Socially Connected Neighborhoods and the Spread of Sexually Transmitted Infections

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ABSTRACT Sexually transmitted infections (STIs) in the United States have been increasing at record levels and exhibit unequal spatial patterning across urban populations and neighborhoods. Research on the effects of residential and nearby neighborhoods on STI proliferation has largely ignored the role of socially connected contexts, even though neighborhoods are routinely linked by individuals' movements across space for work and other social activities. We showcase how commuting and public transit networks contribute to the social spillover of STIs in Chicago. Examining data on all employee–employer location links recorded yearly by the Census Bureau for more than a decade, we assess network spillover effects of local community STI rates on interconnected communities. Spatial and network autoregressive models show that exposure to STIs in geographically proximate and socially proximate communities contributes to increases in local STI levels, even net of socioeconomic and demographic factors and prior STIs. These findings suggest that geographically proximate and socially connected communities influence one another's infection rates through social spillover effects.

KEYWORDS Neighborhood effects • Neighborhood networks • Population health • Sexually transmitted infections

Introduction

Sexually transmitted infections (STIs) in the United States are occurring at unprecedented levels. For example, the Centers for Disease Control and Prevention (CDC 2019) reported that in 2018, chlamydia reached the highest number of reported cases ever, at 1.8 million cases in 2018; this represents a 3% increase since 2017 and a 19% increase since 2014, and is likely an underestimate (CDC 2019; Mayer et al. 2012). STIs are an important population health concern because they can reflect and reproduce inequalities. Cases are most highly concentrated among young adults, racial and ethnic minorities, and individuals with low income (Adimora and Schoenbach 2005, 2013; Harling et al. 2014; Thomas and Thomas 1999), and they are disproportionately clustered in urban areas (Adimora and Schoenbach 2005; De et al. 2004; Potterat et al. 1985; Risley et al. 2007). Among the factors contributing to this link are

inequalities in health care access (Nelson 2002), racially segregated sexual networks (Adimora and Schoenbach 2005; Laumann and Youm 1999; Liljeros et al. 2003), and residential location (Dembo et al. 2009).

STIs contribute to population health disparities because untreated infections can lead to life-threatening complications, such as cervical cancer through HPV contraction (Trottier and Franco 2006), as well as other, permanent health problems (Newton and McCabe 2008; Tolnay 1989; Trottier and Franco 2006; Ward and Rönn 2010). The lifetime direct medical cost of STIs has been estimated at several billion dollars, with a large proportion spent on HIV infections (Owusu-Edusei et al. 2013). Further, high rates of STIs may have important implications for at-risk populations' fertility levels (Bongaarts 1978; Tolnay 1989).

Understanding the effects of social, demographic, and ecological factors on these infection patterns and their contribution to individuals' risks of contraction is crucial for decreasing STI prevalence (Adimora and Schoenbach 2013; Frieden 2010; Grassly et al. 2001). Valuable research examining STI patterns has begun to account for the importance of meso-level factors, such as social networks (Bearman et al. 2004; Kohler et al. 2007; Merli et al. 2015), schools (Jiskrova and Vazsonyi 2019), and residential neighborhoods (Jennings et al. 2014; Jennings et al. 2012). In particular, social and sexual networks are highly influential in STI transmission (De et al. 2004; Liljeros et al. 2003; Moody 2002) because these networks can shape sexual partnerships (Bearman et al. 2004; Kretzschmar and Morris 1996), perceptions of sexual risk (Kohler et al. 2007; Morris et al. 1995), and contraceptive use (Behrman et al. 2002; Kohler 1997; Valente et al. 1997).

However, recent work in the neighborhood effects literature has highlighted the importance of looking beyond residential neighborhoods[1] and toward activity spaces—that is, destination places of routine population mobility—to better understand the dynamics of selection effects, social interactions, and other contextual factors that shape health outcomes (Browning et al. 2017; Browning et al. 2004; Levy et al. 2020; Matthews and Yang 2013). The connection of neighborhoods through individuals' everyday mobility may contribute to spatially stratified STI patterns by influencing factors such as dating markets, norms, attitudes surrounding sexual risk, and access to medical resources (Crosby and Holtgrave 2006; Cubbin et al. 2005; Jennings et al. 2014; Singer et al. 2006; White et al. 2017). Although sexual behavior would not generally be observable in these networks, we build our study on research finding that even without being directly observed, social relationships and social contexts can influence sexual beliefs and behavior (Browning et al. 2004; Jiskrova and Vazsonyi 2019; Upchurch et al. 1999), perceptions of sexual risk (Jennings et al. 2012; Kohler et al. 2007; Morris et al. 1995), and contraceptive use (Behrman et al. 2002; Kohler 1997; Valente et al. 1997). These processes can occur through multiple pathways, such as social learning, diffusion, or role modeling of behaviors (Ali et al. 2011; Kohler 1997; Upchurch et al. 1999). For example, friends might discuss their contraception use or STI contraction in their social network, which might encourage individuals to adopt an effective method to prevent STIs (Kohler 1997; Morris et al.

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[1] We use the terms "neighborhood" and "communities" interchangeably. Both terms refer to a group of people living within a geographically bounded area. In Chicago, these terms refer to Chicago's 77 community areas.

1995). Using this foundation, we extend these ideas to our analysis of community networks and their implications for STIs.

Our study examines the significance of public transit networks and workers' commuting networks for the shaping and maintenance of STI patterns across neighborhoods in the urban setting of Chicago. We seek to determine whether the areas to which neighborhoods are socially tied are more important for their STI rate than the areas they are geographically nearby. One important theoretical line of debate in the neighborhood effects research has been the conceptual definition of neighborhoods and understanding the spatial interaction mechanisms within areas of larger geographic scales. Some studies have focused on theoretical mechanisms relevant for small-scale influence, such as census blocks or tracts; others have highlighted the importance of mechanisms relevant for wider contexts, such as counties or metro areas, including neighborhood effects from socially connected neighborhoods (Sampson 2012). We expect to find wider-scale effects because of population mobility flows and the inherent social interactions and exposures that form as a result of routine activities and mobility patterns, such as commuting.

Historically, neighborhood effects research has highlighted the problem of residential segregation and the concentration of social disadvantage and vulnerability. However, recent work by Hall et al. (2019) highlighted important differences between nighttime segregation (residential) and daytime segregation (based on commuters' work location). Our approach builds on and extends this work by focusing on connectivity across social space, above and beyond spatial segregation. Our study thus highlights the importance of looking beyond residential and geographically proximate neighborhoods to understand neighborhood effects by considering the effects of socially connected neighborhoods.

We build on past research by examining the structural networks that spread infectious diseases across Chicago. We adopt a dynamic spatial regression approach to assess how STIs spill over from geographically contiguous neighborhoods and commuting and public transit networks. By examining commuter mobility and public transit networks, the current study draws on existing approaches focused on spillovers among geographically proximate places. Further, the study advances the literature by being the first, to our knowledge, to assess two key structural mechanisms potentially underlying spillover effects (in this case, social spillovers) that feed into and amplify the differential clustering of health problems across urban space.

Literature Review

A Social Epidemiological Approach to STIs

A social epidemiological approach to health turns the focus from the individual to individuals' larger social context to better understand health patterns. These environments shape health outcomes through multiple forces, such as norms, social control, and opportunities (Berkman and Kawachi 2014), that produce constraints and incentives for an individual's health-related behaviors. Although social scientists recognize the importance of a social epidemiological perspective on health, STI research continues to focus primarily on the importance of individual-level factors for prevention,

such as gender (Burstein et al. 1998), sexual partnerships (Kelley et al. 2003), race (Laumann and Youm 1999), condom use (Chatterjee et al. 2006), and socioeconomic status (Adimora et al. 2006; Harling et al. 2014; Thomas and Thomas 1999).

However, these infections transmit through social interactions and are best studied interdependently through their interpersonal and environmental exchanges. Although individuals may contract an STI directly from their sexual partners, understanding the social structures within which people choose partners and they or their partners become infected allows for better identification of the social and ecological forces that shape and perpetuate disparate STI patterns. Additionally, STIs are one of many adverse health conditions associated with socioeconomic status, which contributes to it being a fundamental cause of disease (Phelan et al. 2010). The understanding and modification of individual behaviors and risks needs to account for ecological inequalities stemming from socioeconomic status, which will continue to replicate even if individual-level determinants are addressed (Phelan et al. 2010). These factors suggest that research must shift its focus beyond individual-level factors and behaviors to understand the disproportionate spread of STIs in urban environments.

Residential Neighborhood Effects on STIs

A crucial step in recognizing the ecological and social drivers of STIs is understanding how residential locations shape individuals' risk of STI contraction. Residential neighborhoods are influential in shaping and maintaining patterns of STIs and risky sexual behaviors (Brahmbhatt et al. 2014; Cubbin et al. 2005; Ellen et al. 2004; Jennings et al. 2014, 2010), as well as other health behaviors (Arcaya, Tucker-Seeley et al. 2016; Cubbin et al. 2005; Sampson 2003). One pathway through which these environments influence STIs is the prevailing attitudes and norms surrounding sexual risk and behavior that in turn shape individuals' beliefs and behaviors (Cubbin et al. 2005; Jennings et al. 2014; Singer et al. 2006). These norms might transmit through individuals' social interactions with their neighbors and other individuals in these contexts. Social relationships may also inform individuals' health decisions (Hernandez et al. 2019) and safer sex practices (Crosby and Holtgrave 2006) because they allow individuals to learn about health practices and information through their social networks. Additionally, sexual behaviors and STI patterns might be influenced by community-level factors, such as social cohesion, which provides social support to individuals in their residential community. Research has found that lower social cohesion is associated with higher rates of STIs (Ellen et al. 2004) and that higher levels are positively linked to condom use (Kerrigan et al. 2006). Residential neighborhoods may also influence STI rates by providing medical resources to their residents, such as clinics where free STI testing or condoms are provided.

Beyond Residential Neighborhoods

A social epidemiological approach to STIs looks beyond residential barriers to consider other places people inhabit every day. Neighborhoods are not isolated islands; spatially contiguous neighborhoods often exert health-relevant spillover effects

(Baller et al. 2001). Moreover, most individuals spend enormous amounts of time in areas outside their neighborhood, which might make these communities even more influential for individual health outcomes than places of residency. STI outbreaks tend to occur in concentrated clusters in urban environments (De et al. 2004; Potterat et al. 1985; Risley et al. 2007). However, past interventions targeting only these highly infected areas have not been successful (Rothenberg et al. 2005). Additionally, some outbreaks occur in random areas quite distant from highly infected areas (De et al. 2004). Perhaps past interventions could not address the spillover occurring from spatially proximate neighborhoods or from distant neighborhoods socially connected by population mobility flows. Focusing only on residential areas ignores the many meaningful connections individuals make in other social spaces (Small and Adler 2019).

People in the social spaces individuals visit during their routine activities may have different attitudes surrounding sexual behaviors than people in an individual's residential neighborhood (Cubbin et al. 2005; Jennings et al. 2014; Jiskrova and Vazsonyi 2019; Singer et al. 2006). Socially connected communities might shape dating patterns, which in turn shape and maintain STI patterns. Individuals are more likely to have social ties to (Small and Adler 2019) and sexual relationships with (Adimora and Schoenbach 2005; Zenilman et al. 1999) those who are spatially or socially proximate. Individuals encounter others through social organizations and routine activities that may expose them to potential sexual partners living in different communities. Laumann et al. (2004) showed that the distribution of sexual partnership ties in Chicago is sometimes spread far and wide. Highly mobile people may serve as sexual links, termed "bridges," that connect one neighborhood and sexual network to the other, thus increasing the risk of STI spread (Aral 2000; Cassels et al. 2017). In sum, we hypothesize that inter-neighborhood networks are structural drivers of STI patterns and spread across urban spaces.

Inter-Neighborhood Commuting Ties

We focus specifically on the importance of inter-neighborhood networks based on commuting. Work environments are particularly important in people's lives: they are individuals' second most frequently inhabited activity spaces, after residential areas (Kahneman et al. 2004). Inter-neighborhood commutes may shape STI patterns through social spillover or selection. Social spillover can occur when infected workers serve as bridges by introducing STI risk from their work neighborhoods into their residential neighborhoods via sexual partnerships (Aral 2000; Cassels et al. 2017; Morris et al. 1996). Infected neighborhoods with many commuters may increase the possibility of long-distance transmission and STI outbreaks. Additionally, the places where people work and their surroundings are important environments where daily social interactions occur. In these interactions, individuals might be exposed to beliefs and norms surrounding health and sexual risk that might reaffirm or change their current views on STIs. Selection may also explain why some neighborhoods may be connected through their commuters. Workers may select into communities that are like their residential neighborhoods. Individuals select into the social spaces they inhabit, which can help perpetuate systems of inequality (Arcaya, Graif et al.

2016; Sampson and Sharkey 2008; van Ham et al. 2018). If individuals self-select into work environments that have STI rates similar to those of their residential neighborhood, these rates may persist over time. These individuals would be exposed to infected potential partners and would be exposed to the same norms of sexual risk in their work and residential environments. Although our data preclude us from examining selection effects, we can investigate community similarities in an outcome of interest by examining autocorrelation. We account for social spillovers in addition to social autocorrelation between home and work communities to understand how commuting ties influence STI rates.

Inter-Neighborhood Public Transit Ties

Public transit ties between communities may also shape STI patterns as individuals use public transit to conduct their routine activities. Inter-neighborhood public transit ties are less malleable than inter-neighborhood commuting ties. Building or removing public transportation connections is an economic and political endeavor that takes time and resources (Farmer 2011). Although the literature demonstrates that advantaged communities are often adept at influencing such processes (Karner and Niemeier 2013; Sanchez 2008), we believe that public transit ties may influence STI patterns through processes of social spillover more than selection. Communities directly linked by a public transportation line (i.e., a bus route or a train line) are bridged by individuals using public transportation during their routine activities. Individuals can easily visit communities connected through public transportation lines for shopping, routine medical visits, and social outings. These communities are the locations where individuals may meet potential sexual partners during social outings and may provide them access to resources (e.g., health clinics) that are not present in their own neighborhoods. Although we cannot study the routine activity spaces of all individuals in Chicago, we propose that inter-neighborhood public transit ties may be a feasible and reasonable way to assess how communities connected through their residents' routine activity spaces influence STI patterns. We account for social spillovers in addition to social autocorrelation between communities sharing the same public transit lines to understand how Chicago's public transit infrastructure influences STI rates.

Methods

Study Setting

We situate our study in the urban environment of Chicago. As in many U.S. cities, the prevalence of STIs in Chicago has steadily increased in recent years, with chlamydia being the most pervasive (Illinois Department of Public Health (IDPH) 2017). Illinois had the 9th highest rate of chlamydia and the 16th highest rate of gonorrhea among U.S. states in 2018 (CDC 2019). These higher STI rates are due to Chicago's urban environment, which heavily weights the state's STI statistics. Chicago was ranked second as the city with the most STI cases in 2018, preceded by Los Angeles

(CDC 2019). As in other large cities, residents of Chicago have higher infection rates than those that reside in other areas of the state (IDPH 2017). Although Chicago is highly segregated, Sampson (2012) demonstrated that the processes shaping spatial inequalities in Chicago are not unique. Additionally, like other cities, Chicago has a large population that commutes for work. Importantly, public transportation in a city like Chicago is used not only by individuals of lower socioeconomic status but also by more affluent city residents (Farmer 2011). Even though our study focuses on Chicago as a case study, the community networks we examine will likely operate similarly in other urban environments.

Data

We use multiple data sources to assess our research question. We configure the inter-neighborhood commuting network of Chicago using data from the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES). The LEHD, sponsored by the U.S. Census Bureau, uses unemployment insurance forms to collect information on the location of employers and employees. To protect individuals' confidentiality, the study aggregates these data to commuting flow statistics within and between communities (Abowd et al. 2005). The commuting flow statistics allow researchers to examine connections between the geographic locations of employers and employees. From these data, we create an inter-neighborhood commuting network of Chicago's 77 community areas.[2] Public transit data on Chicago Transit Authority (CTA) bus stops, rapid transit system stations (elevated train, or "L"), and commuter rail (Metra) stations are from the City of Chicago's data portal. We geocode the stations' geographic coordinates to identify their CTA location and define the links between any two communities based on whether they share CTA bus routes, rapid transit lines, or Metra rail commuter lines.

We obtain sociodemographic indicators of these communities using data from the decennial census and the American Community Survey (ACS). Finally, data from the City of Chicago's Data Portal provide information on STI prevalence among different Chicago neighborhoods. These data are provided by the Surveillance, Epidemiology and Research Section, STI/HIV Division, of the Chicago Department of Public Health.

Measures

STI Prevalence

We combine multiple measures to assess the STI prevalence in each area. The Chicago Department of Public Health tracks the yearly number of lab-confirmed cases of chlamydia and gonorrhea among males and females aged 15–44. The City of Chicago

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[2] Chicago's 77 community areas are historically defined and well-established neighborhood boundaries comprising approximately 38,000 residents (Sampson 2012).

Data Portal provides the incidence rates per 100,000 people for each of Chicago's 77 community areas. Incidence rates are provided for chlamydia and gonorrhea among both females and males aged 15–44.[3] We combine these four items into a single standardized measure representing each community's STI prevalence. We create this measure for each year of our study: 2002 to 2014.[4] We also include a time-lagged variable that accounts for previous STI rates—referred to as *prior STI rate*—which allows us to control conservatively for processes of selection and homophily that may have shaped these connections. Our reliance on lab-confirmed cases of STIs might underestimate community rates, given that many cases are unrecorded because of a lack of regular testing for STIs in clinical examinations, individuals' lack of access or unwillingness to seek testing, and the high prevalence of asymptomatic cases (CDC 2019; Mayer et al. 2012).

Community Sociodemographic Variables

We account for several community area sociodemographic variables using the 2000 decennial census and the 2008–2012 ACS five-year estimates. We include measures of community disadvantage, residential stability, and racial/ethnic diversity. We create standardized indexes for community disadvantage and residential stability using factor-weighted principal component analyses. The measures included in our index of community disadvantage are the percentage of residents living below the poverty line, the percentage unemployed, the percentage receiving public assistance, and the percentage of female-headed families with children. The measures included in our index of residential stability are the percentage of residents older than 5 who have lived in the same house for the past five years and the percentage of owner-occupied housing units. We use a Herfindahl concentration index to calculate a community's level of racial/ethnic diversity. This index is equal to 1 minus the sum of squares of the population proportions of each racial/ethnic group living in the community area; these racial/ethnic groups are non-Hispanic Whites, non-Hispanic Blacks, Hispanics, Asians, Native Americans, and others. We standardize this index such that higher numbers indicate greater diversity.

We also use LODES data to assess the importance of the number of local workers who do not commute to work. We measure the number of local workers by standardizing the proportion of jobs located in the community that are occupied by individuals who also live in the community. We standardize the measure of local workers in a community so that all variables in the model are standardized.

Table 1 shows the descriptive statistics by data sources. Because many of our variables are indexed measures, we also show values for the variables that make up these measures.

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[3] In some years, STI values are not large enough to be recorded. We impute missing values as 0. For females' rates, we impute up to 2 and 16 observations each year for chlamydia and gonorrhea, respectively. For males' rates, we impute up to 4 and 18 observations each year for chlamydia and gonorrhea, respectively.

[4] We also explore models predicting each of our STI measures separately (see online Appendix F).

Table 1 Descriptive statistics

	Mean	SD	Min.	Max.
STI Prevalence (2002–2014) (incidence)				
Chlamydia (females)	2,705.62	2,358.25	89.59	8,340.05
Chlamydia (males)	1,093.90	1,049.56	0	3,813.21
Gonorrhea (females)	804.25	918.90	0	3,275.16
Gonorrhea (males)	771.33	851.25	0	2,999.44
Disadvantage (2000 decennial census) (%)				
Living below poverty line	20.12	13.09	2.40	56.31
Unemployed	11.72	7.31	2.80	33.53
Receiving public assistance	8.12	6.83	0.23	29.03
Female-headed families with children	14.79	10.60	1.52	50.28
Disadvantage (2008–2012 ACS) (%)				
Living below poverty line	23.30	12.12	2.95	58.32
Unemployed	15.38	7.53	4.74	35.87
Receiving public assistance	4.54	3.50	0.57	19.81
Female-headed families with children	21.07	12.74	2.75	55.08
Stability (2000 decennial census) (%)				
Residents living in same house in past five years	57.30	11.19	30.14	77.03
Owner-occupied housing units	48.30	22.10	8.94	91.14
Stability (2008–2012 ACS) (%)				
Residents living in same house in past five years	88.77	4.73	78.42	97.66
Owner-occupied housing units	49.11	18.93	12.88	90.65
Diversity (2000 decennial census) (%)				
Non-Hispanic Whites	31.20	29.87	0.32	93.33
Non-Hispanic Blacks	40.89	41.10	0.17	98.09
Hispanic	21.77	25.15	0.59	88.90
Asians	4.34	8.62	0.03	60.71
Native Americans	0.14	0.07	0.03	0.40
Others	1.66	1.09	0.34	5.42
Diversity (2008–2012 ACS) (%)				
Non-Hispanic Whites	28.42	27.88	0	92.22
Non-Hispanic Blacks	39.33	40.24	0	99.43
Hispanic	25.42	27.94	0	90.20
Asians	5.47	9.80	0	66.95
Native Americans	0.10	0.13	0	64.19
Others	1.31	0.93	0	4.89
Local Workers (2002–2014) (%)	1.94	3.45	0.07	26.38

Note: The values for 2002–2014 are averaged over time.

Analysis

In our analyses, we model spatial and network autoregressive models. Spatial methods account for spatial dependence—that is, the tendency for variables measured in spatially proximate areas to be correlated. Spatial lag models assess spatial spillover by examining whether the dependent variable in neighboring places has a spillover effect into the focal spatial unit. Spatial error models assess whether there is spatial autocorrelation in the error term, which would indicate

that spatially correlated omitted variables influence the outcome of interest. Because communities that share commuters or public transit users are also linked through geographic space, spatial spillover processes likely occur across commuting and public transit boundaries and not only across spatially contiguous boundaries.[5]

We run our autoregressive models using three row-standardized spatial weights matrices. We find significant spatial dependence of our dependent variable (STI prevalence) on all three matrices using the global Moran's I test. Our first spatial weights matrix is based on geographic contiguity, with neighbors defined as communities that are immediately proximate to the community of interest (the Queen 1 criterion). Our second spatial weights matrix is based on communities that share lines of public transportation. Two communities are considered connected if they share a bus or train line. Our third spatial weights matrix is defined by commuting ties. Two communities are considered connected by a commuting tie if at least 0.5% of the home community commuted to the work community in 2002, the first year in our study.[6] In line with our conceptualization of the commuting and public transit spatial weights as inter-neighborhood networks representing potential social ties between communities, we refer to all three spatial weights matrices as networks: spatial network, commuting network, and public transit network.

Because our data are longitudinal, we estimate fixed-effects spatial models that include both a spatial lag and spatial error term.[7] We estimate our models using the *spxtregress* command in Stata (StataCorp 2019). We estimate fixed-effects models to account for unobserved neighborhood variation and to examine within-unit changes in the STI rate in neighborhoods across time. The fixed-effects spatial autoregression model is represented by the following equations:

$$y_{nt} = \lambda W y_{nt} + \beta \mathbf{X}_{nt} + c_n + u_{nt}$$

$$u_{nt} = \rho M u_{nt} + \mathbf{v}_{nt},$$

where the subscript n represents the spatial unit for time t. In our three models, our spatial weighting matrices are represented by W and M. $\mathbf{X}$ represents a vector of time-varying covariates, c represents individual effects, u represents the spatially lagged error term, and $\mathbf{v}$ represents a vector of innovations. In addition to our three fixed-effects spatial autoregressive models, we estimate a fixed-effects model without the inclusion of any spatial terms. Our fixed-effects models include dummy variables for time.

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[5] To assess the appropriateness of spatial and network autoregressive models, we first estimate the global Moran's I, which tests for spatial dependence in the data set. The coefficient can be interpreted as a correlation coefficient summarizing the complete spatial distribution of the data. A statistically significant coefficient indicates a higher level of spatial dependence in the observed data than would be expected by chance.

[6] Commuting ties in Chicago are relatively stable across the period we study. Descriptive statistics are presented in online Appendix B. Additionally, we examine our commuting tie cutoff threshold of 0.5% in online Appendix G.

[7] The Hausman test indicated that fixed-effects models were more appropriate than random-effects models (see online Appendix I).

Results

Maps and Network Graphs

Looking beyond the formation of sexual partnerships resulting from spatial proximity, Laumann et al. (2004) assessed the spatial distribution of dating ties between their study sites and areas across Chicago to understand how factors such as organizations, social networks, and urban spaces lead to partnerships that are geographically distant. They referred to these dating ties as "sex-market ties" because individuals must navigate social and structural barriers to find sexual partnerships. In Figure 1, we reproduce a map Laumann et al. (2004) published for their study of sex-market ties (shown on the left). Their map charts the ties between four communities in their study and the areas where residents' sex partners reside by different percentage cutoffs. For comparison, we also provide a map using our data on commuting ties and STI prevalence (shown on the right). We adopt similar cutoffs and highlight the same sample communities as Laumann et al. did, but we show how the communities are connected through their residents' commuting flows. The Laumann et al. map shows that sexual partnerships connect Shoreland (i.e., Lakeview) and Southtown (i.e., Roseland) to many other communities, both near and far, in the city. Although Erlinda (i.e., Hermosa) and Westside (i.e., Lower West Side) are connected to fewer communities, they are also connected to geographically distant ones. Their study demonstrates that sexual partnerships are not limited to geographically proximate communities. Our comparison map using our commuting data shows an important overlap in which communities are connected through commuting and sexual relation ties. The commuting ties also demonstrate that communities are connected both near and far. Commuting often connects communities with similar STI rates. Overall, the visualization offered by Figure 1 indicates that commuting networks may be an avenue for individuals to meet their sexual partners: people may meet their sexual partners at their work destinations and influence the spread of STIs.[8]

Figure 2 presents our three networks: spatial, commuting, and public transit. Across networks, the nodes represent neighborhoods and are colored based on their STI tercile, with blue denoting the bottom tercile, yellow indicating the middle tercile, and orange indicating the upper tercile. Nodes are sized by outdegree—that is, the number of ties a community sends to another based on the tie definition (i.e., geographic contiguity, commuting, or public transit). The leftmost network presents our spatial network, which shows the ties between communities based on geographic contiguity. Although spatial patterning of STIs is evident, geographic contiguity does not completely drive these trends. Highly infected areas (orange nodes) occur in the bottom and top areas of Chicago, and communities of varied STI rates are situated in between.

The middle network graph represents the 2002 commuting network but, to minimize visualization crowdedness, shows only ties between clusters. Although ties between communities within the same STI cluster are significant, this map shows that commutes make communities highly connected to other areas with varied STI rates.

8 See online Appendix A for a detailed map of Chicago and STI trends over time.
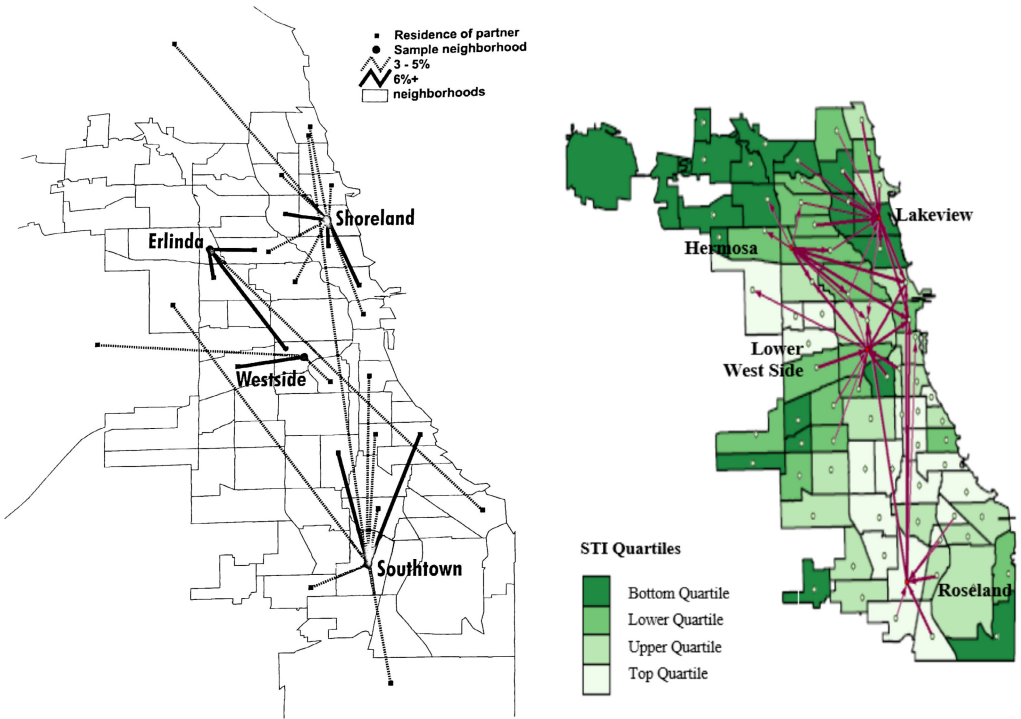
Fig. 1 Map of Chicago commuting ties comparison with the Laumann et al. (2004) dating ties map. The leftmost map is reproduced with permission from Laumann et al. (2004). In the rightmost map, nodes are positioned using the geographic coordinates of the centroids of community areas, represented as ovals. The community areas are colored using the quartile category of their STI levels. The map displays only those commuting ties with origin or destination in any of Laumann et al.'s (2004) four study communities and only ties with values of 3% to 5% of commuters (thin lines) or more than 5% (thick lines).

This figure highlights how commuters may expose their residential communities to STI risks from their work environments. It also suggests the potential for low-STI work communities to drive down STI rates in high-STI residential areas.

The network on the right shows the public transit network, focusing again on the between-cluster links. We observe a large concentration of nodes with a high degree value and a high infection rate, indicating that infected communities are highly connected by individuals through public transit connections. In comparison, communities with lower STI rates are connected to fewer communities by public transportation, making them less reachable.

Figure 3 highlights the difference between social space and geographic space when commuting and public transit networks—versus the geographic contiguity ties—are used. The leftmost network graph shows geographic proximity ties. The middle graph shows commuting ties but excludes ties between geographically proximate communities. The rightmost graph shows transportation ties, excluding those between geographically proximate communities. All graphs are produced from the same spring embedding procedure: the Kamada–Kawai algorithm in Pajek (Kamada and Kawai 1989), which produces a force-directed layout using a random starting
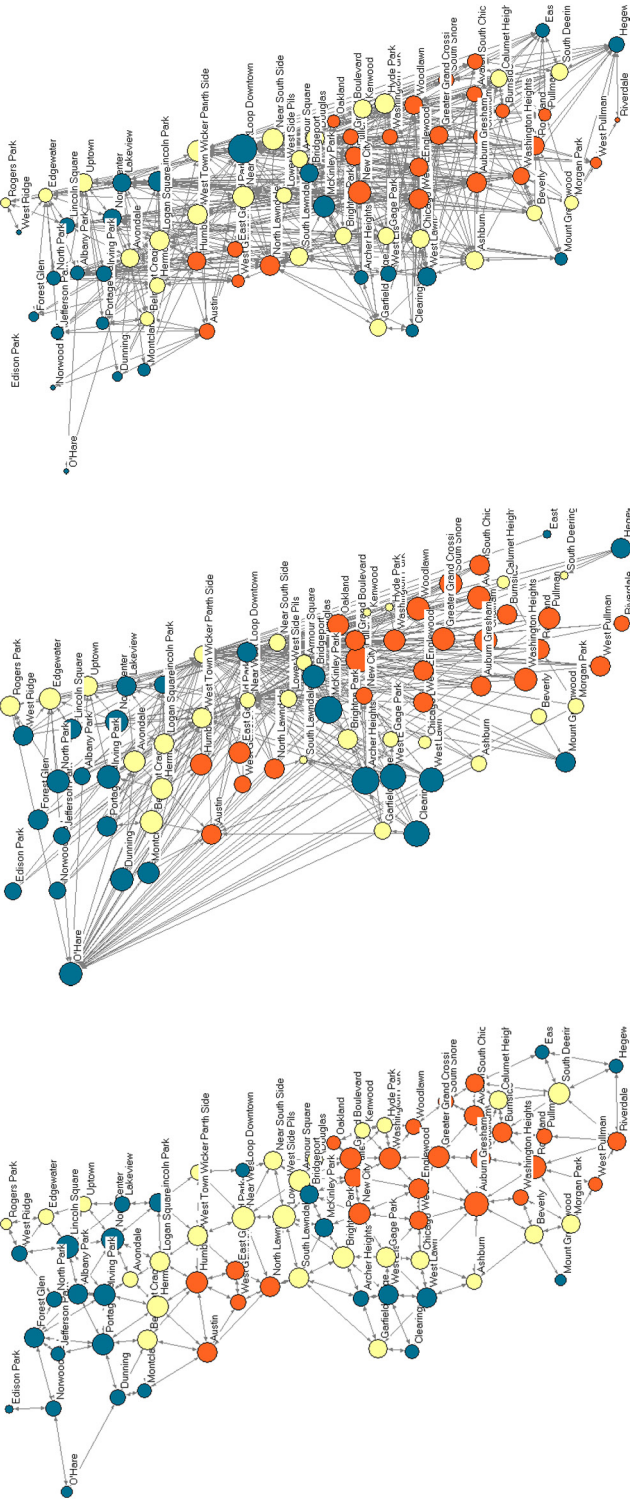
Fig. 2 Map of Chicago's spatial, commuting, and public transit networks by network degree and STI rate. Community areas are represented as nodes positioned according to the geographic coordinates of their centroids. The color of nodes is based on STI tercile categories in 2002 (blue for the bottom tercile, yellow for the middle tercile, and orange for the upper tercile). Across all three maps, the size of nodes represents outdegree (the number of ties to different connected areas based on the corresponding tie definition). The leftmost graph's ties are based on spatial contiguity. The middle graph's ties are based on the 0.5% commuting cutoff, and only ties between STI clusters are shown (ties within each of the STI tercile categories are removed). The rightmost map shows ties between STI clusters based on the public transit network.
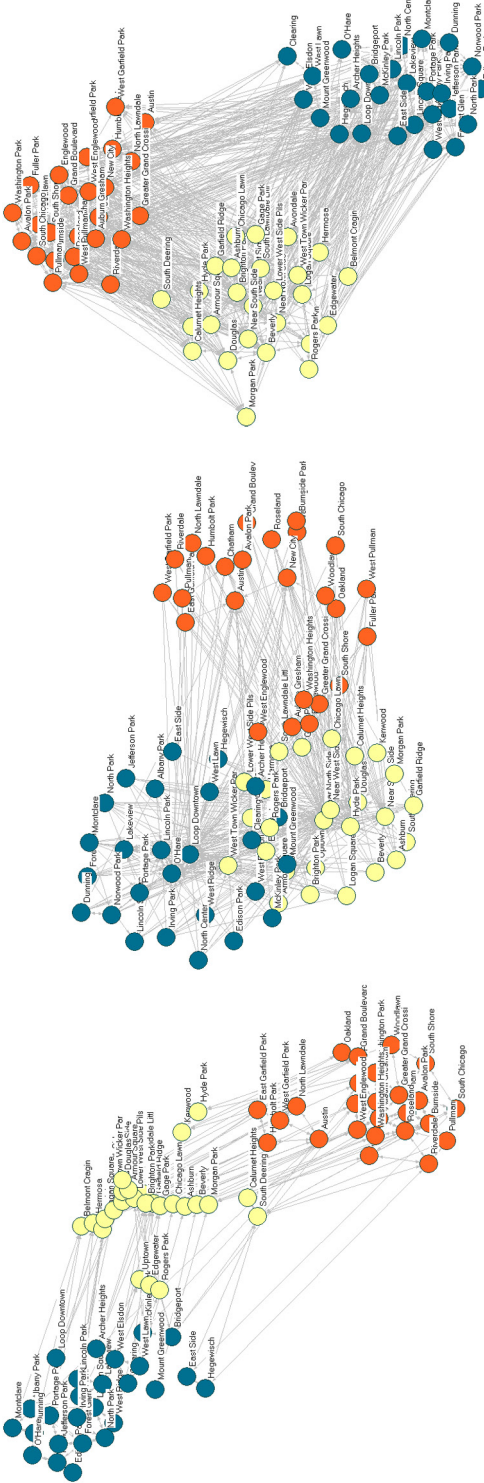
Fig. 3 Comparing connectivity in geographic and social space and links to STI. Community areas are represented as nodes positioned in geometric space using the Kamada–Kawai spring embedding procedure, with within-clusters optimization and using a random starting point to determine the location of communities in geometric space relative to each other on the basis of their connections (i.e., the actual geographic location is ignored). The color of nodes is based on STI tercile categories in 2002 (blue for the bottom tercile, yellow for the middle tercile, and orange for the upper tercile). The leftmost graph's ties are based on spatial contiguity. The middle graph's ties are based on the 0.5% commuting cutoff (excluding commuting ties between geographically proximate communities). The rightmost map shows ties based on the public transit network (excluding transportation ties between geographically proximate communities).

point and optimizing within clusters that determine the optimal location of communities in geometric space relative to one another based on their ties to one another. In contrast to Figure 2, the geographic location in Figure 3 is ignored. Note that high-STI communities are rarely tied to low-STI communities in the geographic space, whereas such ties are much more common in the social space graphs. Communities with lower STI levels, such as O'Hare and the Loop, often function as employment hubs that connect many higher-STI communities. The transportation network exhibits the most connections between communities of different socioeconomic levels, demographic composition, and STI levels. Additional tests support the visual indications that commuting has more of a core–periphery structure than the transportation network. Notably, the denser groups in both networks exhibit a lower STI prevalence on average than the more weakly connected group, indicating the need for a deeper understanding of the link between connectivity and STI.

Spatial and Network Autoregressive Models of STI Diffusion

To determine how STIs can spill over and exhibit autocorrelation across geographic and social space, we estimate spatial and network autoregressive models. Our models include spatial lag and spatial error terms. The spatial lag term is a spatial lag of the dependent variable and represents the correlation between the focal communities' STI prevalence and connected communities' average STI prevalence, as defined by the spatial weights matrix used. The spatial lag term thus indicates the *network STI risk* and represents a spatial and social spillover process. Including a spatial lag of our dependent variable modifies the effects of our independent variables. A change in a community independent variable will modify the STI prevalence of that community, which will in turn modify the STI prevalence in all the communities to which that community is connected through spatial and social spillovers. As a result, all the independent variables have direct and indirect effects on STI prevalence. The spatial error term represents spatial dependence in our error terms, which indicate spatially dependent omitted variables predicting similar STI rates in the focal community and the neighborhoods to which it is connected as defined by the spatial weights matrix. Table 2 presents the results of the dynamic fixed-effects models examining data for all the periods in our study. The table starts with models predicting STI prevalence without any spatial terms and then moves to each of the three models that use the different spatial weights matrices. We estimate each spatial and network model with and without disadvantage.

Model 1 is a fixed-effects model without accounting for spatial or social dependence. Models 2 and 3 examine how spatial dependence in geographically contiguous areas influences STI prevalence. Models 4 and 5 examine how communities connected through work commuting ties influence STI prevalence. Models 6 and 7 examine how communities connected through public transit lines influence STI prevalence. As expected, a community's previous STI prevalence is the strongest community-level predictor of continued STI prevalence. Prior high STI rates influence the persistence of high STI rates in consecutive years. In all but Models 3–5, residential diversity is also a consistent predictor of STI prevalence, with an increasing level of diversity associated with a lower STI rate. These findings support other

Table 2 Spatial lag and error models predicting STI rates

	Without Network	Spatial Network		Commuting Network		Public Transit Network	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Disadvantage	-0.060*	-0.064**		-0.038		-0.054	
	(0.029)	(0.022)		(0.031)		(0.030)	
Stability	-0.000	-0.004	-0.004	-0.020	-0.019	-0.021	-0.023
	(0.019)	(0.013)	(0.013)	(0.023)	(0.023)	(0.023)	(0.023)
Diversity	-0.047*	-0.037*	-0.013	-0.039	-0.029	-0.053**	-0.037*
	(0.018)	(0.016)	(0.014)	(0.021)	(0.020)	(0.019)	(0.017)
Local Workers	0.008	0.002	0.005	-0.007	-0.008	-0.001	-0.002
	(0.021)	(0.018)	(0.018)	(0.018)	(0.018)	(0.021)	(0.021)
Prior STI Rate	0.390***	0.296***	0.289***	0.380***	0.373***	0.385***	0.375***
	(0.030)	(0.031)	(0.032)	(0.032)	(0.032)	(0.033)	(0.032)
Network STI Risk		0.603***	0.589***	0.960***	0.960***	0.883***	0.883***
		(0.064)	(0.070)	(0.011)	(0.011)	(0.006)	(0.006)
Error Variance Parameter		-0.629***	-0.588***	0.961***	0.962***	0.883***	0.883***
		(0.108)	(0.116)	(0.010)	(0.010)	(0.006)	(0.006)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	-894.57	-921.79	-915.45	-1,268.55	-1,269.08	-3,391.84	-3,390.63
BIC	-806.21	-823.62	-822.18	-1,170.38	-1,175.81	-3,293.66	-3,297.36

Notes: Number of neighborhoods = 77. Number of observations = 1,001. Standard errors are shown in parentheses. All models include year dummy variables. AIC = Akaike information criterion. BIC = Bayesian information criterion. The Wald test of spatial autocorrelation is significant across all models at $p < .001$.

*$p < .05$; **$p < .01$; ***$p < .001$

research identifying assortative mating as a driver of STI prevalence. As diversity increases, the chances that individuals might choose interracial sexual partners also increases, which might reduce the flow of STIs within a neighborhood. Interestingly, we find that higher levels of disadvantage decrease STI prevalence in Model 1, which includes no terms for spatial autocorrelation, and in Model 2, which accounts for spatial dependence in contiguous communities. However, this result should be interpreted cautiously because the inclusion of time-lagged STI rates may account for this slight negative effect. Given that these models are fixed-effects models, they assess only variation across time within a neighborhood, and levels of disadvantage do not vary much over time. Disadvantage is quite persistent across Chicago, and few communities would be expected to vary substantially over time in their level of disadvantage.

The spatial lag and error term are significant across Models 2–7. A higher prevalence of STIs in geographically contiguous communities is associated with an increase in a focal community's STI rate. These results suggest that STIs can diffuse across spatially contiguous neighborhoods, given that neighborhood boundaries are not capable of physically blocking the flow of people and, subsequently, STIs across space. Interestingly, our spatial model has a negative spatial error term, implying the possibility of omitted variables that decrease STIs in a focal community when its geographically contiguous neighbors have a high STI prevalence.

The public transit and commuting models also show significant effects of connected communities' influences on a focal community's STI prevalence. We also find a positive and significant spatial error term in the transit and commuting models, suggesting that unexplained spatial variance in the models increases STI prevalence among communities that are connected via transportation and commuting ties. The model fit statistics indicate that the public transit model is the best model for explaining the diffusion of STIs across space. The fit estimates also imply that the commuting model better explains the diffusion of STIs across space than the spatial proximity model.

Supplementary Analyses

Our results demonstrate that spatially contiguous neighbors affect changes in STI prevalence over time, as do the communities that are connected through public transit and worker's commutes, which may be stronger influences. We further assess the importance of neighborhood connections in supplementary analyses that combine the three main spatial weight matrices into their four varying combinations that build on the concept of spatial proximity and extend it to the broader idea of social proximity (Kelling et al. 2021). The spatial lag term of STI prevalence is significant across all groupings of combined weight matrices. Models that include the public transit network and the commuting network in various combinations also fit the data better than models that account only for spatial interdependencies (see online Appendix D for more details). These findings highlight the benefit of an expanded view of inter-neighborhood connections, above and beyond geographic contiguity ties, to better understand the diffusion of risk for infectious diseases like STIs.

As noted in our discussion on the potential role of selection in tying communities together by commuting ties, we explore bootstrapped temporal exponential random graph models (TERGMs) in online Appendix C. We estimate TERGMs to better understand how communities' STI prevalence rates predict the presence of commuting ties. We find a significant homophily effect in which commuters tend to work in environments with STI rates similar to those of their residential neighborhood. These results support our main results of a significant error variance parameter with our commuting network, indicating significant social autocorrelation between communities connected through commuting.

Because STI prevalence varies dramatically across demographic groups, we present additional analyses in online Appendix E using more detailed information on the community's racial/ethnic composition and the neighborhood's age structure, marriage rates, and average household size. We also consider how the teenage birth rate, the age-adjusted total fertility rate, total population logged, and population density could influence neighborhood STIs. Our results remain robust to these additional controls. We retain the more parsimonious models in the main tables because of consistently better model fit scores. Additionally, the inclusion of prior STI rates naturally absorbs the effects of the additional STI determinants from these larger models.

In online Appendix G, we explore using both weak and strong commuter tie thresholds to examine how the relationship between STI prevalence and commuting varies by tie strength. We incorporate two commuting networks with a weaker tie threshold cutoff (0.1% and 0.25%) and two commuting networks with a stronger tie threshold cutoff (1% and 2.5%). We find a stronger effect with smaller cutoffs and no effect with stronger cutoffs. This finding likely reflects that the smaller commuting tie thresholds lead communities to be connected to most other communities in the network, whereas the stronger commuting tie thresholds lead communities to be connected to only a select few hub communities, such as O'Hare and the Loop.

Discussion

The results of the current study suggest that spatial spillovers of STIs and STI preventive information and risk behaviors occur not only between geographically proximate communities but also between communities that are socially connected within the city, even if they are geographically distant. Our findings reveal that the commuting and public transit networks explain STI transmission across space better than the geographic contiguity model. These results suggest that as a neighborhood's residents travel beyond their immediate residence to work or conduct their daily routines using public transportation, they facilitate the spillover of STIs and related risk factors across communities. We illustrate two key ways that individuals moving across space connect communities, with important consequences for influencing community processes, such as the spread of STIs and STI-related norms and behaviors.

Our findings advance prior research that has largely focused on individual-level determinants (Burstein et al. 1998; Chatterjee et al. 2006; Kelley et al. 2003; Laumann and Youm 1999) and residential neighborhood effects (Ellen et al. 2004; Jennings et al. 2012). Importantly, our results suggest that structural network influence is likely an important part of the long-term reproduction of community-level

health disadvantages. The significance of the commuting and the public transit networks for STI risk spillovers indicates that beyond spatial proximity, social proximity related to broader patterns of mobility and activities influences the spread of STI risk across urban space. Although we can map connections between neighborhoods via transit lines, we cannot document individuals' unique transit patterns. Some individuals might use multiple transit lines during a trip and connect to neighborhoods that are directly tied to their residential neighborhood. This data limitation might prevent exact estimates of the effects of transit lines on STI rates. However, we can precisely map where commuters work and live, for which we find effects on STIs that are similar to those of transit lines. Laumann et al. (2004) showed that dating ties can stretch across a city, given that individuals sometimes find their sexual partners through their social activities. Our findings are consistent with this work and further advance the literature by documenting how community networks defined by commuting and public transportation can contribute to the flow of STIs across a city**.**

Implications

The current findings have theoretical implications for advancing scholarship on neighborhood effects, residential segregation, and population mobility by demonstrating the value of connections beyond residential neighborhood boundaries and geographic proximity space to better understand the effects of population-level mobility flows on local health and other demographic outcomes. These findings are consistent with the growing body of research on activity space exposures and residential mobility (which often focuses on individuals). Our study further advances knowledge by demonstrating that inter-neighborhood ties are significant in shaping the health and well-being of entire communities.

This study also contributes to current methodological knowledge by demonstrating the value of combining longitudinal spatial and network autoregressive models to address questions important to demographers and social epidemiologists alike. The results help us better understand how population mobility and socially connected communities contribute to changes in STI patterns over time, with relevance to other infectious diseases. Future research might look more closely at the diffusion of infections across neighborhoods. Although our study can assess the autocorrelation in STI rates among neighborhoods, more precise data and methods might be able to assess the diffusion of these infections more accurately across space. Additionally, our research documents connections between neighborhoods as dichotomous. Future research might build on this methodology by using weighted networks to understand important nuances by tie strength.

Past research has indicated the importance of spatial clustering for STI patterns in an urban environment (De et al. 2004; Potterat et al. 1985; Risley et al. 2007), but focusing only on these areas has proven ineffective for STI-targeted interventions (Jolly and Wylie 2013; Rothenberg et al. 2005). Our results suggest that interventions would benefit from considering how people interact with their environment and the implications of connected communities for infectious diseases. Instead of focusing only on highly infected communities, future interventions should consider contact tracing to better track and treat STIs across communities. Additionally, information

about STI prevention might be circulated in communities that are highly connected by commuters and public transit, given that exposure to this information can decrease STI incidence (Warner et al. 2008).

Going beyond prior studies that documented the effects of residential neighborhoods on health (Arcaya, Tucker-Seeley et al. 2016; Cubbin et al. 2020, Cubbin et al. 2005; Sampson 2003), the current study highlights a great need for future research to explore the implications of connected communities on health outcomes. For example, future studies could explore how exposures to different racial/ethnic groups in people's work environments influence interracial marriage, above and beyond such exposures in residential neighborhoods or perhaps even despite strong segregation patterns in residential neighborhoods. Future research might also pay closer attention to the ways race and ethnicity shape STI patterns across cities, given that some groups are more predominantly affected by STIs than others (Adimora and Schoenbach 2005, 2013; Harling et al. 2014; Thomas and Thomas 1999).

A social epidemiological approach that highlights the importance of inter-neighborhood connections will also be particularly valuable in illuminating the unequal spatial distribution of other infectious disease patterns—such as COVID-19 (Jia et al. 2020) or the seasonal influenza virus—across commuting, public transportation, and other population mobility pathways. Other major population outcomes likely depend not only on physical exposures to risks or resources but also on behavioral and normative influences through mobility pathways and exposure to factors such as pollution or food environments—for example, violent victimization and crime rates (Kelling et al. 2021; Levy et al. 2020); asthma, obesity, or smoking prevalence (Christakis and Fowler 2008, 2013; Zhang and Centola 2019); and infant mortality and birth weight.

Our research investigates the structural mechanisms of socio-spatial spillovers: specifically, public transportation networks and worker commute networks. Future research would benefit from further investigation of how these networks facilitate the underlying social interactions and mechanisms that influence health behaviors and outcomes. Connected communities likely play an important role in shaping STI rates through exposure to infected sexual partners or through social contagion of health behaviors (Christakis and Fowler 2013). Further, STIs are likely dependent on social learning and contagion of preventive health behaviors, which occur more slowly through social reinforcements from multiple sources (Zhang and Centola 2019). Health behaviors and the normativity of risky health behaviors are influenced by reinforcing messages from multiple network ties about the acceptability and safety of contraceptives (Behrman et al. 2002; Guilkey et al. 2020; Kohler 1997; Valente et al. 1997). Such messages are particularly relevant for behaviors that involve other people and are subject to normative pressure (Christakis and Fowler, 2008; de Vaan and Stuart 2019). Better knowledge of how these connections shape or constrain sexual partnerships might highlight inequality in opportunities to partner with uninfected individuals. Our research identifies the structural networks that contribute to STI spillovers across communities, but future research might investigate how specific mechanisms—such as dating and the spread of sexual norms or behaviors—contribute to these patterns.

More broadly, our research highlights the importance of going beyond the standard approach to neighborhood effects to better understand population health patterns and social behaviors. Our results show that socially connected communities

are key drivers of STI infection patterns in Chicago. Future research would benefit from assessing how connected communities shape other population health and demographic patterns. ∎

Note Lauren Newmyer and Megan Evans had equal authorship.

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