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Deviant Behavior

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/udbh20

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To cite this article: Ieke de Vries (2022): A Network Approach to Examine Neighborhood Interdependence Through the Target Selection of Repeat Buyers of Commercial Sex in the United States, Deviant Behavior, DOI: 10.1080/01639625.2022.2110542

To link to this article: https://doi.org/10.1080/01639625.2022.2110542

Published online: 26 Aug 2022.

DEVIANT BEHAVIOR
https://doi.org/10.1080/01639625.2022.2110542

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ABSTRACT

The geographic concentration and diffusion of crime and deviancy are long-standing criminological inquiries, yet few studies have examined how certain illicit behaviors transcend neighborhood borders and connect neighborhoods in patterns of crime and deviancy. A structural neighborhood interdependence may account for the enduring nature and spread of crime, making it critical to understand how neighborhoods are connected in crime patterns to guide crime prevention and disruption efforts. This study examines neighborhood interdependence through the case of repeat buyers of commercial sex in illicit massage businesses in a metropolitan city in the United States. By frequenting venues for illicit commercial sex in multiple neighborhoods, buyers create inter-neighborhood connections through which the demand for an illicit market can spread across neighborhoods. Using online review data about buyers of commercial sex, this study analyzes this neighborhood interdependence as a network comprised of nodes ("neighborhoods") and edges ("connections between neighborhoods"). Exponential random graph models were used to analyze how characteristics of neighborhoods, the space between neighborhoods, and the overall network of neighborhoods explain inter-neighborhood connectivity in an illicit market for commercial sex. The implications for research, policy, and practice will be discussed.

ARTICLE HISTORY
Received 17 October 2021
Accepted 1 August 2022

Introduction

The spatial and geographic patterning of crime and deviancy is central to an environmental criminology (Andresen 2019; Wortley, Mazerolle, and Rombouts 2016). In particular, extant research has addressed the concentration, diffusion, and displacement of crime and deviancy, in regard to which ample evidence on the spatial concentration of crime (Lee et al. 2017; Weisburd 2015) has informed targeted crime control and crime prevention strategies such as hot spots policing or focused deterrence (Braga et al. 2019). Such targeted efforts have been associated with crime reductions, with generally little evidence of crime displacement (Bowers et al. 2011; Braga et al. 2019; Clarke and Weisburd 1994; Weisburd et al. 2006). However, a structural neighborhood interdependence may challenge the effectiveness of certain local intervention strategies by providing the avenues through which crime can spread across neighborhoods (Short et al. 2010). This study seeks to contribute to a better understanding of neighborhood interdependence by focusing on illicit behaviors that transcend neighborhood boundaries.

Although some connections between neighborhoods are strictly spatial through the streets and intersections that create physical pathways from one area to another (Davies and Bowers 2018; Frith, Johnson, and Fry 2017; Porta, Crucitti, and Latora 2006a, 2006b), neighborhoods also become

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symbolically connected through behaviors that transcend neighborhood boundaries (Sampson 2004). This type of neighborhood interdependence can also emerge when illicit behaviors transcend neighborhood boundaries, which can connect neighborhoods in patterns of crime and deviancy in the following ways. First, inter-neighborhood connections can emerge through co-offending ties between offenders that reside in different neighborhoods (e.g., Bastomski, Brazil, and Papachristos 2017; Papachristos and Bastomski 2018; Schaefer 2012). Previous work has demonstrated that these types of inter-neighborhood connections can facilitate a spatial diffusion of crime (Papachristos and Bastomski 2018).

Second, inter-neighborhood connections can result from the spatial mobility patterns of offenders, specifically with respect to their journeys to crime that connect origin to target areas (Rengert 1975, 2004). Previous work has underscored how the ecological and situational characteristics of the starting point (e.g., an offender's home), the distance traveled by an offender, and the direction in which the offender travels determine which areas most likely feature in these journeys to crime (Bernasco and Block 2009; Bernasco and Elffers 2010; Chamberlain and Boggess 2016; Rengert 2004). Although most studies have examined journeys to crime as independent routes, recent work has accumulated these journeys into a network that directly and indirectly connects neighborhoods and helps identify the most central convergent settings for offenders coming from different areas (e.g., Bichler, Malm, and Enriquez 2014).

Third, inter-neighborhood connections can emerge when repeat offenders engage in crime in multiple neighborhoods. Instead of focusing on journeys to crime from offenders' residences to target areas (e.g., Bernasco and Block 2009; Chamberlain and Boggess 2016), this third type of inter-neighborhood connectivity focuses on the destinations of crime of repeat offenders. Although navigating between multiple target areas can also represent a journey to crime if offenders visit these areas in immediate succession, this mobility pattern more likely represents an indirect pathway through which neighborhoods become involved in crime patterns (e.g., from a first target area via an offender's home to a second target area). As much as crime responses are most effective when focused on repeat offending (Braga et al. 2019), the target selections of repeat offenders can challenge interventions by creating a structural neighborhood interdependence through which crime can persist and displace or diffuse across a city.

This study examines the third type of inter-neighborhood connections, specifically unraveling their formation mechanisms, through unique data and an innovative analytical approach. Using online review data about the target selection of repeat buyers of illicit commercial sex in a metropolitan city in the South of the United States (U.S.), this study examines how neighborhoods are connected in an illicit market for commercial sex. Buyers (colloquially called "Johns") determine the demand for illicit sexual services, and their venue selection influences where illicit markets for commercial sex have the most potential to thrive (de Vries 2020; Martin et al. 2017). Furthermore, prior research has shown that a substantial group of buyers repeatedly engage in illicit commercial sex and explore different areas for doing so (Blevins and Holt 2009; Holt and Blevins 2007), which makes the target selection of buyers a compelling case for understanding how neighborhoods are connected in an illicit market.

The target selection of repeat buyers is being examined in the context of illicit massage businesses (IMBs), which are storefronts for illicit commercial sex that operate under the guise of massage businesses (Polaris 2018). Although different types of venues host commercial sex, IMBs have recently received heightened attention in public and policy discourse due to concerns about human trafficking and are now a main location for reported human trafficking victimizations (National Human Trafficking Hotline 2020).[1] These elevated concerns have triggered a series of traditional police responses such as shutdowns of IMBs and police crackdowns (de Vries 2020; de Vries and Farrell 2022) despite criticism on the limited effectiveness of traditional law enforcement tactics (Nagin 2013; Weisburd and Majmundar 2018), especially in the context of human trafficking (de Vries and Farrell

[1]Various other crimes and victimizations concentrate in IMBs, such as abuse and violence by buyers, assaults, exposure to robberies, and organized crime (Dank et al. 2014; Polaris 2018).

2022; Farrell et al. 2019). In addition, previous work warns for a displacement and diffusion of IMBs and buyer demand after shutdowns of IMBs (de Vries 2020; de Vries and Farrell 2022), alluding to the market's velocity and resiliency to such interventions. Because neighborhood interdependence may facilitate displacement and diffusion, this study examines how buyers connect neighborhoods in an illicit market for commercial sex.

The empirical approach involves the modeling of neighborhoods as a network that is comprised of neighborhoods as the "nodes" and the socio-spatial relations as the "edges" (see also Bastomski, Brazil, and Papachristos 2017; Bichler, Malm, and Enriquez 2014; Papachristos and Bastomski 2018; Schaefer 2012). These edges represent the connections between neighborhoods that exist because buyers engaged in commercial sex in different neighborhoods. Statistical network analytical techniques, specifically exponential random graph models (ERGMs), were used to identify how neighborhood characteristics, the space between neighborhoods, and the network itself explain which inter-neighborhood connections emerge. Before further introducing the empirical approach and implications for policy and practice, the next two sections first provide background on the illicit market for commercial sex in the U.S. and a conceptual and theoretical foundation for the network approach through which inter-neighborhood connectivity can be examined.

Illicit commercial sex markets in the U.S. and buyer's risk of being arrested

Commercial sex has been illegal in the U.S. since the early 20th century when Congress passed the Suppression of the White Slave Traffic Act (Mann Act, 1910), which made the transportation of people across state lines for "prostitution, debauchery or any other immoral purposes" a federal crime. Individual states followed with legislation that outlawed any form of commercial sex (see, for a discussion, Farrell and Cronin 2015). With the criminalization of commercial sex, police – especially vice units – were mandated to enforce anti-prostitution laws through undercover investigations, sting operations, and arrests of sellers or buyers (Farrell and Cronin 2015; Hubbard 2013; Matthews 2005). However, the enforcement of anti-prostitution laws varies across states and has gradually shifted in focus over time.

Until a few decades ago, a prohibitionist view on commercial sex work dominated U.S. policies, problematizing commercial sex as a public order offense and promoting the criminalization and arrests of both buyers and providers (see, for a discussion, de Vries and Farrell 2019). With an emphasis on commercial sex as a social disorder and public nuisance, policing interventions aimed to reduce the visibility of commercial sex in public areas. For example, to manage incoming public nuisance concerns, police shut down businesses that hosted commercial sex or moved them away from residential areas to busier city areas to minimize the social impact on residents (Hubbard 2013; Hubbard et al. 2013; Matthews 1990, 1993).

Growing concerns about violence, abuse, and exploitation in the commercial sex industry have increasingly characterized legislation on the commercial sex industry since the 1990s. In particular, concerns about human trafficking were institutionalized by the Trafficking Victims Protection Act (TVPA) of 2000 as the first federal human trafficking statute that criminalized commercial sex acts "induced by force, fraud, or coercion, or in which the person induced to perform such an act has not attained 18 years of age" as human trafficking crimes (TVPA, 2000: Section 103, 8a). Notwithstanding the complexity and controversiality in debates on the association between commercial sex and sex trafficking (de Vries and Farrell 2019), new human trafficking laws reoriented policing efforts in several jurisdictions from traditional arrests of commercial sex workers toward strategies that target the demand for commercial sex (Hughes 2005; Shively et al. 2012) or disrupt trafficking operations (Farrell and Cronin 2015).

In this new policy landscape, buyers of commercial sex face an increased risk of being arrested, yet research provides ample evidence of their continued search for commercial sex venues across the U.S (Roe-Sepowitz et al. 2016, 2019). As shown in prior research, commercial sex advertisements, reviews, and forum posts facilitate this search by listing the venues that host commercial sex and including

detailed information about the sexual encounters of buyers (Blevins and Holt 2009; Holt and Blevins 2007; Sanders 2013). Besides documenting the presence of illicit commercial sex, these online domains allow buyers to be more strategic and geographically mobile (Holt, Blevins, and Kuhns 2008, 2014; Soothill and Sanders 2005). For example, qualitative research examining the content of reviews and forum posts about commercial sex demonstrates that buyers discuss concerns about law enforcement apprehension in more than a quarter of all online posts (Holt and Blevins 2007). The signaling of law enforcement presence can discourage buyers from going to areas with increased law enforcement monitoring (Holt, Blevins, and Kuhns 2008, 2014). Beyond relocations to avoid law enforcement detection, prior research suggests that a substantial group of buyers generally explore different areas when searching for commercial sex venues (Blevins and Holt 2009; Holt and Blevins 2007; Martin et al. 2017).

By selecting commercial sex venues in different neighborhoods, buyers essentially create symbolic pathways between these neighborhoods, which together account for a structural neighborhood interdependence in patterns of crime and deviancy. As further discussed below, a network approach is then a suitable approach to model the connections between neighborhoods.

A network approach to examine neighborhood interdependence

While extant work has examined target selection and journeys to crime (e.g., via discrete choice models, see Bernasco and Block 2009; Chamberlain and Boggess 2016; Johnson and Summers 2015), this study focuses on more complex neighborhood interdependence that results from the target selection of repeat offenders. Evaluating this interconnectivity requires the modeling of an intertwined set of connections between neighborhoods as a network, which is a relational presentation of a set of actors ("nodes") that are connected through a relation ("edge"). Nodes can be actors of any kind (e.g., individuals, businesses, locations). Here, the network comprises neighborhoods as the nodes that are connected through edges, which exist when an offender's illicit behaviors transcend neighborhood boundaries (see also Sampson 2004).

Prior research has applied a network approach to study the formation of such inter-neighborhood connections in the context of crime. To illustrate, a study by Schaefer (2012) examined youth co-offending networks using a sample of over 10,000 delinquent youths residing in Maricopa County, Arizona. A total of 3058 co-offending relationships between youths were identified, 72% of which transcended census tract boundaries because co-offending youths lived in different tracts. Similarly, Papachristos and Bastomski (2018) examined inter-neighborhood connections through co-arrest ties in Chicago between 1999–2004, also reporting that co-arrest ties traverse neighborhood boundaries at rather high levels (see also Bastomski, Brazil, and Papachristos 2017). As mentioned before, inter-neighborhood connections can also emerge through journeys to crime. For example, Bichler, Malm, and Enriquez (2014) utilized data about 5082 delinquent youths residing in Southern California to model trips from schools to self-nominated activity nodes where these youths chose to hang out. These trips resulted in a directed network where the nodes were schools and hangouts, respectively, and edges existed when at least one student from a particular school went to a hangout facility. This approach was used to identify which hangouts were central convergent settings for youths from different schools.

From a network perspective, the characteristics of three network elements can be used to explain the formation of inter-neighborhood connections: 1) Node attributes (i.e., characteristics of the neighborhoods); 2) edge attributes (i.e., characteristics of the connections between neighborhoods); 3) and network attributes (i.e., characteristics of the entire network). As such, a network approach supplements the neighborhood features that prior research has related to target selection by considering the space and overall relationality between neighborhoods. Relevant examples of each attribute type are discussed below.

Characteristics about nodes (neighborhoods) and edges (the space between neighborhoods)

The geographic and spatial characteristics of neighborhoods and the space between neighborhoods (e.g., distance) comprise the node and edge attributes in socio-spatial networks. To decide on relevant characteristics, prior work on target selection and journeys to crime has predominately drawn from ecological and situational theories of crime, especially social disorganization theory and crime opportunity theoretical perspectives (Bernasco and Block 2009; Bernasco and Luykx 2003; Chamberlain and Boggess 2016; Johnson and Summers 2015). These theories may also explain neighborhood interdependence that results from target selection. Moreover, previous work has deemed both theories relevant in explanations of the geography of commercial sex (Huff-Corzine et al. 2017; Lopez, Almquist, and Thomas 2020; Mletzko, Summers, and Arnio 2018), including the placement of venues that host commercial sex, such as IMBs (Chin, Takahashi, and Wiebe 2019; Crotty and Bouché 2018; de Vries 2022), or related facets of the commercial sex industry such as buyer behavior (Holt, Blevins, and Kuhns 2008, 2014). Although buyers of commercial sex in IMBs are limited to the neighborhoods with IMBs, these theories may help explain why buyers are drawn to certain neighborhoods more so than others.

Community opposition and informal social control

Social disorganization theory explains the concentration of crime by the level of informal social control within a neighborhood (Bursik 1988; Sampson and Groves 1989). The theory identifies several structural community factors that signal a neighborhood's social disorganization as they raise social barriers, limit social interaction, and decrease informal social control mechanisms that would otherwise help prevent and control criminality (Bursik 1988; Shaw and McKay 1942). Notwithstanding recent variations and important updates to the theory (see, for a review, Kubrin and Wo 2016), social disorganization is commonly measured through socio-demographic proxy indices such as concentrated disadvantage, racial/ethnic heterogeneity, and residential instability (Bursik 1988; Kubrin and Weitzer 2003; Roe-Sepowitz et al. 2019; Shaw and McKay 1942, 1969). These neighborhood characteristics have been associated with reduced social interaction and cohesion within neighborhoods, which would make it less likely that neighborhood residents collectively call out crime (Sampson and Groves 1989; Sampson, Raudenbush, and Earls 1997). Despite the theory's original focus on intra-community characteristics, recent work supports its applicability to explain why socially disorganized areas also attract offenders from outside areas via similar mechanisms: Neighborhoods become attractive target areas when their residents are less invested in their community and less apt to call the police upon suspicion of criminality (e.g., Bernasco and Block 2009, 2011; Chamberlain and Boggess 2016; Johnson and Summers 2015).

Low levels of community investment and informal social control may also explain why neighborhood residents are less likely to object to the presence of unwanted facilities such as sexually-oriented businesses (Edwards 2010), liquor stores (Snowden 2016), or IMBs generally (de Vries 2022) and are less likely to speak out against behaviors that tend to provoke strong local reactions such as purchasing commercial sex (Hubbard et al. 2013; Lopez, Almquist, and Thomas 2020). Against that background, buyers may be drawn to areas where they expect lower community opposition to purchasing commercial sex. Because these same factors may drive the target selection of repeat offenders, the relevance of social disorganization theory may extend to explaining a structural neighborhood interdependence.

Attractiveness, opportunity, and accessibility

While social disorganization theory emphasizes the factors that make a neighborhood less resilient to crime, crime opportunity theories draw attention to the choice-structuring features of areas that attract offenders and influence a decision to commit a crime (Cullen 2010; Wilcox and Cullen 2018). Within the framework of these theories, crime is an event that occurs within a choice framework of motivated offenders who weigh benefits against the risk and effort of crime (Clarke and Cornish 1985;

Cornish and Clarke 2014; Cullen 2010; Wilcox and Cullen 2018). Offenders can make a calculated decision about where and when to commit a crime based on geographic cues that signal illicit opportunities (e.g., open doors to signal the potential for burglaries), little risk to be detected, and limited effort (Brantingham and Brantingham 2013). In doing so, offenders weigh an area's attractiveness (assessed by anticipated rewards), opportunity (assessed by the likelihood of engaging in illicit behavior without getting caught), and spatial accessibility (Bernasco and Luykx 2003), using geographic cues they may observe in their routine use and awareness of an environment (Curtis-Ham et al. 2020; Wilcox and Cullen 2018).

As more specifically argued by routine activity theory, the places that attract crime operate as a "shared activity space" where the daily routines of suitable targets and offenders facilitate their convergence under weak capable guardianship (Felson 1987; Felson and Clarke 1995; Felson and Cohen 1980; Miró 2014). Capable guardians can be police or other entities exercising formal or informal social control and in whose physical or symbolic presence a crime is less likely to occur (Felson 1987; Felson and Clarke 1995; Felson and Cohen 1980). Routine activity theory thus places the target selection of offenders in a crime triangle where their own behaviors converge with the behaviors of suitable targets in time and space and raise little suspicion by potential capable guardians (Cohen & Felson, 1979; Felson 1987; Felson and Clarke 1995; Felson and Cohen 1980).

In line with routine activity theory, previous work suggests that illicit markets are most likely to flourish in areas where they are known to buyers and sellers and where there is little oversight or accountability by local guardians and place managers who may turn a blind eye to crime (Eck 1995a, 1995b; Felson 1987). By that logic, prior literature has explained the placement of IMBs in areas close to business districts and retail centers to attract a larger pool of potential buyers (Chin, Takahashi, and Wiebe 2019; Crotty and Bouché 2018; de Vries 2022). This assumes that buyers are drawn to business districts and retail centers in their routine travels or when they anticipate more commercial sex venues in these areas. The empirical literature on offender target selection demonstrates that proximity to business districts and retail centers indeed attracts offenders from outside areas (Bernasco and Luykx 2003; Lockwood 2007), including areas further afield (Vandevivier 2015).

Besides physical cues that signal rewards or risks, offenders may be drawn to spatially-proximate and easily-accessible areas as an effort-reducing strategy. The journeys-to-crime literature typically includes distance as a measure of accessibility and effort, often explaining why offenders tend to stay close to their residential areas (Rengert 1975, 2004). This aligns with a general social principle that we are more likely to socialize with others who are spatially proximate to us because it takes the least amount of effort (Blau 1977; Zipf 1949). Small distances can also be a proxy for an offender's relatively narrow awareness space (Brantingham and Brantingham 1993, 2013) or match their regular routines (Felson 1987; Felson and Clarke 1995; Felson and Cohen 1980; Miró 2014) and spatial distance adds a temporal constraint that impedes an offender's familiarity with other areas (Ratcliffe 2006). Ease of access to and familiarity with new target areas may also be facilitated through specific land use features, such as the presence of highways (Brantingham and Brantingham 2013). Highways have been associated with environments conducive to IMBs (de Vries 2022) or commercial sex (Aalbers and Sabat, 2012; Lopez, Almquist, and Thomas 2020) and sex trafficking in the U.S. (Mletzko, Summers, and Arnio 2018), potentially because they attract more buyers of commercial sex. As the target selections of repeat offenders accumulate into a structural neighborhood interdependence, the geographic features for attractiveness, opportunity and accessibility may also explain the interconnectivity between neighborhoods.

Characteristics about network formation processes

In addition to explaining interconnectivity between neighborhoods as a function of node and edge attributes, one can use the characteristics of preexisting connections to explain why new connections between neighborhoods form. In technical terms, inter-neighborhood connections can emerge as a

function of *endogenous network effects*, meaning that "a tie comes into place in response to the existing local social environment within which the two [actors] operate" (Lusher, Koskinen, and Robins 2013: 19, interpretation added).

The broader network literature proposes two central network mechanisms that can also explain tie formation between neighborhoods via specific clustering processes: preferential attachment and triad formation. First, preferential attachment captures the tendency to attract more of something one already has (e.g., popular people are more likely to attract friends in friendship networks), which stems from a general social network idea that "the rich get richer" (Barabási and Albert 1999; Merton 1968). For this study's neighborhood networks, preferential attachment indicates that a neighborhood's attractiveness increases as it becomes more centrally connected to an illicit market for commercial sex. New connections are then more likely to form with and between neighborhoods that already had many preexisting connections instead of other neighborhoods that operate in the periphery of the network, which may ultimately drive a core-periphery structure (Hunter 2007; Lusher, Koskinen, and Robins 2013).

Second, transitive closure reflects a general social mechanism that explains the emergence of new connections between two actors when they have a shared connection. In friendship networks, this network process is commonly described as "a friend of a friend is a friend" (Wasserman and Faust 1994). A similar logic can be applied to identifying new inter-neighborhood connections in neighborhood networks, where it refers to a greater probability for any two neighborhoods to be connected, when they share a connection with a third neighborhood (Schaefer 2012). To illustrate, this implies that a repeat offender is more inclined to engage in crime in both neighborhoods *A* and *B*, when other offenders have already linked A to *C*, and *B* to *C*. Similar to social networks (Schaefer and Marcum 2017), triad formation in neighborhood networks relies on a sense of familiarity and trust and signals a structural clustering of crime and deviancy among a select set of neighborhoods (see, for example, Schaefer 2012), which can expand an offender's individual awareness space by relying on the awareness space of others. In contrast to triad formation, two-paths (dyads) signal an exploration of new target areas, which may account for the diffusion of crime throughout a city (see, for example, Papachristos and Bastomski 2018).

Both network processes imply a more complex interdependency between neighborhoods than a spatial interdependency alone. While recent work has already challenged the traditional ecological approach that depicts neighborhoods as independent units by incorporating several inter-neighborhood spatial dynamics to explain target selection (e.g., accessibility to burglars in nearby neighborhoods, see Bernasco and Luykx 2003), the network processes proposed here involve social mechanisms that can also connect neighborhoods further afield in an illicit market by signaling attractiveness (through preferential attachment) and familiarity (through triad formation). These network processes allow offenders to identify new target areas beyond their awareness space, adding to other mechanisms that increase an offender's familiarity with target areas, such as venturing out to familiar locations (Brantingham and Brantingham 2013), locations with similar characteristics as the ones they are familiar to (Chamberlain and Boggess 2016), or locations where they previously committed crimes (Curtis-Ham et al. 2020),

The current study

This study applies a network approach to examine neighborhood interdependency in an illicit market for commercial sex through the target selection of repeat buyers of commercial sex. As noted before, a substantial group of buyers repeatedly engage in commercial sex and venture out to different neighborhoods to do so (Blevins and Holt 2009; Holt and Blevins 2007; Martin et al. 2017). By engaging in illicit behaviors in multiple neighborhoods, repeat buyers draw symbolic pathways between these neighborhoods through which the demand for an illicit market and deviant norms can persist and spread across geographic space.

The network in question comprises neighborhoods, any two of which are connected when a buyer frequented IMBs for commercial sex in both neighborhoods. In line with the network approach described in the previous section, the probability that neighborhoods are connected is estimated as a function of the attributes of nodes (i.e., neighborhoods), edges (i.e., the connections between neighborhoods), and the overall network of neighborhoods.

Stated formally, the key hypotheses on the node and edge levels project: 1) a positive impact of node attributes that social disorganization theory associates with lower informal social control and less community opposition to crime and deviancy, including concentrated disadvantage, population heterogeneity, and residential instability; 2) a positive impact of node attributes that crime opportunity theories, specifically routine activity theory, associate with an area's attractiveness (assessed by anticipated rewards through the availability of IMBs and proximity to retail centers) and accessibility (assessed by highways), but a negative impact of node attributes associated with increased risk (assessed by the presence of police); and 3) a negative impact of spatial distance between neighborhoods, here considered an edge attribute, as distance increases effort and reduces accessibility and familiarity of potential target areas. The fourth hypothesis on the network level projects positive effects of structural network features that capture the tendency toward preferential attachment and transitive closure as social mechanisms that can connect neighborhoods, both proximate and further afield, to an illicit market (discussed above). Through these hypotheses, this study fuses geographic and network concepts toward a broader understanding of how neighborhoods are connected in an illicit market for commercial sex.

Methods

Case study

Data were collected for Houston, Texas, as one of the largest metropolitan statistical areas in the U.S. that attracted more IMBs than most other cities. The city is a major hub for both commercial sex and sex trafficking (Bouché and Crotty 2018; Crotty and Bouché 2018; Farrell, McDevitt, and Fahy 2008), perhaps because of Houston's geo-economic conditions such as proximity to an international border and a sizable economic sector in sex-related businesses (Farrell, McDevitt, and Fahy 2008: 100). City officials and law enforcement officers in Houston seek to contain commercial sex and potential sex trafficking victimizations in IMBs primarily through its local ordinances and police interventions. Growing concerns about sex trafficking victimizations in IMBs have triggered several police crackdowns on IMBs and sting operations to arrest buyers, although recent research suggests that the risk for buyers to be arrested is still lower than for commercial sex providers (see e.g., Updegrove, Muftic, and Orrick 2019). Paying for commercial sex classifies as a state jail felony, while selling sex is considered a misdemeanor in Texas (Texas Penal Code, §43.021).

Data

Online location and review data of IMBs

This study relies on the addresses and reviews of 454 IMBs in Houston that were reviewed between January 2015 and December 2017 on a popular and publicly accessible national review board for sexual services in IMBs in the U.S.[2] Buyers use this review board to search for and review sexual services at massage parlors. IMBs are listed with their specific address (street and number, city, state, zip code) and user reviews provide additional information on the exterior and interior of the venue, the staff, and graphic details of their sexual encounters. While this online-generated sample may not represent all massage establishments that host illicit sexual services, these data offer a theoretically

[2]The name of the website was not mentioned to preserve the anonymity of the users, commercial sex providers, and locations where potential victimizations occur.

meaningful sample of active buyers and unique information on their target selection (see e.g., Holt, Blevins, and Kuhns 2008, 2014). The 454 IMBs had a total of 3426 reviews, which 1294 unique users posted. The addresses of IMBs, user-IDs of buyers, and the dates of online reviews were extracted from the website. The addresses were geocoded to longitudinal and latitudinal coordinates using Google's Place Automated Programming Interface (API) and then to census tracts within or intersecting with the city's borders using the U.S. Census Shapefiles. The use of census tracts mirrors recent work on the geographies of IMBs (Chin, Takahashi, and Wiebe 2019; Crotty and Bouché 2018; de Vries 2022).

Geospatial and population data

The geocoded online reviewdata were merged with geographically and, as far as possible, time-matching geospatial and population data about the census tracts in the city. Population data were obtained through the 2013–2017 American Community Survey (ACS), downloaded from the National Historical Geographic Information System (Manson, Schroeder, Van Riper, & Ruggles, 2018). Land use information was obtained through OpenStreetMaps, an open-source collaborative platform containing geospatial data. While OSM does not include precise land use estimates, it offers a readily available and relatively reliable presentation of land use (e.g., Arsanjani et al. 2015). As a proxy measure for police presence, the geographical coordinates of police stations were obtained through Google's Place API in and around the Houston area. These coordinates were then used to calculate the shortest distance from a census tract to the nearest police station. Lastly, crime incident data were obtained through the Houston Police Department's (HPD) website. Monthly incident reports from 2017 were aggregated to one file containing an address range for incidents about aggravated assaults, auto theft, burglary, murder, rape, robbery, and theft.[3] Out of the 119,621 offenses, nearly all (99%) were successfully geocoded to the 2017 census tract shapefiles of the U.S. Census Bureau.

Constructing networks comprised of census tracts

These online data were used to construct a network of census tracts. Nodes represent tracts, and edges between any two tracts existed when buyers had frequented IMBs in both tracts. Given the temporal element of buyer behaviors, the edges are directed to account for the areas that buyers frequented first and to correctly measure temporal network mechanisms.

The network was constructed through the following three steps (see Figure 1). First, the online reviews were used to create a buyer-by-IMB edge list, which lists all buyers linked to the IMBs they had reviewed. Given this study's focus on repeat buyers, the sample of buyers was restricted to those buyers who reviewed at least two different IMBs. Nearly half of the buyers ($n = 634$, 49.00%) left reviews for multiple IMBs. Their reviews accumulated to a total of 2543 reviews (74.23% of the total number of reviews). On average, they left reviews for 4.01 different IMBs ($SD = 2.55$).[4] Second, using the dates associated with each review, the buyer-by-IMB edge list was transformed into an asymmetric one-mode IMB-by-IMB matrix, where each cell represents the number of buyers who first visited and posted a review about an IMB *A* (*origin*), followed by a review about IMB *A(destination)* (*A -> B*, see step 2 in Figure 1). A total of 1857 edges between IMBs were observed, representing 1800 *unique* edges.[5] Nearly all these connections transcended census tract borders ($n = 1778$; 98.78%). Third, IMBs were aggregated within tracts to create the final asymmetric one-mode, tract-by-tract, matrix. Here,

[3]The HPD only provides address ranges (e.g., Street name 100–199). These ranges occasionally cross tract borders. Therefore, both the lower and upper bounds were geocoded to tracts. The presented findings are based on the upper bounds. Sensitivity analyses with the lower bounds resulted in similar findings.

[4]Repeated visits to the *same* IMB were infrequent ($n = 349$ reviews) and therefore excluded from the analysis as their inclusion would unnecessarily complicate the interpretation of the findings.

[5]The directionality of 52 trips could not be determined due to reviews being posted on the same date. These few trips were removed from the analysis, resulting in the 2,869 connections between IMBs.

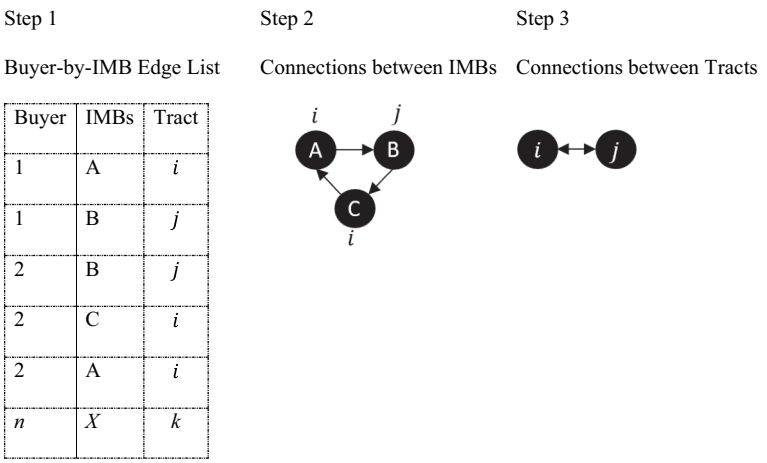

Figure 1. Schematic overview of the network construction.

each of the cells represents the number of buyers that frequented IMBs in tract *i* and subsequently tract *j* (see step 3 in Figure 1). This matrix defines the final network, encompassing a total of 1778 edges (see above) – 1643 *unique* edges – between 193 tracts that had IMBs. [6]

Table 1 presents the structural features of the final network. The density[7] indicates that the observed connections between tracts accounted for 4.4% of all possible connections. The diameter captures the longest observed path from one census tract to another and indicates that, if not directly, any two census tracts with IMBs were indirectly connected through a maximum of only six steps. The average path length was only 2.697 steps. The in-degree centrality ($D(n_i)$) captures the number of unique trips (edges, E) between tracts i and j ($D(n_i) = \sum_{j=1}^{E} I_{ij}$), which was about 8.5 on average and ranged from 0 (no connections, which was the case for four isolated census tracts with IMBs) to 47 (the most well-connected tract attracting buyers who also frequented IMBs in many other areas). Transitivity is calculated as the ratio between the number of observed triads and the total number

Table 1. Structural network measures of census tract networks.

Network feature	Network statistic
Graph Density	0.044
Diameter	6
Average Path Length	2.697
Mean In-Degree	8.513
(*sd*; *min* – *max*)	(8.157; 0–47)
Number of Isolates	4
Transitivity	0.247

[6]Other network constructions were considered but deemed insufficient for this study's purpose of understanding the connections between tracts. For example, the IMB-by-IMB matrix (step 2) would add granularity, but IMBs are here a less relevant unit because of this study's focus on neighborhood interdependence, geographic attributes, and the frequency by which buyers transcended tract boundaries.

[7]$\Delta = \frac{e}{(ct+(ct-1))/2}$, which refers to the sum of all edges (e) in the network, divided by the possible number of edges between all census tracts ct..

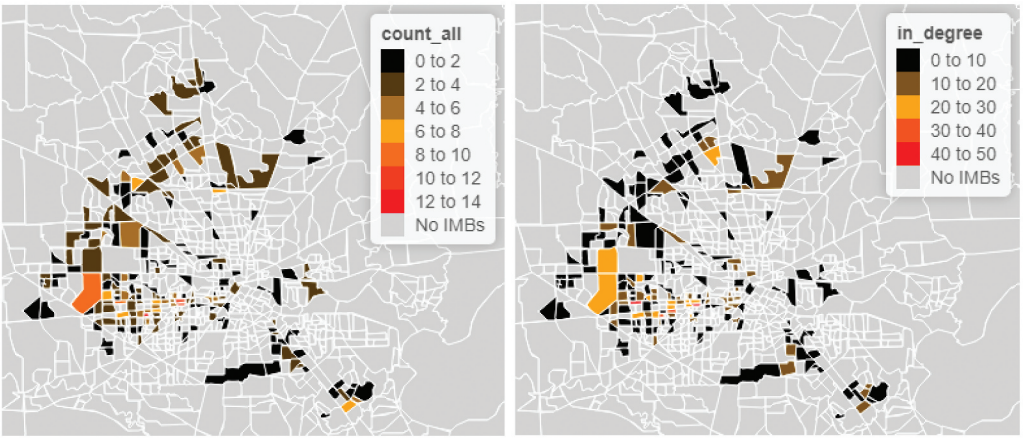

Figure 2. Geographic distribution of IMBs across census tracts (a) and distribution of in-degree centrality of census tracts (b).

of possible triads in the network between any tree nodes (i.e., n_i-n_j; n_i-n_k; and n_j-n_k). About 24.7% of the network's edges were part of a triad, suggesting that there may, in fact, be a tendency toward triad formation.

Figure 2 presents the geographical coverage of IMBs across census tracts (2a) along with the spatial distribution of in-degree centrality of tracts (2b). While the number of IMBs per tract corresponds to some degree with the distribution of in-degree centrality, it is important to note that these geographical coverages are not identical. The probability that buyers connect a new census tract in an illicit market for commercial sex may depend on spatial, geographic, and network measures, which will be introduced below.

Measures

Node attributes

A number of socio-demographic and spatial attributes were included to examine which spatial and geographic tract features affect neighborhood interdependence through the target selections of repeat buyers. Tract attributes were included as either a network statistic that takes the sum of an attribute of tract i and j (for continuous attributes) or the number of times a tract with a certain attribute appears in an edge in the network (for binary attributes). Table 2 provides an overview of the summary statistics of all node and edge attributes.

Using the ACS, social disorganization was measured through indices representing concentrated disadvantage, residential instability, and racial/ethnic heterogeneity. A measure of concentrated social disadvantage was calculated as the averaged sum of the following standardized variables: percent families below the poverty level, percent female-headed households with children, and percent 16+ population that was unemployed (range = −1.662, 3.495, higher range means more concentrated disadvantage).[8] Residential instability was calculated in the same way but then using the following standardized variables: percent renters and percent of the population that changed houses in the past year.[9] Racial/ethnic heterogeneity was calculated as $1 - \sum \pi^2$, where π refers to the proportion of each

[8]Cronbach's alpha = 0.72, 95% CI [0.65, 0.79]). The level of disadvantage was recoded to zero for one tract with missing information. Sensitivity analyses without this tract resulted in similar findings.
[9]Cronbach's alpha = 0.82, 95% CI [0.76, 0.86]).

Table 2. Summary statistics for node ($N = 193$) and edge ($N = 1643$) attributes.

Theory	Variable	$\bar{x}$ (*sd*)/*N* (%)	Range
Social Disorganization[a]	Concentrated Disadvantage (Index)	0 (1)	−1.662, 3.495
	Residential instability (Index)	0 (1)	−1.826, 2.692
	Racial/Ethnic Heterogeneity (Index)	0.575 (0.140)	0.000, 0.761
	IMB Count	2.290 (1.942)	1,14
Crime opportunity[a]	Primary Road (1 = "Yes")	63 (32.64%)	-
	Retail Center (1 = "Yes")	37 (19.17%)	-
	Police within Mile Distance (1="Yes")	34 (17.62%)	-
Covariates[a]	Robbery Incidents (per 1,000)	4.849 (24.280)	0.000, 333.333
	Rape Incidents (per 1,000)	0.393 (0.848)	0.000, 10.611
	Population (Log)	8.595 (0.664)	2.197, 9.987
	Male (%)	0.501 (0.040)	0.420, 0.721
Crime opportunity[b]	Miles in Distance (log)	2.515 (0.735)	−0.994, 3.830

Notes: [a] Node Attributes; [b] Edge Attribute.

racial or ethnic group (Blau 1977). A higher index indicates greater racial/ethnic heterogeneity, which for the current sample ranged between 0 (tract has only one racial or ethnic group) to 0.761 (substantive heterogeneity).

A set of additional tract features were included to examine connections between tracts against the background of crime opportunity theories, using information that represents an area's attractiveness and accessibility, specifically the total number of IMBs in a tract ($\bar{x} = 2.290$, $sd = 1.942$), the proximity to legitimate retail places using the OSM data, indicating whether or not a tract had more retail land use activity than the average in the city (1 = "Yes," $n = 37$, 19.17%),[10] and the presence of a primary road in a tract using the census shapefiles (1 = "Yes," $n = 63$, 32.64%). In addition, to examine whether buyers strategically avoid law enforcement presence, a measure indicating whether or not a census tract was within a mile distance of a police station (1 = "Yes," $n = 34$, 17.62%) was included. While police stations are not representative of patrol, they are a visible stationary presence of police that could signal increased risk and function as a deterrent for illicit behaviors. Using the geocoded locations of police stations through Google's Place API (see above), the shortest distance of each census tract centroid to the nearest police station was calculated with the *geosphere* package in R (Hijmans 2019).

Besides the measures informed by social disorganization and crime opportunity theories, several covariates were included. Law enforcement activity was also assessed through HPD's crime reports, which were used to examine whether buyers would stay away from areas with higher crime incidents per capita, which arguably signal greater levels of crime and more police presence or might not be areas where buyers of illicit sexual services at IMBs routinely travel through. The association with crime incidents was assessed for crime types that have anecdotally been associated with commercial sex and sex trafficking in IMBs, such as robbery incidents per capita ($\bar{x} = 4.849$; $sd = 24.280$) and rape incidents per capita ($\bar{x} = 0.393$; $sd = 0.848$). Lastly, the natural log of the population count ($\bar{x} = 8.595$; $sd = 0.664$) and the proportion men ($\bar{x} = 0.501$; $sd = 0.040$) were included as covariates using the ACS data.

Edge attributes

To account for the least-distance principle based on reduced effort and increased accessibility and familiarity, the shortest distance in miles between each census tract was calculated using the *geosphere* package in R (Hijmans, 2019). The average distance between any two census tracts was 15.366 miles ($sd = 8.959$, $range = 0.370$, 46.085). Because distance likely exhibits a decay effect (Zipf 1949), this distance measure was log-transformed ($\bar{x} = 2.515$ miles; $sd = 0.735$). This measure was included as an attribute of all potential edges between tracts.

[10]This binary measure was preferred instead of percentage land use because it reduces the impact of the spatial size of tracts on this measure. When land use would be included as a proportion of total land use in a tract, the same amount of retail land use would comprise a lower percentage in bigger tracts (where it covers smaller percentages of total land use) compared to smaller tracts (where it covers higher percentages of total land use).

Network attributes

Structural network measures were included to account for higher-order interdependencies between census tracts. Specifically, the role of preferential attachment was assessed through a geometrically weighted in-degree distribution (GWIDEGREE): A significant negative coefficient is evidence of a preferential attachment mechanism, which indicates that connections are more likely to be *absent* between tracts with low in-degree centralities compared to tracts with high in-degree centralities (therefore, connections are more likely to be present between tracts with high in-degree centralities compared to tracts with low in-degree centralities). The tendency toward triad formation was examined through directed geometrically weighted edgewise shared partners (DGWESP) that capture transitive triads. Triad formation exists when tracts *i* and *j* are connected, and both share a connection with tract *k*. A directed geometrically weighted dyad-wise shared partners (DGWDSP) term was included to account for the possibility that ties arise from two-paths (dyads) instead of three-paths (triads).

Analyses

Exponential random graph models (ERGMs) were used to examine the probability of a crime trip between any two census tracts ($y_{ij} = 0|1$). ERGMs can be interpreted as modified logistic regressions that do not violate the assumption of independence, which is unrealistic in network data where a single node (here, census tract) can be involved in multiple dyads. ERGMs have been successfully applied in analyses on the formation of crime networks (Bright Koskinen, and Malm, 2019; Duxbury and Haynie, 2018), journeys to crime (Bichler et al., 2014), and co-offending ties between neighborhoods (Papachristos and Bastomski, 2018; Schaefer, 2012). This study's network approach to examining neighborhood interdependence requires using ERGMs to identify which spatial, geographic, and network features explain the formation of neighborhood connections.

ERGMs estimate the probability of a set of ties, *Y*, as a function of node attributes (i.e., characteristics of neighborhoods), edge attributes (i.e., spatial distance), and network terms. The parameters for these statistics are obtained through a stochastic process that compares the observed network with random networks. A basic ERGM is formalized as follows:

$$\Pr(Y = y) = \left(\frac{1}{C}\right) \exp\left\{\sum_{a=1}^{A} \eta_a g_a(y)\right\} \tag{1}$$

Here, n_a is the sum of the coefficients for each network statistic g_a, a is the index for each statistic in the network $g(y)$, and c is the normalizing constant for the network distribution (Duxbury and Haynie 2018; Lusher, Koskinen, and Robins 2013). Models with only node and edge attributes were estimated through Maximum Pseudolikelihood Estimations (MPLE), which present regular logistic regression formats. Models with the network statistics were estimated through Markov Chain Monte Carlo (MCMC) simulation methods. All data processing and analytical tasks were conducted in R, using the *statnet* suit of packages for ERGMs (Handcock et al., 2008).

Results

Table 3 presents the log-odds of features explaining the formation of connections between census tracts as observed through buyers frequenting IMBs in multiple tracts. The first model was conditioned on spatial and geographic features, followed by a second model that added the network effects. The "edges" term operates as the intercept, and its negative coefficient suggests that connections between tracts had an overall low probability of existing. The following discusses the results for both models.

Model 1 suggests that whether or not buyers connected tracts in an illicit market for commercial sex depends on several of these tracts' features. As projected by social disorganization theory, a higher residential instability increased the probability for neighborhoods to be connected in an illicit market for

Table 3. ERGM results. Explaining the formation of connections between census tracts.

		(1) β (SE)	(2) β (SE)
Node Attributes	Concentrated Disadvantage (Index)	−0.029 (0.020)	−0.008 (0.011)
	Residential Instability (Index)	0.093 (0.024)***	0.017 (0.013)
	Racial/Ethnic Heterogeneity	−0.657 (0.163)***	−0.186 (0.092)***
	IMB Count	0.226 (0.008)***	0.068 (0.008)***
	Primary Road (1 = "Yes")	−0.044 (0.046)	0.019 (0.026)
	Retail Land Use (1 = "Yes")	0.167 (0.048)***	0.038 (0.027)
	Police within Mile Distance (1 = "Yes")	−0.248 (0.052)***	−0.082 (0.029)**
	Reports of Robbery Offenses (per 1,000)	0.002 (0.001)*	0.001 (0.001)~
	Reports of Rape Offenses (per 1,000)	0.040 (0.026)	0.004 (0.015)
	Population (Log)	−0.009 (0.042)	0.009 (0.025)
	Male (%)	−0.734 (0.564)	−0.137 (0.310)
Edge Attributes	Spatial Distance (Log)	−0.435 (0.032)***	−0.217 (0.026)***
Network Attributes	Preferential Attachment (GWIDEGREE)	-	−0.977 (0.205)***
	Dyad Formation (DGWDSP)	-	−0.011 (0.003)***
	Triad Formation (DGWESP)	-	0.798 (0.035)***
Edges (Intercept)		−1.698 (0.911)~	−3.684 (0.526)***
	AIC	12,023	11,456
	BIC	12,134	11,592

Notes: * $p < .05$; ** $p < .01$; *** $p < .001$. Coefficients are logit coefficients.

commercial sex. However, the models provide little support for the first hypothesis otherwise: In contrast to the theory, concentrated disadvantage had no significant impact on the formation of connections between tracts, and a greater racial and ethnic heterogeneity reduced the probability of an inter-tract connection.[11]

In line with the second hypothesis, geographic features that signal an area's attractiveness and opportunities increase the probability of connections between tracts through the target selection of buyers. Specifically, the probability for tracts to be connected was significantly more likely for tracts with more IMBs and those that operated as the city's retail centers, both of which increase an area's attractiveness by signaling more availability of illicit opportunities. Moreover, retail centers may feature in the routine travels of potential buyers, who may also be drawn to areas where their illicit behaviors blend into a legitimate context. In addition, connections were less likely between tracts that had or were within a mile distance of a police station (which signals the risk of law enforcement presence). However, higher per-capita rates of robbery offenses were significantly, albeit marginally, associated with an increased probability of an inter-tract connection. Lastly, in line with the third hypothesis, spatial distance was a key impediment to the formation of connections between tracts, supporting the idea that buyers were substantially less likely to frequent IMBs in tracts that were further afield from one another. A primary road, which may also increase an area's accessibility, had no significant impact.

Model 2 adds the higher-order interdependencies between census tracts, indicating that new connections between tracts form through preexisting network conditions (hypothesis 4). First, the model supports a preferential attachment mechanism, indicating that an area's attractiveness increases as it has more connections with other neighborhoods. Specifically, the significant GWIDEGREE term in the model demonstrates that a few census tracts with IMBs centrally feature in an illicit market for commercial sex through the target selections of buyers while other tracts with IMBs operate in the periphery of the market.[12] Another pattern of clustering can be identified through the tendency toward triad instead of dyad formation. The positive coefficient for the DGWESP term (i.e., triad formation) along with the negative coefficient for the DGWDSP term (i.e., dyad formation) confirm that inter-tract connections were more likely to exist as a function of transitive triads as opposed to dyads. Triad formation signals a structural clustering of buyer behaviors within a select set of

[11]However, sensitivity analyses indicated that a larger racial/ethnic minority (replacing the variable racial/ethnic heterogeneity) was positively associated with neighborhood interconnectivity.

[12]Technically, the negative coefficient for GWIDEGREE implies a lower probability for connections between tracts with low in-degree centralities compared to tracts with high in-degree centralities.

neighborhoods that were reviewed by others (and thus feature in the awareness space of others), whereas dyads represent a buyer's exploration of new target areas. When controlling for these structural network mechanisms, the edges term indicates that connections between tracts had a substantially lower probability of existence when they were not directed to the most popular tracts or not part of transitive triad formation. Although these types of clustering effects may, in part, be triggered by the spatial proximity between tracts (given that the spatial distance effect decreased in Model 2 compared to Model 1), the network effects were retained while accounting for spatial distance.

Altogether, the final model suggests that tracts were most likely to be connected in an illicit market for commercial sex when they 1) had multiple IMBs; 2) were at least a mile away from a police station, 3) were spatially proximate to each other, and 4) cluster in the overall illicit market for commercial sex in a way that increased an area's attractiveness and familiarity.[13]

Multiple sensitivity analyses were conducted. First, analyses were re-estimated while excluding 18 hyperactive reviewers, each of whom reviewed more than 9 different places (i.e., more than two *SDs* above the average number of reviewed places). This resulted in a network with the same 193 tracts that had IMBs and 1,479 unique trips between tracts. ERGMs yielded comparable results overall, except for the insignificance of the network term for dyad formation, which further supports the tendency toward triad formation (see Appendix B). Second, analyses were re-estimated via a discrete choice framework using a conditional logit model, which estimates the probability of connections between tracts without accounting for the network terms (see Bernasco and Block 2009; Bernasco and Nieuwbeerta 2005; Chamberlain and Boggess 2016; Johnson and Summers 2015). The findings yielded comparable results to Model 1 in Table 3, except that residential instability was no longer significant (Appendix C).[14]

Discussion

This study applied a network approach to examine how the target selection of repeat buyers of commercial sex connected different neighborhoods in an illicit market for commercial sex in the U. S. Online review data from a national review board were used to identify 454 IMBs that operated as commercial sex venues in a metropolitan city in the U.S. South. Repeat buyers comprised nearly half (49%) of the sample of 1,294 buyers who had left reviews about paying for sexual activities in these IMBs, which accounted for nearly 75% of all reviews posted. In nearly all instances, repeat buyers posted reviews about IMBs in different census tracts, corroborating prior research that a substantial group of buyers are geographically mobile and explore different areas for illicit commercial sex (Blevins and Holt 2009; Holt and Blevins 2007; Martin et al. 2017; Soothill and Sanders 2005). These target selections of repeat buyers symbolically connected census tracts in an illicit market for commercial sex. The accumulation of these connections was modeled as a network comprised of census tracts as the nodes, any two of which were connected by an edge when a repeat buyer chose to engage in illicit commercial sex in both tracts. Statistical network models were used to explain connections between tracts as a function of tract characteristics, the distance between tracts, and network processes.

[13]See Appendix A for an overview and explanation of acceptable goodness of fit indices.

[14]Multiple sensitivity analyses were conducted. First, analyses were re-estimated while excluding 18 hyperactive reviewers, each of whom reviewed more than 9 different places (i.e., more than two *SDs* above the average number of reviewed places). This resulted in a network with the same 193 tracts that had IMBs and 1,479 unique trips between tracts. ERGMs yielded comparable results overall, except for the insignificance of the network term for dyad formation, which further supports the tendency toward triad formation (see Appendix B). Second, analyses were re-estimated via a discrete choice framework using a conditional logit model, which estimates the probability of connections between tracts without accounting for the network terms (see Bernasco and Block 2009; Bernasco and Nieuwbeerta 2005; Chamberlain and Boggess 2016; Johnson and Summers 2015). The findings yielded comparable results to Model 1 in Table 3, except that residential instability was no longer significant (Appendix C).

The main findings indicate that connections were most likely with tracts signaling greater attractiveness (which was assessed through a greater presence of IMBs, proximity to retail centers, and a network process of preferential attachment), opportunity given reduced risk to be detected (which was measured through greater distance to a police station), and accessibility and familiarity (which was observed through spatial proximity between tracts and a network process representing the tendency toward triad formation).

These findings provide little support for social disorganization theory. Although there is some evidence that residential instability, a key pillar of social disorganization theory (Bursik 1988; Kubrin and Weitzer 2003; Shaw and McKay 1942, 1969), increased neighborhood interdependence in an illicit market for commercial sex, this finding was accounted for by network processes (discussed below). In addition, concentrated disadvantage had no significant impact on the interconnectivity between tracts, while racial/ethnic heterogeneity had a negative impact. Several explanations might apply. Previous work has suggested that resource constraints in disadvantaged areas can impede the mobility associated with behaviors that transcend neighborhood boundaries, which would explain a negative effect of concentrated disadvantage (Schaefer 2012). However, the current findings indicate that tracts were connected regardless of their level of concentrated disadvantage, perhaps because buyers are willing to travel to different target areas when they are aware of illicit opportunities (e.g., through online reviews, see Holt, Blevins, and Kuhns 2014; Martin et al. 2017) or when areas have other features that increase their attractiveness.

The negative impact of racial/ethnic heterogeneity may be explained by the profile of buyers of commercial sex who, according to recent research, are predominately white and from middle- and upper socioeconomic backgrounds (Martin et al. 2017; Polaris, 2018). Buyers may choose areas with a demographic profile similar to their own because similarity may come with a sense of affinity and familiarity, as suggested in the broader literature on target selection (see Bernasco and Block 2009; Bernasco and Nieuwbeerta 2005; Boivin and D'Elia 2017). At the same time, sensitivity analyses suggest that buyers are drawn to tracts with a larger racial and ethnic minority (not: heterogeneity). These findings raise questions about the motivations for buyers to purchase commercial sex, specifically regarding their role in amplifying racial and ethnic stereotypes in the commercial sex industry and broader societal inequalities (Martin et al. 2017). Altogether, these findings demonstrate that social disorganization theory does not seem to provide a relevant explanation for neighborhood interdependence through the target selection of buyers, even though previous work supports at least a partial relevance of the theory to describe the general placement of IMBs (Chin, Takahashi, and Wiebe 2019; Crotty and Bouché 2018; de Vries 2022).

The results provide more support for crime opportunity theories. In line with expectations from crime opportunity theories (Clarke and Cornish 1985; Cornish and Clarke 2014; Cullen 2010; Wilcox and Cullen 2018), the findings translate to an increased willingness of buyers to transcend tract boundaries to frequent IMBs when choice-structuring features of these tracts signal high rewards but low risk and effort. Specifically, buyers may perceive greater rewards in tracts with multiple IMBs or in proximity to retail centers, which aligns with prior research demonstrating that retail centers generally attract more crime because they attract more individuals from outside areas (Bernasco and Luykx 2003; Lockwood 2007), feature in the awareness space of offenders (e.g., Bernasco and Block 2009, 2011), and conceal illicit behaviors by nesting these within legitimate settings (Eck 1995a).

Furthermore, the findings indicate that areas close to police stations are less likely to feature in an interconnected illicit market for commercial sex, as the risk of detection is likely a key motivator behind buyers' target selections. Previous work using online reviews has shown that buyers are aware of the illicit nature of their behaviors and the risk of arrests, and seek to avoid police attention by selecting – or relocating to – areas where they perceive the risk of law enforcement apprehension to be lower (Holt and Blevins 2007; Holt, Blevins, and Kuhns 2008, 2014; Soothill and Sanders 2005). Nonetheless, it is important to acknowledge that police presence may be related to other land use measures (e.g., the presence of certain businesses) that increase neighborhood interdependence, encouraging further research to unpack the role of police presence.

Lastly, the current findings identify spatial distance as a key impediment for buyers to transcend tract boundaries to frequent IMBs, which is consistent with the principle of least effort (Blau 1977; Zipf 1949) and might align with buyers' routine behaviors (Felson 1987; Felson and Clarke 1995; Felson and Cohen 1980; Miró 2014) and an awareness space of buyers that is limited to spatially proximate areas (Brantingham and Brantingham 1993, 2013). However, it is noteworthy that the presence of a highway, another measure of accessibility, had no significant impact on the interconnectivity between tracts. Future research should further examine how buyers weigh accessibility and discreteness in their target selection.

Besides ecological and situational features, two network processes determined how census tracts became connected in an illicit market for commercial sex. In particular, the current findings demonstrate a clustering of tracts that is more complex than merely a spatial clustering as it involves social behaviors that transcend tract boundaries and connect both proximate and more distant tracts in an illicit market. More specifically, the findings demonstrate that a tract's attractiveness increased with a higher level of interdependency with other tracts. This preferential attachment mechanism drove a network formation that centralized a few highly connected tracts that attracted buyers from different areas, while many other tracts with IMBs operated at the periphery of the market and attracted fewer buyers. This network process likely reflects the tendency of repeat buyers to choose – and navigate between – tracts with IMBs that others have frequently (or positively) reviewed (i.e., signaling attractiveness).

Furthermore, connections between tracts were more likely to be part of triads instead of dyads, which in the context of neighborhood networks signals a structural clustering among a select set of neighborhoods based on social mechanisms of trust, familiarity, and affinity (Papachristos and Bastomski 2018; Schaefer 2012). Triad formation may be facilitated by the reviews of credible and trusted buyers based on which one can expand upon their individual awareness space. While more research is warranted to further unpack these network effects in buyers' use of online reviews, previous research suggests that buyers do indeed read review boards to screen for new commercial sex venues (Holt and Blevins 2007; Holt, Blevins, and Kuhns 2008; Martin et al. 2017; Soothill and Sanders 2005).

Before outlining the key contributions of this study, some limitations need to be considered. First, the findings may be contextual to the study area and IMBs, which should encourage future research to replicate this study's approach in the context of other illicit markets. Second, although this study focused on geographic attributes, the findings would benefit from future data collection and analyses about the characteristics of buyers and IMBs, which may also impact target selection. Third, it is possible that the interconnectivity between areas may look different for smaller geographic units such as blocks or street segments. While prior studies on IMBs informed the focus on census tracts (Chin, Takahashi, and Wiebe 2019; Crotty and Bouché 2018; de Vries 2022), future work may apply this study's approach to different units of analysis. Fourth, digital trace data such as online reviews are not typically designed for research. While it captures detailed information about social phenomena (see also de Vries and Radford 2021), future work is needed to examine the representativeness of online data and to unpack the mechanisms that bring about the social outcomes by these data (Snaphaan and Hardyns 2019). Relatedly, future work might also examine how technology impacts how behaviors transcend neighborhood boundaries. After all, motivated offenders can now identify potential crime locations through online domains, while the implications of this new digital environment for the social organization and location of criminal behaviors are poorly understood (Goldsmith and Brewer 2015).

Notwithstanding these limitations and potential for further research, the present study contributes to a broader understanding of how neighborhoods are connected in illicit behaviors that transcend neighborhood boundaries (see also Bastomski, Brazil, and Papachristos 2017; Bichler, Malm, and Enriquez 2014; Papachristos and Bastomski 2018; Sampson 2004). In doing so, this study draws attention to a socio-spatial neighborhood interdependence as an important dimension of an environmental criminology and adds to existing knowledge on what may increase a target area's attractiveness and familiarity (e.g., Bernasco and Luykx 2003; Brantingham and Brantingham 2013; Chamberlain and Boggess 2016; Curtis-Ham et al. 2020). Although this study focuses on neighborhood

interdependence through the target selection of repeat buyers of commercial sex, the analytical approach can also be used to examine the formation of other symbolic pathways between neighborhoods through which crime and deviancy may persist, displace, or diffuse across a city.

The structural connectivity between neighborhoods yields important implications for crime control and prevention strategies. In particular, by showing that buyers frequently travel across census tract borders to visit different IMBs, this work hints at the limitations of current criminal justice strategies such as on-the-ground vice operations that shut down IMBs in particular areas. These shutdowns may have a limited effect when buyers are willing to relocate to different regions (de Vries 2020; de Vries and Farrell 2022). Besides general concerns about the ineffectiveness of traditional law enforcement techniques (Nagin 2013; Weisburd and Majmundar 2018), and current policing strategies targeting commercial sex and sex trafficking in particular (de Vries and Farrell 2022; Farrell et al. 2019), structural connections between neighborhoods can make an illicit market more resilient to local interventions as they create the avenues for the displacement and diffusion of crime and deviancy.

Crime control and crime prevention strategies might especially be needed in those neighborhoods that attract repeat buyers (i.e., in "high-degree" tracts) and most centrally feature in the illicit market (as opposed to neighborhoods that operate in the periphery of the market), where they have greater potential to curb the diffusion of illicit behaviors and deviant norms across neighborhoods. Prevention efforts may raise awareness among buyers or their social contexts about potential abuse and victimizations and should seek to reduce a neighborhood's suitability and popularity for crime and deviancy. For example, the findings suggest that the mere presence of a police station may be an effective mechanism to keep away buyers who fear apprehension by law enforcement. However, more research is needed to identify which specific crime response models are most effective in reducing crime and victimization in the commercial sex industry. To conclude, this study illuminates the connections between neighborhoods caused by illicit behaviors that transcend neighborhood boundaries, and encourages research, policy, and practice to further account for this type of neighborhood interdependence.

Acknowledgments

The author is grateful for feedback received from the audience at the American Society of Criminology (ASC) in San Francisco (2019), from faculty and students at the School of Criminology and Criminal Justice at Northeastern University, and from her dissertation committee members Amy Farrell (Chair), Anthony Braga, Nick Beauchamp, and Andrew Papachristos who read and commented on previous versions of this manuscript.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This project was supported by Award No. 2018-R2-CX-0005, awarded by the National Institute of Justice, Office of Justice Programs, U.S. Department of Justice. The opinions, findings, and conclusions or recommendations expressed in this publication are those of the author and do not necessarily reflect those of the Department of Justice.

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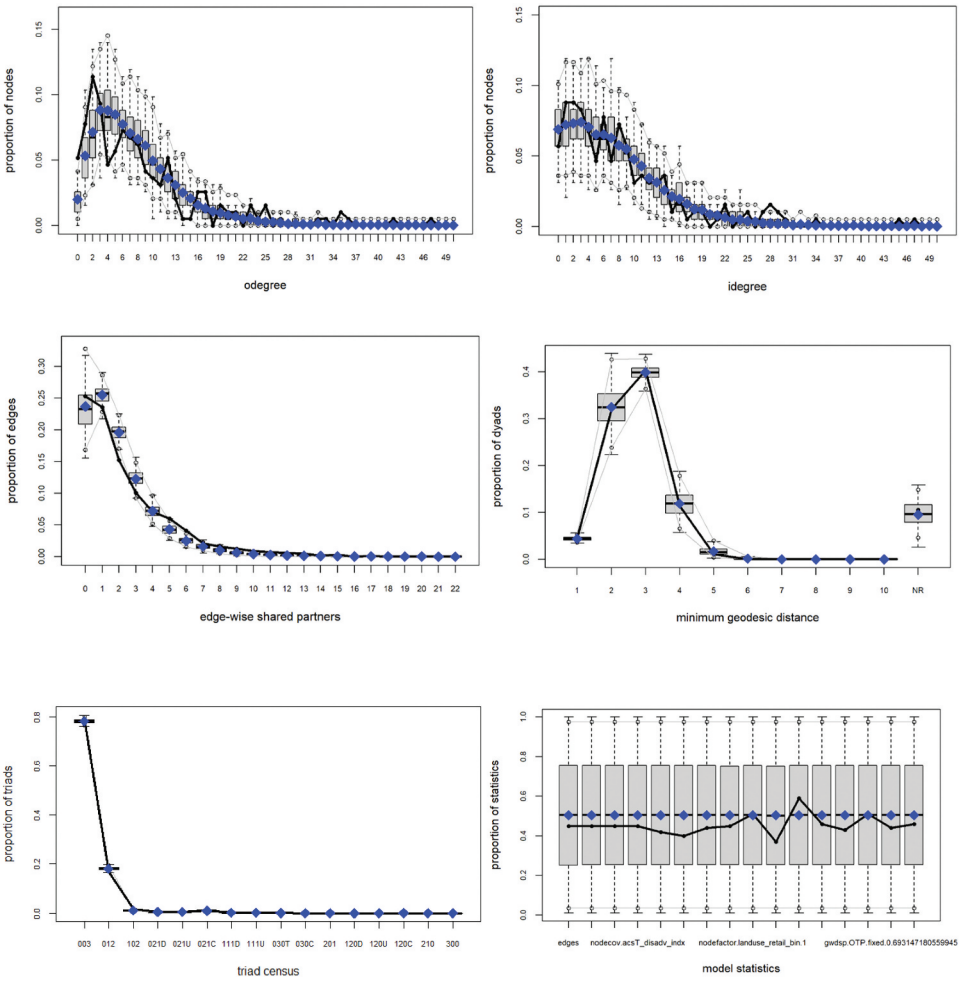
Appendix A Goodness of fit indices

Goodness of fit statistics for ERGMs help evaluate whether the network model replicates key characteristics of the observed network, which would support the reliability and validity of the findings. To examine the reliability of the ERGM model, 1000 simulated networks were generated randomly from the coefficients in the simulated networks and the original network (Model 2 in Table 3). The figures below demonstrate a strong similarity between the simulated networks and the observed network regarding several structural terms (in-degree, dyad-wise partners, edgewise partners, triad census) and model statistics for each of the covariates.



Appendix B ERGMs without the target selections of super users

		(1) β (SE)	(2) β (SE)
Node Attributes	Population (Log)	0.012 (0.044)	0.008 (0.029)
	Male (%)	−0.601 (0.591)	−0.171 (0.377)
	Concentrated Disadvantage (Index)	−0.029 (0.021)	−0.011 (0.013)
	Residential Instability (Index)	0.083 (0.025)***	0.016 (0.015)
	Racial/Ethnic Heterogeneity	−0.676 (0.171)***	−0.261 (0.108)*
	IMB Count	0.223 (0.008)***	0.106 (0.010)***
	Primary Road (1 = "Yes)	0.004 (0.048)	0.036 (0.030)
	Retail Land Use (1 = "Yes)	0.169 (0.050)***	0.058 (0.033)~
	Police within Mile Distance	−0.231 (0.055)***	−0.097 (0.036)**
	Reports of Robbery Offenses (per 1,000)	0.003 (0.001)**	0.002 (0.001)*
	Reports of Rape Offenses (per 1,000)	0.029 (0.027)	0.005 (0.017)
Edge Attributes	Spatial Distance in Miles (Log)	−0.434 (0.033)***	−0.260 (0.028)***
Network Attributes	Preferential attachment (GWIDEGREE)	-	−2.334 (0.183)***
	Dyad Formation (DGWDSP)	-	−0.006 (0.005)
	Triad Formation (DGWESP)	-	0.590 (0.033)***
Edges (Intercept)		−2.300 (0.960)*	−3.419 (0.639)***
	AIC	11,163	10,644
	BIC	11,273	10,781

Notes: * p < 0.05; ** p < 0.01; *** p < 0.001. Coefficients are logit coefficients.

Appendix C Results from a Conditional Logit Model

		(1) β (SE)
Tract Attributes	Population (Log)	−0.048 (0.060)
	Male (%)	−1.196 (0.805)
	Concentrated Disadvantage (Index)	−0.008 (0.992)
	Residential Instability (Index)	0.053 (0.030)~
	Racial/Ethnic Heterogeneity	−0.748 (0.233)**
	IMB Count	0.234 (0.011)***
	Primary Road (1 = "Yes)	−0.051 (0.065)
	Retail Land Use (1 = "Yes)	0.179 (0.069)**
	Police within Mile Distance	−0.226 (0.074)**
	Reports of Robbery Offenses (per 1000)	0.001 (0.001)
	Reports of Rape Offenses (per 1000)	0.063 (0.037)
Edge Attributes	Spatial Distance in Miles (Log)	−0.414 (0.035)***

Notes: ~ $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$. Coefficients are logit coefficients. Sample: $n = 1643$ inter-tract travels (out of 37,056 possible inter-tract travels), $n = 193$ census tracts.