.788$ (median $\beta = .687$). These effects are significant in all cases. Specifically, the model with optimal AIC values reports that an increase in local betweenness centrality substantially increases the odds for a segment to have an IMB.

To examine the combined effect of betweenness and local betweenness, we included an interaction term between these variables in an additional model across the 100 samples. The coefficients for this expanded model are presented in figure 5 and model 2 in table 2. The results indicate that, consistently across all samples, the effect of local betweenness is highly conditional on a segment's betweenness. For segments with lower betweenness (e.g., 1 SD below the mean), the probability of having an IMB increases substantially as local betweenness increases. For high-betweenness streets, however, the effect of local betweenness is negligible, and its main effect is no longer significant when the interaction term is included. That the effect of local betweenness should be specific to low-betweenness segments makes theoretical sense: If a segment

TABLE 2 IMB placement: results from the multilevel models with optimal AIC scores.

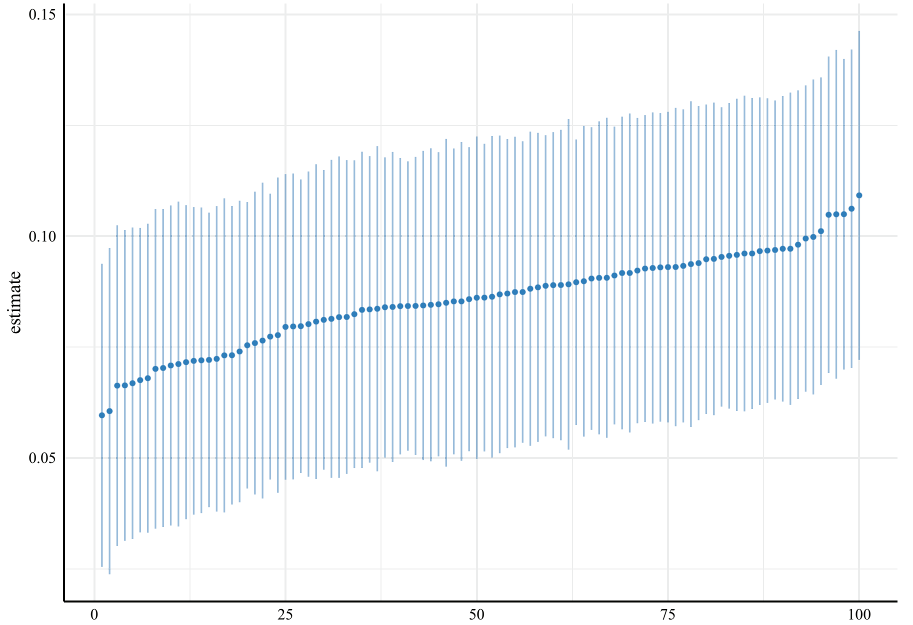
Variable	Model 1 *B*	Model 1 SE	Model 1 OR	Model 2 *B*	Model 2 SE	Model 2 OR
Intercept	−1.360***	.098	.257	−1.376***	.108	.252
Level 1 (*N* = 1,432)						
Betweenness (log)	−.064**	.025	.938	−1.098***	.185	.333
Local betweenness (log)	.766***	.088	2.151	.093	.133	1.097
Betweenness × local betweenness				.097***	.017	1.102
Level 2 (*N* = 385 (1); *N* = 380 (2))						
Population (log)	−.424*	.181	.654	−.224	.184	.800
Concentrated disadvantage	−.068	.127	.934	−.022	.143	.978
Residential instability	.186	.101	1.204	.195	.116	1.216
Racial/ethnic heterogeneity	2.030**	.721	7.616	1.957*	.785	7.076
Income inequality	.914	.484	2.495	.138	.542	1.148
Commercial land use	−.021***	.005	.980	−.021***	.005	.979
Retail land use	.003	.003	1.003	.000	.003	1.000
Industrial land use	−.008	.004	.992	−.001	.005	.999
Residential land use	−.005*	.002	.995	−.005*	.002	.995
Primary road	−.420*	.193	.657	−.413	.221	.661
Police within mile	−.029	.224	.972	.064	.265	1.066
Violent crime (per 1,000)	−.007	.010	.994	−.009	.010	.991
Random effects tracts σ^2	.619			1.112		
	(.787)			(1.054)		

Note. Level 2 sample sizes may slightly differ due to the downsampling strategy explained in our "Analytical Strategy" section. *B* = logit coefficient; SE = standard error; OR = odds ratio.
**p* < .05; ***p* < .01; ****p* < .001.

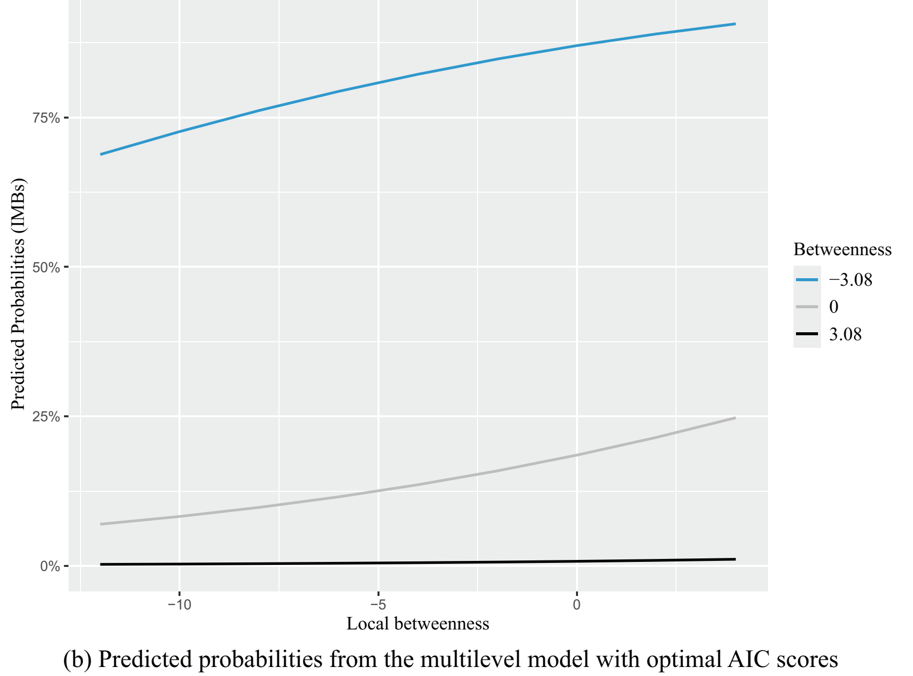
has high betweenness, then its inherent centrality is likely to render the local context immaterial.[10] Altogether, these results confirm our main hypothesis that IMBs are placed in streets that have low betweenness centrality, yet are in the vicinity of other streets with high betweenness centrality.

The effect sizes of betweenness and local betweenness remain similar while controlling for several covariates at the census tract level, some of which affect the average likelihood for segments to have IMBs. In particular, the findings from the final model (model 2 in table 2) demonstrate a role of the socioeconomic makeup of tracts: The odds for street segments to have IMBs are substantially higher within census tracts with greater levels of racial and ethnic heterogeneity (β = 1.957, odds ratio [OR] = 7.076, p < .05), yet lower within census tracts with a greater percentage of land use devoted to commercial activity (β = −.021, OR = .979, p < .001) or residential buildings (β = −.005, OR = .995, p < .05) compared with other types of land usage. Although previous studies have deemed other tract features (e.g., retail land use, residential instability, the presence of a primary road, and more violent crimes) important, our findings indicate that

[10] Indeed the nature of betweenness means that the relationship between segments and their neighbors is asymmetric: High-betweenness segments are likely to have at least some high-betweenness neighbors, but the converse is not true.



(a) Specification curve showing coefficient estimates across 100 samples



(b) Predicted probabilities from the multilevel model with optimal AIC scores

FIGURE 5 Results for the interaction term (betweenness × local betweenness). [Color figure can be viewed at wileyonlinelibrary.com]

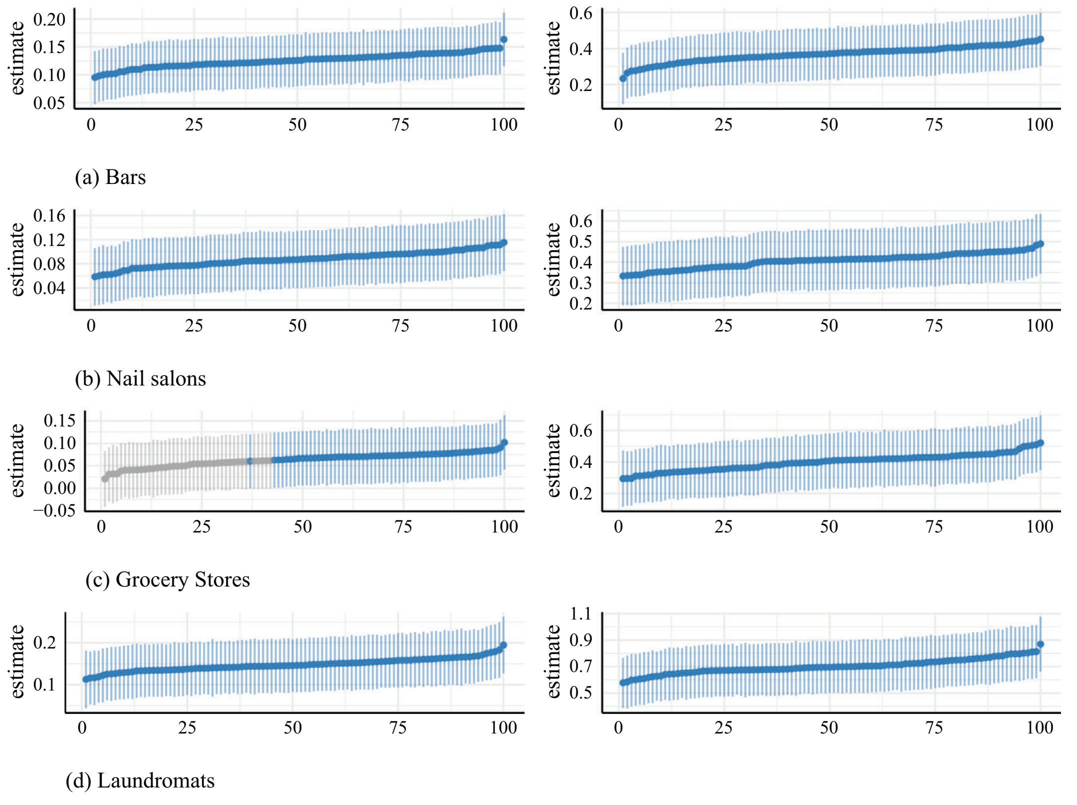


FIGURE 6 Specificity curves for betweenness (left) and local betweenness (right) effects for retail businesses (name-based method). [Color figure can be viewed at wileyonlinelibrary.com]

these variables have no significant associations with the placement of IMBs at the segment level, where their placement thus depends on centrality metrics indicating the usage potential of a street.

The locational strategies of retail businesses seem to differ from those of IMBs. As suggested by figure 6, both betweenness and local betweenness increase the likelihood for segments to have bars, nail salons, laundromats, or grocery stores (although the significance of the relation between betweenness and the placement of grocery stores is alternately significant and insignificant). These findings suggest that, in contrast to IMBs, retail businesses seem to be located on *and* near streets with higher betweenness centralities (see Tables A1-A4 in appendix A for detailed findings). Although the effects of (local) betweenness are generally consistent across the different retail facilities, the role of tract-level features depends on the specific type of facility. All types of facilities are more likely located on street segments in less-populated tracts and tracts with less racial and ethnic heterogeneity (in which they also differ from IMBs). Yet, besides these features, bars are more likely to be located on streets within tracts that have lower concentrated disadvantage levels, higher residential instability levels, and more violent crime incidents; nail salons are more likely to be located on streets within tracts that have less industrial land use; grocery stores are more likely to be located on streets within tracts with greater concentrated disadvantage and higher violent crime incident rates; and laundry services are more likely to be found on street segments within tracts with greater income inequality.[11,12,13]

6 | DISCUSSION

In this study, we aimed to unravel what type of urban infrastructure creates structural opportunities for illegitimately operating facilities, specifically IMBs. Such venues are associated with illicit events that cause high levels of harm, and understanding the conditions in which they thrive is a key step in formulating problem-oriented responses. Although an increasing body of evidence has considered the influence of urban morphology on crime—and the role of the street network in particular—this has so far been limited to the context of property and violent crimes (Davies & Johnson, 2015; Kim & Hipp, 2020). The theoretical context for illegitimately operating facilities differs markedly from these forms of crime, in particular because the activities take place at fixed locations: Although the spatial distribution of property and violent crimes tends to be opportunistic, the placement of illegitimately operating facilities requires some level of strategic decisions of their proprietors who favor locations optimal for their purpose. Accessibility and (in)visibility remain key concerns, however, particularly for venues concerned with the sale of illegal goods or services. As such, routine activities and the way these are shaped by urban infrastructure remain important considerations. Against that background, this study unravels the type of street network structure in which these businesses thrive.

To test how accessibility and visibility determines the placement of illegitimately operating facilities, we focused on the case of U.S.-based IMBs that host illicit commercial sex. IMBs are a compelling example of crime-hosting venues that operate on the intersections of crime and legitimate activity. The illicit nature of commercial sex in the United States likely affects the placement

[11] To assess the robustness of our findings, we conducted sensitivity analyses using a distance-based matching procedure to link business locations to their segments; see appendix C. We identified similar results for the placement of IMBs on street segments with low betweenness and high local betweenness (see Figure C1). We found, however, in contrast to our main analyses, that the odds for segments to have retail facilities for which there were no substantiated concerns of illegitimate activity were lower on segments with higher betweenness centrality (see Figure C2). When interpreting this, note that distance-based matching can give misleading outcomes in cases where the closest segment to a business is an alley or service road (typically with low betweenness), but the entrance to the business is located on a different, higher betweenness segment (a scenario more likely for retail businesses). This discrepancy does not exist for the location of IMBs: All findings corroborate that lower betweenness segments are favored. A discreet service road or alley may in fact be the online-reported street from where customers enter the business).

[12] We also included an interaction term to assess the combined effects of betweenness and local betweenness on the placement of retail businesses without substantiated concerns. Across 100 samples, the interaction effect was significant for all four business types: bars, grocery stores, nail salons, and laundry services. In contrast to the placement of IMBs, however, low betweenness streets become *less* appealing for presumably legitimate retail businesses when local betweenness increases—most likely because of increased competition from better-placed businesses on the high-betweenness segments nearby. The optimal placement of retail businesses seems to be on streets that have high betweenness levels themselves, for which the added influence of local betweenness is marginal. Illustrative interaction plots are included in Figure B1 in appendix B.

[13] To further assess the robustness of the findings, we included a spatial lag of the level-two residuals of every model (see the online supporting information). Given our downsampling technique, the spatial lag of the residuals concerns a subset of the tracts only. This measure helps to control for potential spatial autocorrelation but does not represent true spatial concentration across tracts. Including the spatial lag in the models did not substantially change our findings regarding the impact of betweenness and local betweenness. Additional supporting information can be found in the full text tab for this article in the Wiley Online Library at https://onlinelibrary.wiley.com/doi/full/10.1111/1745-9125.12381.

of venues that host commercial sex. Specifically, IMBs have been subject to aggressive law enforcement responses in several U.S. states, including arrests of buyers and shutdowns of IMBs (de Vries, 2020; de Vries & Farrell, 2023), which have influenced the locational strategies of both parties (see, e.g., de Vries, 2023b; Holt et al., 2008, 2014). Moreover, previous research has suggested that sexually oriented facilities like IMBs may be perceived as undesirable and that neighborhood residents may object to the presence of such facilities "in their backyard" (see, e.g., Hubbard et al., 2013; Lopez et al., 2020).

Partly for these reasons, the placement of IMBs is subject to competing influences: Although they require ease of access and visibility to attract buyers—much like their legitimate counterparts—they also have an incentive to remain inconspicuous to avoid law enforcement attention and provide discretion for their buyers. Against this background, we examined the relationship between IMB placement and two key network metrics. The first of these was betweenness, which is a proxy measure for the likely level of usage of a street and which has been used in several previous studies (e.g., Davies & Johnson, 2015; Kim & Hipp, 2020). The second was a novel variant of this—termed "local betweenness"—which reflects levels of activity on nearby streets. We examined the importance of these measures in multilevel models that also accounted for broader tract-level dynamics that previous studies have linked to the locations of IMBs (e.g., Chin et al., 2023; Crotty & Bouché, 2018; de Vries, 2020, 2023a; Mletzko et al., 2018). We then compared the locational strategies of IMBs with four Yelp-listed retail businesses without substantiated concerns of illegitimate activities (bars, nail salons, grocery stores, and laundromats).

Our findings demonstrate that IMBs are more likely to be located on street segments that have lower betweenness levels but also in the vicinity of segments with higher betweenness levels. The tendency toward lower betweenness segments (i.e., those that are quieter) is consistent with strategic behavior on the part of proprietors, who wish to maintain a certain level of concealment and reduce the (perceived) chance of the business being shut down (Cohen & Felson, 1979; Felson, 1987). As noted in previous work, this element of discretion also seems to be crucial for the locational strategies of buyers of commercial sex (de Vries, 2023b; Holt & Blevins, 2007; Holt et al., 2008, 2014), which may also motivate IMBs relying on these buyers to locate in less visible areas. Although the reduced accessibility and visibility on low-betweenness streets implies that IMBs will have less exposure to passing trade, this is likely to be mitigated by their online promotion, which increases their visibility for motivated buyers while maintaining physical discretion (see also de Vries, 2023b). As such, online visibility may serve as a potential replacement of physical visibility, and render this aspect of their placement less important.

In addition, however, the positive association with local betweenness implies that IMBs do, nevertheless, favor locations that have high levels of activity in their vicinity. These places are likely to be preferred because they have a ready supply of potential buyers, for whom the IMBs lie close to their routine activity spaces. Indeed, previous research has shown that potential buyers of commercial sex are drawn to areas that feature centrally in their awareness spaces, such as neighborhoods with greater population density that intersect with a highway (another means of accessibility) and those with substantive retail land use (e.g., Chin et al., 2023; Crotty & Bouché, 2018; de Vries, 2020, 2023a; Huff et al., 2018; Lopez et al., 2020; Mletzko et al., 2018). Our local betweenness measure provides an alternative perspective on the same principle and represents a more direct and publicly available approximation of the activity levels of nearby street segments than do population and land use features. Altogether, the combination of low betweenness with high local betweenness seems to create the most favorable conditions for IMBs: Such locations offer a large pool of buyers, for whom such areas are visited in the course of routine activities, while remaining sufficiently removed to maintain their discretion. In other words, IMBs are located at places where the element of discretion can be combined with accessibility and visibility. Most contextual tract-level features, which reflect the socioeconomic markup of neighborhoods and were deemed important in other studies (e.g., Chin et al., 2023; Crotty & Bouché, 2018; de Vries, 2023a), were found to be less relevant in shaping the location strategies of these facilities at the micro level.

The element of discretion distinguishes illegitimately operating facilities like IMBs from retail businesses without substantiated concerns of illegitimate activities, which we found were located on street segments with higher values of both betweenness and local betweenness. As the broader literature on the placement of legitimate retail businesses has suggested, these types of businesses optimally benefit from central streets with high levels of movement, where usage potential—as observed through greater betweenness levels—may generate a larger pool of clientele (Ozuduru et al., 2021; Porta et al., 2009, 2012; Zhang et al., 2019). Although the previous literature has suggested that prominence may not be as crucial for some specialty stores that draw people through their function rather than through their location (see, e.g., Lin et al., 2018; Wang et al., 2014), it may still be essential for those retail businesses that offer similar types of services across a city: When buyers assume that certain business types offer similar services, they may frequent the ones within their routine travels and awareness space rather than actively searching for a business further afield offering better services.

The relationship between IMB placement and network structure also differs from that which has been observed in previous research on property and violent crimes, which has found that segments with greater betweenness levels are at higher risk (e.g., Johnson & Bowers, 2010; Kim & Hipp, 2020; Summers & Johnson, 2017). A plausible explanation lies in the differing nature of these crimes and the theoretical frameworks invoked to explain them. Property crimes are often rationalized in terms of opportunity, and they require the convergence of motivated offenders and targets in places with low capable guardianship and low informal social control (Andresen, 2019; Cohen & Felson, 1979; Felson, 1987), which are typically the high-activity streets (e.g., Davies & Bishop, 2013; Davies & Bowers, 2018; Johnson & Bowers, 2010; Summers & Johnson, 2017). Whereas these high-activity streets may give rise to property crimes, they seem to be less favorable for illegitimately operating facilities that tend to provoke strong local reactions, such as facilities hosting commercial sex (Hubbard et al., 2013; Lopez et al., 2020). Considering growing public concerns along with intensified law enforcement monitoring, their placement on high-activity streets would be a risk too high, especially when an alternative possibility exists of combining reduced visibility with accessibility.

Notwithstanding the theoretical importance of high-betweenness and low-betweenness streets for environmental criminology, a few limitations may temper our conclusions and merit future analyses. First, although we use a unique and theoretically relevant sample of online-promoted IMBs from the most popular review board in the United States, some IMBs might not have been promoted through these online reviews (see also de Vries, 2023a, 2023b). Their exclusion could introduce bias if they are placed on streets with betweenness levels that deviate systematically from those observed in our analytical sample. Second, it is possible that some of the facilities within the comparison group of retail businesses also serve as crime generators, attractors, or enablers for violence or property crimes, or they host serious crimes such as money laundering or labor exploitation. Even if this is the case, however, the facilities that comprise our comparison groups still differ from IMBs in that their online promotion did not explicitly signal illicit events. Even if illicit events had occurred in these venues, more discreet locations—as seen in the context of IMBs—are unlikely to be appealing because the lack of online visibility of illicit events would mean they would still require physical accessibility and visibility to an interested and motivated pool of clientele. Moreover, we stress that our conclusions about the locations of facilities without substantiated concerns of illegitimate activity hold across four different types of facilities, supporting our finding that these types of facilities are systematically located on streets different from those streets with IMBs. Third, we applied a single-city approach, thereby providing little knowledge about the interaction between within-city street configurations and city-level centrality metrics and other features. Future work should examine whether the association between street network features and facility placement differs by city.

A further opportunity for refinement concerns the measurement of betweenness. In its standard form, the calculation of betweenness assumes that an equal number of trips will occur between each pair of intersections, which is unlikely to reflect the true nature of human movement. Refinements to betweenness aimed at addressing this have been proposed, in which the contribution of each path is weighted according to the (measured or estimated) traffic likely to be flowing along it (e.g., Wu et al., 2022). Such approaches require fine-grained human movement data (e.g., in-flows and out-flows associated with each intersection), which was not available for our study, but incorporating these refinements would add value to future research.

Furthermore, since we examined only one type of illegitimately operating facilities, our conclusions here are limited to the context of online-promoted IMBs that host illicit commercial sex. The principles we examined, however, may be expected to apply more widely, and so we encourage future work to examine the structural features associated with other types of facilities. IMBs display a rare combination of characteristics: They present as businesses offering legitimate services, but they also host illicit activity, with the additional factor that the services in question carry a particular social stigma and are potentially linked to more serious human trafficking victimization (although the nature and scale of human trafficking victimization in IMBs cannot be quantified using our data; but see de Vries & Radford, 2022). Nevertheless, other types of facilities may share some of these features. Perhaps most similar are other businesses that seem to be legitimate but structurally host labor exploitation or other violations and victimization, such as hand car washes. In addition, facilities associated with drug dealing or gambling might also be expected to be subject to similar influences with respect to their placements. More generally, an interesting example might relate to businesses for which legality is variable: Cannabis dispensaries, for example, have recently become legal in some jurisdictions, and the question of whether their location mirrors that of "traditional" retail businesses would represent a distinctive case study. The findings in the current study offer a relevant case for future work to continue assessing whether the dual requirement of being both "visible" and "hidden" is particularly important for those types of businesses that act as fronts for illegal activity and, in doing so, combine both legitimate and illicit events. In contrast, facilities set up for the sole purpose of illegal activity may require less visibility. At the other extreme, legitimate facilities where no crime incidents occur (and perhaps also legitimate facilities where some incidents occur, such as premises operating as crime generators or attractors) have no reason to be "hidden" and are likely to require more accessibility and visibility to reach clientele.

Lastly, our theoretical focus on environmental criminology offers a partial explanation for the placement of illegitimately operating facilities and is best seen as complementary to a political economy approach that accounts for more complex social, economic, and political dynamics (see, e.g., Logan & Molotch, 2007). In fact, even though our analyses establish a clear link between the physical infrastructure of a city and the placement of illegitimately operating facilities, many sociological processes are at play in determining both the physical layout of a city and the specific use of areas (Logan & Molotch, 2007). To illustrate, previous research about the commercial sex industry has highlighted the importance of social actors besides those who engage in illicit events (e.g., neighborhood residents, city officials, and landlords) whose negotiations determine who and what occupies space (Hubbard & Sanders, 2003; Lopez et al., 2020). For example, incoming concerns about commercial sex facilities as "public nuisance" or "unwanted" facilities have urged city officials in several settings to move these facilities away from residential areas and toward busier city areas (Hubbard, 2013; Hubbard et al., 2013; Matthews, 1990, 1993, 2005). Such processes might also explain the finding of this study that IMBs tend to be located in the vicinity of busier areas.

Although our study highlights the particular relevance of street segment betweenness centralities, relative to contextual tract-level features, we note that the social and environmental mechanisms that influence facility placement may not act independently. In particular, the extent to which structural features—in this case network centrality—are predictive of the presence of IMBs may be contingent on broader socioeconomic contexts beyond the features that we measured on the level of census tracts. The nature of local economic activity may also have a moderating influence: In areas with a lack of legitimate businesses, and potentially a larger market for IMBs, there may be less of a need to avoid busy streets. Similarly, communities that lack political capital (or where law enforcement is weak) may struggle to exert their influence in such a way that IMBs are pushed to the margins; facilities are simply not motivated (or mandated) to avoid high-visibility areas. These differences are likely to reflect spatial inequality more broadly and, indeed, reinforce existing structures. Examining for interaction effects (between street segment features such as betweenness and socioeconomic features) would be a valuable topic for future research.

Notwithstanding these limitations and avenues for further research, the findings presented here have several important implications for the prevention of harms associated with IMBs. We have found that IMBs are located in places that, although accessible, exhibit a degree of removal from primary areas of routine activity and movement. This finding raises concerns that not only illicit commercial sex but also the serious victimization that the commercial sex industry is notoriously more vulnerable for, such as human trafficking, likely remain hidden. The fact that the spatial patterns differ from those of high-volume crimes means that policing strategies focused on those offenses (e.g., high-visibility hot-spot policing) are unlikely to have an effect on activity at IMBs. Furthermore, such locations do not benefit from the general guardianship effects associated with high levels of legitimate activity. In this sense, such facilities are ideally placed to keep their activities concealed while retaining the functional benefits of central locations. Our work draws attention to the importance of considering the wider ecological settings, specifically here the infrastructural relations, to better understand the geographical settings where hard-to-observe events such as illicit commercial sex—and potentially human trafficking—occur (Cockbain et al., 2022).

A key question, therefore, concerns which types of intervention will be most effective in preventing illicit and victimizing behaviors in these locations. Current policing strategies, which are often reactive—in the sense that they respond to citizen concerns rather than proactively addressing underlying causes and vulnerabilities—have proven to be ineffective, and potentially even harmful. Not only do these strategies often lack a victim-centered approach, but shutdowns of IMBs—a common police and municipality response to the existence of IMBs—are ineffective since many IMBs simply displace to alternative premises, or even reopen at the same location (de Vries, 2020; de Vries & Farrell, 2023). Rather than this short-term approach, problem-oriented strategies are needed to identify and address the structural factors that allow these facilities to thrive, as well as to thrive in these places specifically. These types of strategies have consistently been found to be successful in addressing a range of crime problems (Hinkle et al., 2020), including many relating to crime-hosting venues, and the characteristics of IMBs mean that they would represent a natural application. Problem-oriented strategies address the specific areas where illegitimately operating facilities tend to thrive, which in the context of IMBs are discreet areas (low betweenness) spatially proximate to busier/more visible areas (high local betweenness). Those responsible for crime prevention and crime control (e.g., police, city planners, and residents) should thus consider places "around the corner" from busier districts.

Problem-oriented strategies in relation to IMBs may be informed by previous work concerning similar facilities. Bichler et al. (2013), for example, reported a strategy aimed to address the problem of "nuisance motels" in California; these were motels that hosted large volumes of criminal activity, including commercial sex. The intervention included focused enforcement of city codes toward problem locations, ultimately progressing to the introduction of operating permits for such locations. A more recent example, which was originally applied with respect to violence but that has natural analogies with this work, involves the investigation of "place networks" (Eck et al., 2023). Place networks are sets of locations interlinked in terms of their use and that together contribute to crime problems: Although the problem itself may only manifest in one of the locations (e.g., a drug market), the others play a role in facilitating it (e.g., supply locations, local stores). Such a configuration exemplifies the phenomenon whereby local infrastructure provides an environment conducive to crime. Successful previous efforts to tackle such networks have involved coordinated efforts across multiple agencies, including building code enforcement, traffic interventions, and business generation (Hammer et al., 2017). Knowing where such facilities tend to locate is the first step in attempting to apply such strategies in this context, making certain places less attractive (and profitable) for crime-hosting venues.

Identifying vulnerable locations is also an essential first step for implementing outreach strategies to further identify the harms caused by these facilities. Police monitoring could be one approach, although recent work has suggested the need to partner with victim services and community organizations that may be better positioned to identify the underlying conditions of crime (Weisburd et al., 2015). Agencies outside the criminal justice system may need to have a particularly prominent role, given the historically poor and complex relation between the police and the commercial sex industry in the United States (Farrell & Cronin, 2015; Farrell et al., 2019). We encourage a combination of qualitative and quantitative research to further disentangle the presence and geographies of human trafficking and other victimizing events with which the illicit commercial sex industry is commonly associated (see also Cockbain et al., 2022).

In the even longer term, our findings may have implications for the design and planning of cities. Here we have found that segments that are simultaneously central but unlikely to receive high levels of traffic themselves—such as alleyways or service roads off busy streets—are conducive to this particular form of illicit activity. One natural implication might therefore be to try to avoid such structures when designing future cities, in the same way as planning guidelines for new housing developments have suggested that criminogenic configurations—such as permeable, grid-like structures—are avoided (Cozens, 2008). Whether such a strategy is beneficial, however, depends crucially on the question of causality: whether such configurations give rise to crime that would otherwise not take place, or whether they simply determine *where* it takes place. Such questions—which are common to research on the relationship between urban morphology and crime—will be important topics for future research.

Although it would be hoped that such strategies would result in the harms associated with IMBs being prevented, displacement is nevertheless a possibility. In this context, the consequences of potential spatial displacement should be considered; that is, where IMBs might otherwise locate if not in the places—central but somewhat removed—that they were found to in this study. One possibility is that they may be driven further "underground" to less accessible and visible places. Considering the nature of the associated harm, such a change may well even exacerbate the problem and would certainly not be a desirable outcome. On the other hand, an intriguing possibility is that IMBs may begin to move toward the more central areas occupied by legitimate retail businesses. Such a move may come as part of a "legitimization" of massage businesses, whereby the legal services they provide become less stigmatized, while illicit and potentially victimizing services are eliminated. From a harm-reduction perspective, this "nothing-to-hide" approach would be beneficial, although it would bring other policy challenges that lie beyond the scope of this article.

In conclusion, this research has shown that the placement of IMBs is strongly associated with urban form in a way that signals the kind of structural and environmental conditions under which such businesses thrive: accessibility *and* discretion. The pattern of risk for this form of crime differs substantially from that which has been identified for acquisitive and violent crimes, and this can be rationalized in terms of the different theoretical mechanisms at play. Furthermore, IMBs are not like other retail businesses: Although they seem to be subject to similar economic forces to some extent, they avoid prominent locations (and may indeed rely on online promotion as a replacement for physical visibility). These findings improve our understanding of the behavior of IMB proprietors and the conditions that facilitate illegitimately operating facilities. Altogether, our findings provide opportunities to inform problem-oriented approaches to address the harms associated with such businesses.

ORCID

Ieke de Vries https://orcid.org/0000-0002-9306-7620

REFERENCES

Alessandretti, L., Aslak, U., & Lehmann, S. (2020). The scales of human mobility. *Nature*, *587*(7834), 402–407.

Andresen, M. A. (2019). *Environmental criminology: Evolution, theory, and practice*. Routledge.

Baran, P. K., Smith, W. R., & Toker, U. (2006). *Conflict between space and crime: Exploring the relationship between spatial configuration and crime location* [Paper presentation]. Environmental Design Research Association (EDRA) 37th Annual Conference, Atlanta, GA.

Baran, P. K., Smith, W. R., & Toker, U. (2007). The space syntax and crime: Evidence from a suburban community. In A. S. Kubat, O. Ertekin, Y. I. Guney, & E. Eyuboglu (Eds.), *Proceedings of the 6th International Space Syntax Symposium*, Istanbul, Turkey.

Bates, D., Maechler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1–48.

Beavon, D. J., Brantingham, P. L., & Brantingham, P. J. (1994). The influence of street networks on the patterning of property offenses. *Crime prevention studies*, *2*, 115–148.

Bernasco, W. (2019). Adolescent offenders' current whereabouts predict locations of their future crimes. *PLOS ONE*, *14*(1), e0210733.

Bernasco, W., & Block, R. (2011). Robberies in Chicago: A block-level analysis of the influence of crime generators, crime attractors, and offender anchor points. *Journal of Research in Crime and Delinquency*, *48*(1), 33–57.

Bevis, C., & Nutter, J. (1977). *Changing street layouts to reduce residential burglary*. Minnesota Crime Prevention Center.

Bichler, G., Schmerler, K., & Enriquez, J. (2013). Curbing nuisance motels: An evaluation of police as place regulators. *Policing: An International Journal of Police Strategies & Management*, *36*(2), 437–462.

Blau, P. M. (1977). A macrosociological theory of social structure. *American Journal of Sociology*, *83*(1), 26–54.

Boeing, G. (2017). OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. *Computers, Environment and Urban Systems*, *65*, 126–139.

Boessen, A., & Hipp, J. R. (2015). Close-ups and the scale of ecology: Land uses and the geography of social context and crime. *Criminology*, *53*(3), 399–426. Advance online publication. https://doi.org/10.1111/1745-9125.12074
Bouché, V., & Crotty, S. M. (2018). Estimating demand for illicit massage businesses in Houston, Texas. *Journal of Human Trafficking*, *4*(4), 279–297.
Brantingham, P., & Brantingham, P. (1993a). Environment, routine and situation: Toward a pattern theory of crime. *Advances in Criminological Theory*, *5*(2), 259–294.
Brantingham, P., & Brantingham, P. (1993b). Nodes, paths and edges: Considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology*, *13*(1), 3–28.
Chin, J. J., Kim, A. J., Takahashi, L., & Wiebe, D. J. (2015). Do sexually oriented massage parlors cluster in specific neighborhoods? A spatial analysis of indoor sex work in Los Angeles and Orange Counties, California. *Public Health Reports*, *130*(5), 533–542.
Chin, J. J., Takahashi, L. M., & Wiebe, D. J. (2023). Where and why do illicit businesses cluster? Comparing sexually oriented massage parlors in Los Angeles County and New York City. *Journal of Planning Education and Research*, *43*(1), 106–121.
Cockbain, E., Bowers, K., & Hutt, O. (2022). Examining the geographies of human trafficking: Methodological challenges in mapping trafficking's complexities and connectivities. *Applied Geography*, *139*, 102643.
Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review*, *44*(4), 588–608.
Cozens, P. M. (2008). New urbanism, crime and the suburbs: A review of the evidence. *Urban Policy and Research*, *26*(4), 429–444.
Crotty, S. M., & Bouché, V. (2018). The red-light network: Exploring the locational strategies of illicit massage businesses in Houston, Texas. *Papers in Applied Geography*, *4*(2), 205–227.
Cui, C., & Han, Z. (2015). *Spatial patterns of retail stores using POIs data in Zhengzhou, China* [Paper presentation]. 2015 2nd IEEE International Conference on Spatial Data Mining and Geographical Knowledge Services (ICSDM), Fuzhou, China.
Curtis-Ham, S., Bernasco, W., Medvedev, O. N., & Polaschek, D. L. L. (2021). A national examination of the spatial extent and similarity of offenders' activity spaces using police data. *ISPRS International Journal of Geo-Information*, *10*(2), 47.
Davies, T., & Bowers, K. J. (2018). Street networks and crime. In G. J. Bruinsma & S. D. Johnson (Eds.), *The Oxford handbook of environmental criminology*. Oxford University Press.
Davies, T., & Johnson, S. D. (2015). Examining the relationship between road structure and burglary risk via quantitative network analysis. *Journal of Quantitative Criminology*, *31*(3), 481–507.
Davies, T. P., & Bishop, S. R. (2013). Modelling patterns of burglary on street networks. *Crime Science*, *2*(1), 10.
de Vries, I. (2020). *Crime, place, and networks in the age of the internet: The case of online-promoted illicit massage businesses*. Northeastern University Press.
de Vries, I. (2023a). Examining the geography of illicit massage businesses hosting commercial sex and sex trafficking in the United States: The role of census tract and city-level factors. *Crime & Delinquency*, *69*(11), 2218–2242. SAGE.
de Vries, I. (2023b). A network approach to examine neighborhood interdependence through the target selection of repeat buyers of commercial sex in the United States. *Deviant Behavior*, *44*(6), 876–899. Advance online publication. https://doi.org/10.1080/01639625.2022.2110542
de Vries, I., & Farrell, A. (2023). Explaining the use of traditional law enforcement responses to human trafficking concerns in illicit massage businesses. *Justice Quarterly*, *40*(3), 337–362.
de Vries, I., & Radford, J. (2022). Identifying online risk markers of hard-to-observe crimes through semi-inductive triangulation: The case of human trafficking in the United States. *The British Journal of Criminology*, *62*(3), 639–658.
Dear, M. (1992). Understanding and overcoming the NIMBY syndrome. *Journal of the American Planning Association*, *58*(3), 288–300. Advance online publication. https://doi.org/10.1080/01944369208975808
Eck, J. E. (1995). A general model of the geography of illicit retail marketplaces. *Crime and Place*, *4*, 67–93.
Eck, J. E., Linning, S. J., & Herold, T. D. (2023). The extended place manager II: Hidden crime-involved places and place networks. In J. E. Eck, S. J. Linning, & T. D. Herold (Eds.), *Place management and crime: Ownership and property rights as a source of social control* (pp. 67–77). Springer International.

Farrell, A., & Cronin, S. (2015). Policing prostitution in an era of human trafficking enforcement. *Crime, Law and Social Change*, *64*(4), 211–228.

Farrell, A., Dank, M., de Vries, I., Kafafian, M., Hughes, A., & Lockwood, S. (2019). Failing victims? Challenges of the police response to human trafficking. *Criminology & Public Policy*, *18*(3), 649–673.

Farrell, A., & de Vries, I. (2020). Measuring the nature and prevalence of human trafficking. In J. Winterdyk & J. Jones (Eds.), *The Palgrave international handbook of human trafficking* (pp. 147–162). Palgrave Macmillan.

Felson, M. (1987). Routine activities and crime prevention in the developing metropolis. *Criminology*, *25*(4), 911–932.

Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry*, *40*(1), 35–41.

Hammer, M., Christenson, B., & Madensen, T. D. (2017). *PIVOT: Place-based investigations of violent offender territories* [Technical report]. Cincinnati Police Department.

Han, Z., Cui, C., Miao, C., Wang, H., & Chen, X. (2019). Identifying spatial patterns of retail stores in road network structure. *Sustainability*, *11*(17), 4539.

Hillier, B., & Hanson, J. (1984). *The social logic of space*. Cambridge University Press.

Hillier, B., & Sahbaz, O. (2005). *High resolution analysis of crime patterns in urban street networks: an initial statistical sketch from an ongoing study of a London borough* [Paper presentation]. 5th International Space Syntax Symposium, Delft, The Netherlands.

Hinkle, J. C., Weisburd, D., Telep, C. W., & Petersen, K. (2020). Problem-oriented policing for reducing crime and disorder: An updated systematic review and meta-analysis. *Campbell Systematic Reviews*, *16*(2), e1089.

Hollis, M. E., Felson, M., & Welsh, B. C. (2013). The capable guardian in routine activities theory: A theoretical and conceptual reappraisal. *Crime Prevention and Community Safety*, *15*(1), 65–79.

Holt, T. J., & Blevins, K. R. (2007). Examining sex work from the client's perspective: Assessing johns using on-line data. *Deviant Behavior*, *28*(4), 333–354.

Holt, T. J., Blevins, K. R., & Kuhns, J. B. (2008). Examining the displacement practices of johns with on-line data. *Journal of Criminal Justice*, *36*(6), 522–528.

Holt, T. J., Blevins, K. R., & Kuhns, J. B. (2014). Examining diffusion and arrest avoidance practices among johns. *Crime & Delinquency*, *60*(2), 261–283.

Hubbard, P. (2013). Out of touch and out of time? The contemporary policing of sex work. In R. Campbell & M. O'Neill (Eds.), *Sex work now* (pp. 22–53). Willan.

Hubbard, P., Boydell, S., Crofts, P., Prior, J., & Searle, G. (2013). Noxious neighbours? Interrogating the impacts of sex premises in residential areas. *Environment and Planning A*, *45*(1), 126–141.

Hubbard, P., & Sanders, T. (2003). Making space for sex work: Female street prostitution and the production of urban space. *International Journal of Urban and Regional Research*, *27*(1), 75–89. Advance online publication. https://doi.org/10.1111/1468-2427.00432

Huff, J., Wallace, D., Riggs, C., Katz, C. M., & Choate, D. (2018). Examining the association between massage parlors and neighborhood crime. *Crime & Delinquency*, *65*(11), 1537–1569.

Jacobs, J. (1961). *The life and death of great American cities*. Random House.

Jensen, P. (2006). Network-based predictions of retail store commercial categories and optimal locations. *Physical Review E*, *74*(3), 035101.

Jensen, P. (2009). Analyzing the localization of retail stores with complex systems tools. In N. M. Adams, C. Robardet, A. Siebes, & J.-F. Boulicaut (Eds.), *IDA '09: Proceedings of the 8th International Symposium on Intelligent Data Analysis: Advances in intelligent data analysis VIII* (pp. 10–20). Springer.

Jiang, B. (2007). A topological pattern of urban street networks: Universality and peculiarity. *Physica A: Statistical Mechanics and its Applications*, *384*(2), 647–655.

Johnson, S. D., & Bowers, K. J. (2010). Permeability and burglary risk: Are cul-de-sacs safer? *Journal of Quantitative Criminology*, *26*(1), 89–111.

Kalapala, V., Sanwalani, V., Clauset, A., & Moore, C. (2006). Scale invariance in road networks. *Physical Review E*, *73*(2), 026130.

Karamshuk, D., Noulas, A., Scellato, S., Nicosia, V., & Mascolo, C. (2013). Geo-spotting: Mining online location-based services for optimal retail store placement. In R. Ghani, T. E. Senator, P. Bradley, R. Parekh, & J. He (Eds.), *KDD'13: Proceedings of the 19th ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 793–801). Association for Computing Machinery.

Kelsay, J. D., & Haberman, C. P. (2021). The influence of street network features on robberies around public housing communities. *Crime & Delinquency*, *67*(9), 1353–1380.

Kim, Y.-A., & Hipp, J. R. (2020). Pathways: Examining street network configurations, structural characteristics and spatial crime patterns in street segments. *Journal of Quantitative Criminology*, *36*, 725–752.

Kinney, J. B., Brantingham, P. L., Wuschke, K., Kirk, M. G., & Brantingham, P. J. (2008). Crime attractors, generators and detractors: Land use and urban crime opportunities. *Built Environment (1978-)*, *34*(1), 62–74.

Kubrin, C. E., Hipp, J. R., & Kim, Y.-A. (2018). Different than the sum of its parts: Examining the unique impacts of immigrant groups on neighborhood crime rates. *Journal of Quantitative Criminology*, *34*(1), 1–36.

Levy, J. M. (2016). *Contemporary urban planning*. Taylor & Francis.

Lin, G., Chen, X., & Liang, Y. (2018). The location of retail stores and street centrality in Guangzhou, China. *Applied Geography*, *100*, 12–20.

Logan, J. R., & Molotch, H. (2007). *Urban fortunes: The political economy of place, 20th anniversary edition, with a new preface*. University of California Press.

Lopez, J. J., Almquist, D., & Thomas, P. (2020). The geography of prostitution arrests in Virginia, USA, 2002–2013. *Crime, Law and Social Change*, *73*(2), 133–157.

Mahfoud, M., Bernasco, W., Bhulai, S., & van der Mei, R. (2021). Forecasting spatio-temporal variation in residential burglary with the integrated laplace approximation framework: Effects of crime generators, street networks, and prior crimes. *Journal of Quantitative Criminology*, *37*(4), 835–862.

Manson, S., Schroeder, J., Van Riper, D., & Ruggles, S. (2018). *National Historical Geographic Information System: Version 13.0*. IPUMS. </Dataset>.

Marcus, L. (2010). Spatial capital. *The Journal of Space Syntax*, *1*(1), 30–40.

Masucci, A. P., Smith, D., Crooks, A., & Batty, M. (2009). Random planar graphs and the London street network. *The European Physical Journal B*, *71*(2), 259–271.

Masur, P. K., & Scharkow, M. (2020). *specr: Conducting and visualizing specification curve analyses*. https://CRAN.R-project.org/package=specr

Matthews, R. (1990). Developing more effective strategies for curbing prostitution. *Security Journal*, *1*(3), 182–187.

Matthews, R. (1993). *Kerb-crawling, prostitution and multi-agency policing: Crime Prevention Unit Series Paper No. 43*. Crime Prevention Unit Series. Home Office.

Matthews, R. (2005). Policing prostitution: Ten years on. *The British Journal of Criminology*, *45*(6), 877–895.

Menting, B., Lammers, M., Ruiter, S., & Bernasco, W. (2020). The influence of activity space and visiting frequency on crime location choice: Findings from an online self-report survey. *The British Journal of Criminology*, *60*(2), 303–322.

Mletzko, D., Summers, L., & Arnio, A. N. (2018). Spatial patterns of urban sex trafficking. *Journal of Criminal Justice*, *58*, 87–96.

Newman, O. (1972). *Defensible space: Crime prevention through urban design*. Macmillan.

Omer, I., & Goldblatt, R. (2016). Spatial patterns of retail activity and street network structure in new and traditional Israeli cities. *Urban Geography*, *37*(4), 629–649.

Ozuduru, B. H., Webster, C. J., Chiaradia, A. J. F., & Yucesoy, E. (2021). Associating street-network centrality with spontaneous and planned subcentres. *Urban Studies*, *58*(10), 2059–2078.

Perkins, D. D., Wandersman, A., Rich, R. C., & Taylor, R. B. (1993). The physical environment of street crime: Defensible space, territoriality and incivilities. *Journal of Environmental Psychology*, *13*(1), 29–49.

Polaris. (2018). *Human trafficking in illicit massage businesses* [Technical report].

Polaris. (2021). *Polaris Analysis of 2021 data from the National Human Trafficking Hotline* [Technical report].

Porta, S., Crucitti, P., & Latora, V. (2006a). The network analysis of urban streets: A dual approach. *Physica A: Statistical Mechanics and its Applications*, *369*(2), 853–866.

Porta, S., Crucitti, P., & Latora, V. (2006b). The network analysis of urban streets: A primal approach. *Environment and Planning B: Planning and Design*, *33*(5), 705–725.

Porta, S., Latora, V., Wang, F., Rueda, S., Strano, E., Scellato, S., Cardillo, A., Belli, E., Càrdenas, F., Cormenzana, B., & Latora, L. (2012). Street centrality and the location of economic activities in Barcelona. *Urban Studies*, *49*(7), 1471–1488.

Porta, S., Latora, V., Wang, F., Strano, E., Cardillo, A., Scellato, S., Iacoviello, V., & Messora, R. (2009). Street centrality and densities of retail and services in Bologna, Italy. *Environment and Planning B: Planning and Design*, *36*(3), 450–465.

R Core Team. (2021). *R: A language and environment for statistical computing. R Foundation for Statistical Computing*.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (Vol. 1). SAGE.
Reynald, D. M., & Elffers, H. (2009). The future of Newman's defensible space theory: Linking defensible space and the routine activities of place. *European Journal of Criminology*, *6*(1), 25–46.
Schively, C. (2007). Understanding the nimby and lulu phenomena: reassessing our Knowledge Base and Informing Future Research. *Journal of Planning Literature*, *21*(3), 255–266.
Schneider, M. (1989). *The competitive city: The political economy of suburbia*. University of Pittsburgh Press.
Scoppa, M. D., & Peponis, J. (2015). Distributed attraction: The effects of street network connectivity upon the distribution of retail frontage in the city of Buenos Aires. *Environment and Planning B: Planning and Design*, *42*(2), 354–378.
Simonsohn, U., Simmons, J. P., & Nelson, L. D. (2020). Specification curve analysis. *Nature Human Behaviour*, *4*(11), 1208–1214.
Summers, L., & Johnson, S. D. (2017). Does the configuration of the street network influence where outdoor serious violence takes place? Using space syntax to test crime pattern theory. *Journal of Quantitative Criminology*, *33*(2), 397–420.
Taylor, R. B., & Gottfredson, S. (1986). Environmental design, crime, and prevention: An examination of community dynamics. *Crime and Justice*, *8*, 387–416.
Wang, F., Antipova, A., & Porta, S. (2011). Street centrality and land use intensity in Baton Rouge, Louisiana. *Journal of Transport Geography*, *19*(2), 285–293.
Wang, F., Chen, C., Xiu, C., & Zhang, P. (2014). Location analysis of retail stores in Changchun, China: A street centrality perspective. *Cities*, *41*, 54–63.
Weisburd, D., Davis, M., & Gill, C. (2015). Increasing collective efficacy and social capital at crime hot spots: New crime control tools for police. *Policing: A Journal of Policy and Practice*, *9*(3), 265–274.
White, G. F. (1990). Neighborhood permeability and burglary rates. *Justice Quarterly*, *7*(1), 57–67.
Wilcox, P., & Cullen, F. T. (2018). Situational opportunity theories of crime. *Annual Review of Criminology*, *1*, 123–148.
Wo, J. C. (2019). Understanding the differential effects of land uses on crime: An examination across Philadelphia neighbourhoods. *The British Journal of Criminology*, *59*(6), 1432–1454.
Wu, X., Cao, W., Wang, J., Zhang, Y., Yang, W., & Liu, Y. (2022). A spatial interaction incorporated betweenness centrality measure. *PLOS ONE*, *17*(5), e0268203.
Yamaoka, K., Kumakoshi, Y., & Yoshimura, Y. (2021). Local betweenness centrality analysis of 30 European Cities. In S. C. M. Geertman, C. Pettit, R. Goodspeed, & A. Staffans (Eds.), *Urban informatics and future cities* (The Urban Book Series, pp. 527–547). Springer International.
Zhang, Y., Yang, B., Zhang, M., Zhang, G., Song, S., & Qi, L. (2019). Exploring location pattern of commercial stores in Shichahai, Beijing from a street centrality perspective. *Chinese Geographical Science*, *29*, 503–516.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: de Vries, I., & Davies, T. (2024). Understanding the role of street network configurations in the placement of illegitimately operating facilities. *Criminology*, 1–42. https://doi.org/10.1111/1745-9125.12381

APPENDIX A: REGRESSION ANALYSES FOR RETAIL BUSINESSES WITHOUT SUBSTANTIATED CONCERNS OF ILLEGITIMATE ACTIVITY

TABLE A1 Results from the optimal multilevel models for bars

	Bars (Model 1)			Bars (Model 2)		
Variable	*B*	**SE**	**OR**	*B*	**SE**	**OR**
Intercept	−1.684***	.089	.186	−1.634***	.087	.195
Level 1 (*N* = 3,220)						
Betweenness (log)	.128***	.023	1.136	−.869***	.146	.419
Local betweenness (log)	.408***	.075	1.504	−.290*	.119	.748
Betweenness × local betweenness				.092***	.014	1.097
Level 2 (*N* = 467)						
Population (log)	−.493**	.178	.611	−.471**	.178	.624
Concentrated disadvantage	−.393***	.098	.675	−.333**	.097	.717
Residential instability	.490***	.101	1.632	.444***	.101	1.558
Racial/ethnic heterogeneity	−3.175***	.573	.042	−3.191***	.572	.041
Income inequality	.671	.439	1.956	.621	.437	1.861
Commercial land use	.002	.004	1.002	.002	.004	1.002
Retail land use	.005	.003	1.005	.005	.003	1.005
Industrial land use	−.001	.003	.999	−.001	.003	.999
Residential land use	.001	.002	1.001	.001	.002	1.001
Primary road	.285	.177	1.330	.282	.176	1.326
Police within mile	.249	.204	1.283	.203	.204	1.225
Violent crime (per 1,000)	.021**	.008	1.021	.021**	.008	1.021
Random effects tracts σ^2	1.235			1.198		
	(1.111)			(1.095)		

Note. *B* = logit coefficient; SE = standard error; OR = odds ratio.
*$p < .05$; **$p < .01$; ***$p < .001$.

TABLE A2 Results from the optimal multilevel models for nail salons

	Nail Salons (Model 1)			Nail Salons (Model 2)		
Variable	*B*	**SE**	**OR**	*B*	**SE**	**OR**
Intercept	−1.307***	.087	.271	−1.333***	.092	.264
Level 1 (*N* = 2,576)						
Betweenness (log)	.087***	.024	1.091	−1.111***	.145	.329
Local betweenness (log)	.467***	.073	1.595	−.376**	.117	.686
Betweenness × local betweenness				.115***	.014	1.122
Level 2 (*N* = 547 (1); *N* = 553 (2))						
Population (log)	−.585***	.165	.557	−.534**	.183	.586
Concentrated disadvantage	−.101	.097	.904	.048	.106	1.049

(Continues)

TABLE A2 (Continued)

Variable	Nail Salons (Model 1)			Nail Salons (Model 2)		
	B	SE	OR	*B*	SE	OR
Residential instability	.215*	.098	1.240	.117	.107	1.124
Racial/ethnic heterogeneity	−2.184***	.592	.113	−2.269***	.632	.103
Income inequality	.918*	.462	2.503	.595	.486	1.813
Commercial land use	−.003	.004	.997	−.009	.005	.991
Retail land use	.005	.003	1.005	.006	.003	1.006
Industrial land use	−.003	.003	.997	−.009*	.004	.991
Residential land use	−.001	.002	.999	.002	.002	1.002
Primary road	−.423*	.182	.655	−.325	.195	.722
Police within mile	.342	.203	1.408	.260	.221	1.297
Violent crime (per 1,000)	−.004	.008	.996	.004	.009	1.004
Random effects tracts σ^2	1.614			1.992		
	(1.271)			(1.411)		

Note. Level 2 sample sizes may slightly differ due to the downsampling strategy explained in our "Analytical Strategy" section. *B* = logit coefficient; SE = standard error; OR = odds ratio.
$^*p < .05$; $^{**}p < .01$; $^{***}p < .001$.

TABLE A3 Results from the optimal multilevel models for grocery stores

Variable	Grocery Stores (Model 1)			Grocery Stores (Model 2)		
	B	SE	OR	*B*	SE	OR
Intercept	−1.135***	.083	.321	−1.122***	.082	.326
Level 1 (*N* = 1,300)						
Betweenness (log)	.078*	.030	1.081	−.987***	.201	.373
Local betweenness (log)	.502***	.088	1.651	−.324	.169	.723
Betweenness x local betweenness				.101***	.019	1.107
Level 2 (*N* = 408)						
Population (log)	−.699***	.153	.497	−.696***	.154	.499
Concentrated disadvantage	.206*	.090	1.229	.268**	.092	1.307
Residential instability	.055	.089	1.056	.028	.089	1.029
Racial/ethnic heterogeneity	−1.916***	.521	.147	−1.929***	.525	.145
Income inequality	.420	.407	1.522	.460	.414	1.584
Commercial land use	−.003	.004	.997	.004	.004	.996
Retail land use	.002	.003	1.002	.002	.003	1.002
Industrial land use	−.004	.003	.996	−.004	.003	.996
Residential land use	−.001	.002	.999	−.001	.002	.999
Primary road	.004	.162	1.004	−.037	.164	.964
Police within mile	−.153	.183	.858	−.209	.186	.811
Violent crime (per 1,000)	.015*	.006	1.015	.015*	.006	1.015
Random effects tracts σ^2	.146			.137		
	(.382)			(.369)		

Note. *B* = logit coefficient; SE = standard error; OR = odds ratio.
$^*p < .05$; $^{**}p < .01$; $^{***}p < .001$.

TABLE A4 Results from the optimal multilevel models for laundry services

Variable	Laundry Services (Model 1) *B*	SE	OR	Laundry Services (Model 2) *B*	SE	OR
Intercept	−1.370***	.101	.254	−1.305***	.098	.271
Level 1 ($N = 1{,}612$)						
Betweenness (log)	.179***	.033	1.196	−.849***	.235	.428
Local betweenness (log)	.693***	.103	2.000	−.091	.196	.913
Betweenness × local betweenness				.094***	.022	1.099
Level 2 ($N = 448$)						
Population (log)	−.564**	.186	.569	−.542**	.189	.581
Concentrated disadvantage	−.138	.107	.871	−.096	.109	.908
Residential instability	.139	.105	1.149	.098	.108	1.103
Racial/ethnic heterogeneity	−2.025***	.606	.132	−1.971**	.618	.139
Income inequality	1.263*	.521	3.535	1.359*	.530	3.891
Commercial land use	−.001	.004	.999	−.001	.004	.999
Retail land use	.003	.003	1.003	.003	.003	1.003
Industrial land use	.000	.004	1.000	.000	.004	1.000
Residential land use	.003	.002	1.003	.003	.002	1.003
Primary road	−.316	.192	.729	−.335	.197	.715
Police within mile	.078	.221	1.081	.036	.226	1.036
Violent crime (per 1,000)	.007	.008	1.007	.008	.008	1.008
Random effects tracts σ^2	.888			.967		
	(.942)			(.983)		

Note. *B* = logit coefficient; SE = standard error; OR = odds ratio.
$^*p < .05$; $^{**}p < .01$; $^{***}p < .001$.

APPENDIX B: INTERACTING BETWEENNESS AND LOCAL BETWEENNESS FOR RETAIL BUSINESSES WITHOUT SUBSTANTIATED CONCERNS OF ILLEGITIMATE ACTIVITY

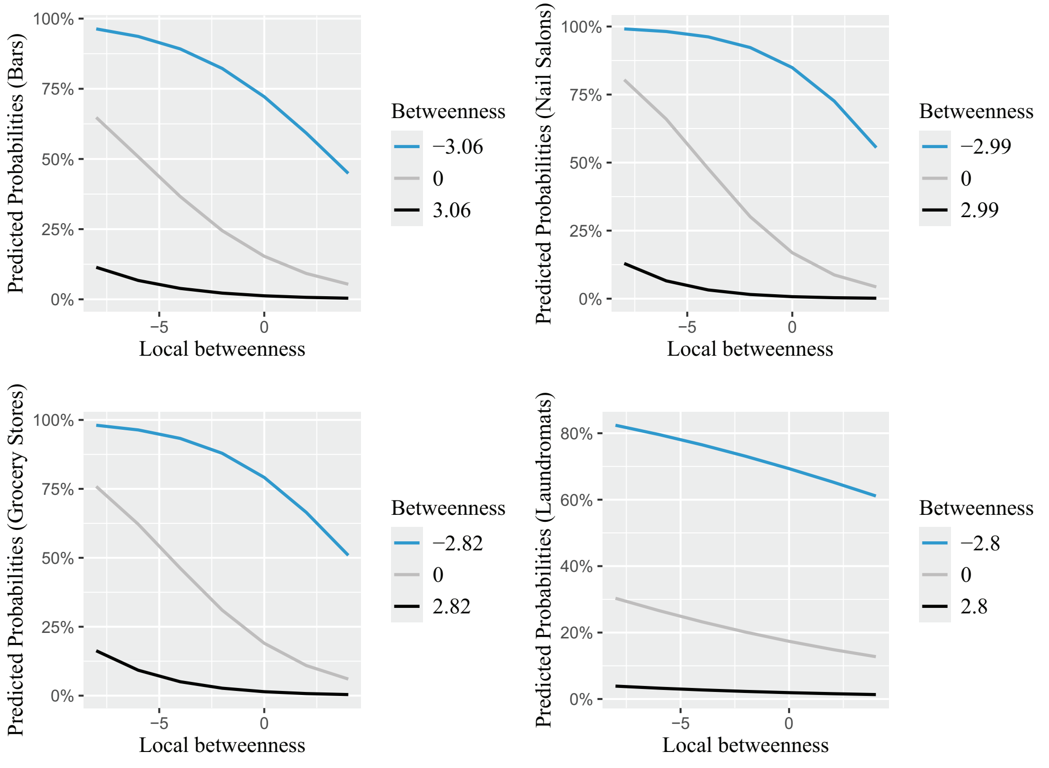
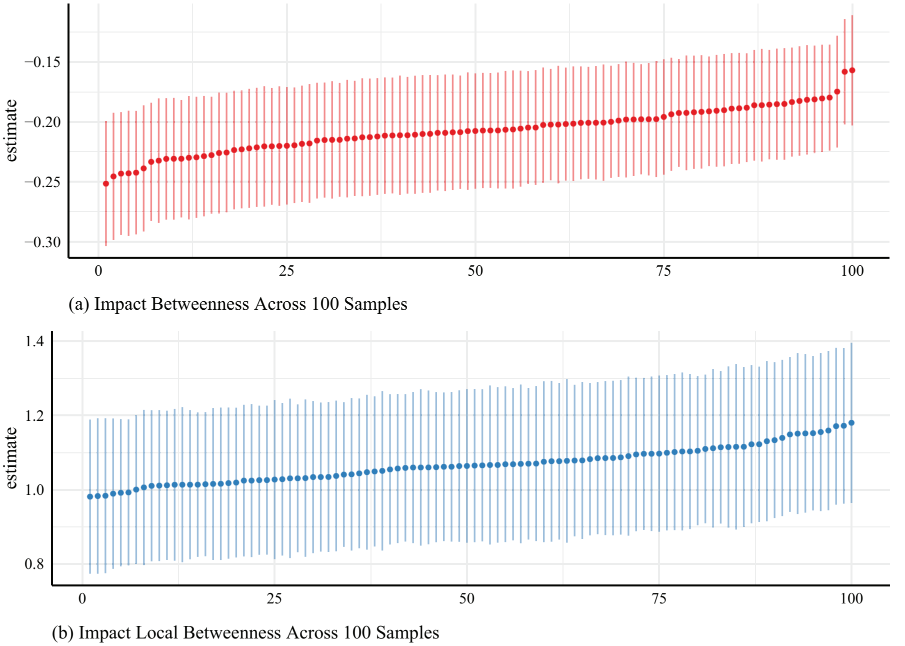


FIGURE B1 Interaction plots (betweenness × local betweenness) for retail businesses without substantiated concerns of illegitimate activity [Color figure can be viewed at wileyonlinelibrary.com]

APPENDIX C: ROBUSTNESS ANALYSES

To assess the robustness of our findings, we conducted sensitivity analyses using different procedures for matching business locations to their segments. Here we show results obtained when the matching was based purely on distance; that is, unlike the analysis shown in the main text, street names were ignored. We identified similar, albeit stronger, results for the placement of IMBs on street segments with low betweenness, yet high local betweenness, when using the distance-based method. Note, however, an ambiguity that arose when repeating this analysis for businesses without substantiated concerns of illegitimate activity. In these cases, the effect of betweenness is opposite to that found using the name-based matching method: The odds of having a retail business are *lower* on segments with higher betweenness centrality. When matching is done in this way, therefore, the effects are the same for both IMBs and retail businesses (although the effects of betweenness centrality are weaker for retail businesses).

An explanation for this difference might concern a limitation of using the distance-based method. When matching points to streets, often the street closest to a business does not match the address of the business and is not the actual street from where customers enter the business. This mismatch has particularly substantial consequences when the closest streets are alleys or service roads since these typically have low betweenness: If the address itself is on a high-betweenness segment, then a discrepancy will arise between the values derived in the two cases. Distance-based matching may then result in businesses being associated with lower betweenness segments (consistent with the negative effect in figures C2), whereas name-based matching will associate them with the higher betweenness segments where their entrances are located (consistent with the positive effect in figure 6). No such discrepancy would be expected for IMBs: Our name-based findings indicate that lower betweenness segments are favored anyway, matching instead to a service road or alley would make no material difference. Since name-based matching is more likely to represent the "true" locations of the businesses, we present this version in the main text. Nonethe-



(a) Impact Betweenness Across 100 Samples

(b) Impact Local Betweenness Across 100 Samples

FIGURE C1 Results from the specificity curve analyses (distance-based method). [Color figure can be viewed at wileyonlinelibrary.com]

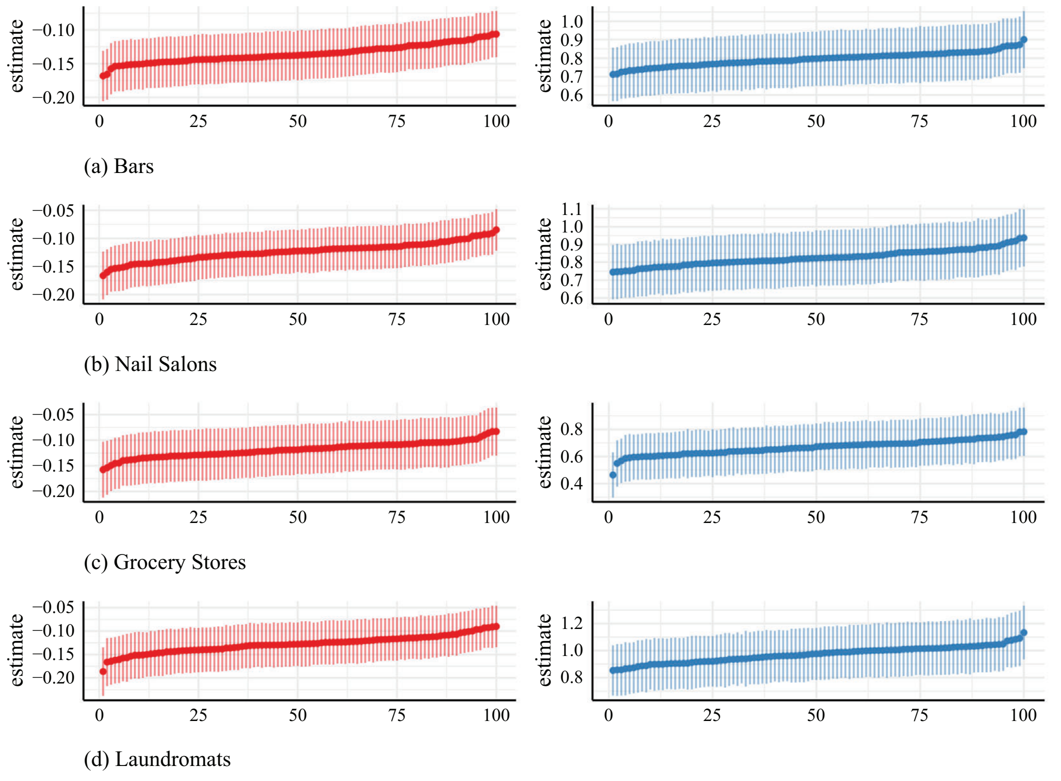


FIGURE C2 Specificity curves for betweenness (left) and local betweenness (right) effects for retail businesses (distance-based method). [Color figure can be viewed at wileyonlinelibrary.com]

less, our findings in relation to our main issue of interest—the placement of IMBs—are consistent across both approaches. IMBs are most likely to be placed on streets with low betweenness, yet high local betweenness. The combined effects of low betweenness and high local betweenness, however, are insignificant in the models based on the distance-based matching procedures most likely because of introducing inaccuracies due to linking IMBs to segments most proximate in technical terms but do not represent the segments from where buyers enter IMBs.

AUTHOR BIOGRAPHIES

Ieke de Vries is an assistant professor in criminology at the Institute of Criminal Law and Criminology at Leiden University. She applies both qualitative and quantitative analyses to advancing knowledge on the social ecology and the urban aspects of crime and victimization, victimization risk, and human trafficking.

Toby Davies is an associate professor in criminal justice data analytics at the University of Leeds. He is a quantitative criminologist, and his research interests include the modeling of crime patterns in space and time, the influence of urban structure on the distribution of crime, and network analysis.