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Ecological Networks and Neighborhood Social Organization[1]

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Abstract

Drawing on the social disorganization tradition and the social ecological perspective of Jane Jacobs, the authors hypothesize that neighborhoods composed of residents who intersect in space more frequently as a result of routine activities will exhibit higher levels of collective efficacy, intergenerational closure, and social network interaction and exchange. They develop this approach employing the concept of ecological networks—two-mode networks that indirectly link residents through spatial overlap in routine activities. Using data from the Los Angeles Family and Neighborhood Survey, they find evidence that econetwork *extensity* (the average proportion of households in the neighborhood to which a given household is tied through any location) and *intensity* (the degree to which household dyads are characterized by ties through multiple locations) are positively related to changes in social organization between 2000–2001 and 2006–2008. These findings demonstrate the relevance of econetwork characteristics—heretofore neglected in research on urban neighborhoods—for consequential dimensions of neighborhood social organization.

Research on "neighborhood effects" has expanded dramatically over the last two decades, yielding significant insights into the ecological origins of human well-being, particularly child and adolescent developmental outcomes. Among the central contributions of recent work is the theoretical explication and measurement of neighborhood social processes relevant for children, including collective efficacy (Sampson, Raudenbush, and Earls 1997),

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intergenerational closure among local children and adults (Coleman 1990; Sampson, Morenoff, and Earls 1999), and patterns of social network interaction and exchange (Morenoff 2003; Browning, Feinberg, and Dietz 2004). Leveraging increasingly available high-quality data on neighborhoods, urban research has generated an important body of findings linking neighborhood social processes to youth developmental well-being (Sampson, Morenoff, and Gannon-Rowley 2002; van Ham et al. 2012). Yet, less attention has been directed toward understanding the origins of these processes, leaving insight into how neighborhoods with beneficial social dynamics emerge in an incipient state.

Research on the sources of youth-relevant neighborhood social processes largely has focused on relatively distal structural features of urban neighborhoods, such as poverty rates, race/ethnic segregation, and instability of residential tenure (Shaw and McKay 1942; Sampson et al. 1999). Although critical to illuminating pervasive inequality in neighborhood functioning, an emphasis on these structural attributes as explanations of neighborhood social processes neglects the variably constrained or facilitated actions of urban residents through which features of neighborhood social organization emerge (Hedström and Ylikoski 2010). Drawing on the social disorganization tradition (Shaw and McKay 1942), activity space perspectives (Kwan 2009), and the social ecological approach of Jane Jacobs (1961), we develop hypotheses on the origins of neighborhood social processes employing the concept of *ecological networks*—links between people and the spaces they frequent in the course of ongoing routine activities (Browning and Soller 2014). We argue that contexts in which residents intersect in public space on a repeated basis generate the ecological conditions necessary for public contact, the emergence of place-based familiarity, and, ultimately, a trust-anchored willingness to intervene on behalf of the collectivity (Jacobs 1961; Gehl 2011; Blokland and Nast 2014). Neighborhoods in which residents rarely intersect in public space will be constrained in their capacity to foster beneficial social climates.

Assessing the relevance of ecological network characteristics for neighborhood social processes requires integrating social network analysis (Feld 1997; Robins and Alexander 2004) with methods for the multilevel investigation of neighborhood effects (Raudenbush and Bryk 2002). We construct ecological network structural characteristics for 65 census tracts employing unique data from the Los Angeles Family and Neighborhood Survey (L.A.FANS)on the locations of household members' routine activities (Sastry et al. 2006). We then link tract- and household-level network measures with resident reports of changes in neighborhood social climate along a number of dimensions across two waves of the L.A.FANS. Results from multilevel models of these outcomes represent, to our knowledge, the first investigation of ecological network effects on neighborhood social organization.

BACKGROUND

A long history of research on urban areas emphasizes collective aspects of community life in explaining local area variation in residents' well-being (Kasarda and Janowitz 1974). Early Chicago school theorists identified "social disorganization" as a key process explaining neighborhood differences in outcomes such as crime (Shaw and McKay 1942) and mental health (Faris and Dunham 1939). Shaw and McKay's (1942) approach shaped subsequent articulations of the disorganization concept as capturing “the general inability of a community structure to realize common values and maintain effective social controls” (Sampson and Groves 1989, p. 777). The social disorganization model’s most sophisticated expression emerged in Sampson et al.’s (1997) collective efficacy approach. In this view, neighborhoods vary in levels of mutual trust and the collective willingness to intervene on behalf of the common good. The joint emphasis on trust, norms of mutual support, and expectations for prosocial action has yielded a powerful concept with broad applicability to outcomes relevant for youth well-being. Indeed, collective efficacy has been linked not only with crime and delinquency (Sampson et al. 1997; Morenoff, Sampson, and Raudenbush 2001; Browning et al. 2004; Maimon and Browning 2010) but with a range of behavioral and health outcomes as well (Xue et al. 2005; Sampson 2012).

Prosocial intergenerational orientations are another significant neighborhood-level resource for children. Coleman (1990) emphasized the structural benefits of parents’ knowledge of both their children’s friends and the parents of their children’s friends for maintaining effective information dissemination and informal social control. A neighborhood-level counterpart can be understood as capturing the normative expectation for such linkages across the community and the associated willingness of parents to take collective responsibility for the well-being of local youths other than their own (Sampson et al. 1999). At the neighborhood level, intergenerational closure is conceptually aligned with the notion of collective efficacy, with a distinct emphasis on norms reinforcing parental support of local children. Extant research has offered evidence of the informal social control benefits of intergenerational closure for urban youths (Leventhal and Brooks-Gunn 2000; Maimon and Browning 2010).

Finally, effective informal exchange networks within urban communities have been a long-standing focus of urban sociological research. Here we distinguish between the structure of network ties (e.g., the prevalence and density of family and friendship connections) and the frequency of mutually supportive exchange (activated ties; Sampson et al. 1999) within neighbor networks. Network ties that can be effectively relied on not only for sociality but also for favor exchange, advice, and other forms of social support capture the neighborhood-level capacity for mutual provision (which may be variably rooted in the prevalence and density of friend and kin ties). Indeed, some research finds protective effects of the frequent exchange of advice and support in urban neighborhoods (e.g., on the prevalence of low birth weight; Morenoff 2003). In light of these findings, a critical question concerns the origins of collective efficacy, intergenerational closure, and network interaction and exchange as features of neighborhood social organization with potentially wide-ranging benefits for urban residents.

THE ORIGINS OF NEIGHBORHOOD SOCIAL ORGANIZATION

What factors give rise to efficacious communities? Evidence of neighborhood structural associations (e.g., concentrated disadvantage, residential instability) with levels of social organization is well established (Sampson et al. 1999), but an emphasis on compositional factors limits insight into the everyday mechanisms that promote or impede beneficial social climates. The dominant urban sociological approach to this question has highlighted the role of neighborhood-based social network ties. We consider the long-standing focus on both the prevalence and strength of network ties as well as more recent attention to the context of network ties in understanding the emergence of socially organized neighborhoods.

Recognition of the need for a more clearly articulated model of the social dynamics differentiating urban neighborhoods led to development of the well-known systemic model of community social organization (Kasarda and Janowitz 1974; Bursik and Grasmick 1993). The systemic model identifies social network ties rooted in family and friendship as well as formal and informal associational links as essential to the neighborhood capacity for self-regulation. In this view, widespread and close interpersonal ties provide incentives for neighborhood residents to avoid norm violation and the subsequent potential for social sanction. The benefits of these intimate (private) ties are supplemented by the supervisory capacity of less intimate but established friendship and acquaintanceship (parochial) ties based on local voluntary organization and institutional involvements (e.g., school, church). Finally, extraneighborhood (public) network ties yield additional resources to bolster internally generated social organization capacities. Neighborhoods that maintain these forms of relational network ties are expected to more effectively socialize and supervise local youth, mobilize on behalf of shared goals, and provide mutual support.

Although the systemic approach offered a coherent explanation of the processes fostering socially organized neighborhoods, the model's emphasis on the benefits of social integration —dense, close-knit social networks—has been the subject of critique as the ambiguous implications of such network ties for neighborhoods have increasingly come into view (Wilson 1996; Putnam 2000; Browning et al. 2004; Browning 2009; Sampson 2012). While seminal statements of the systemic model point to the benefits of internal social integration, collective efficacy theory highlights the fundamentally neutral nature of urban social networks (Sampson 2012). In this view, information on the level of social network integration characterizing a neighborhood says little about the ability of communities to mobilize residents toward specific ends (Morenoff et al. 2001; Sampson 2012).

Indeed, some urban scholarship moves beyond the notion of network neutrality to highlight the conditions under which social network integration may impede the emergence and impact of beneficial neighborhood social organization. Wilson's (1996) discussion of "social isolation" indicates that highly disadvantaged urban neighborhoods may actually be characterized by strong ties but nevertheless experience disconnection from conventional institutions and other mainstream sources of influence. In these circumstances, Wilson argues, social integration may serve to disseminate problematic behavior. Drawing on Pattillo (1998) and Pattillo-McCoy (1999), and Venkatesh (1997), Browning et al. (2004) demonstrate that social network interaction and exchange limit the effectiveness of neighborhood social control orientations in regulating the prevalence of crime. In this "negotiated coexistence" model, when social interaction and exchange are rooted in high levels of neighborhood social integration, close-knit social ties may come into conflict with generalized expectations for informal social control. For instance, interpersonal obligations may limit inclinations to sanction criminal or delinquent behavior (e.g., when residents choose not to call the police when they observe a close neighbor's child engaging in criminal behavior [Pattillo 1998]).

These findings have encouraged urban researchers to reconsider the role of social integration when examining the origins of neighborhood-based social organization. The potential benefits of weak social ties in urban contexts have received substantial theoretical attention (Granovetter 1973; Putnam 2000), with some evidence suggesting that more distal ties may have benefits for the regulatory capacity of urban neighborhoods (Bellair 1997). The nature of the link between weak network ties at the neighborhood level and key dimensions of social organization, however, has yet to be fully articulated. Beyond questions concerning the benefits of the prevalence and strength of network ties, research has increasingly focused on the context of social tie formation and enactment as relevant for understanding social organization outcomes (Small 2009). We emphasize the importance of regular but superficial social interaction in the context of everyday conventional routines as a critical precursor to the emergence of neighborhood social organization.

PUBLIC CONTACT AND THE EMERGENCE OF PROSOCIAL NORMATIVE ORIENTATIONS

Following the early development and ascension of the social disorganization perspective, the middle of the 20th century saw the rise of modernist philosophies of urban planning, with an emphasis on the separation of residential and commercial uses of space (Le Corbusier [1929] 1987). A well-trodden history of the urban renewal movement recounts the realization of modernist design principles in large-scale urban housing and commercial developments during the 1950s and ’60s and the subsequent decline of this approach to urban planning (Hirsch 1983; Ryan 2012). Jane Jacobs forcefully contested the tenets of this movement in her classic work *The Death and Life of Great American Cities* (1961), arguing that dense, organically developing, and mixed commercial, institutional, and residential land uses encourage frequent, conventional street activity. In turn, street activity yields “eyes on the street” with associated social control benefits for urban neighborhoods (Browning and Jackson 2013). Less frequently considered in the robust discussion of Jacobs’s work is her emphasis on the prevalence and vitality of local organizational and amenity options in producing everyday intersection of neighborhood residents in public space, that is, *public contact*.

A key aspect of Jacobs’s model is the extent to which local neighborhood environments feature destinations that serve to bring residents together in public space as a by-product of ongoing, conventional routine activity. In her view, the extent of public contact among neighborhood residents may vary significantly across urban space. Residents of neighborhoods embedded in urban areas marked by limited options for employment, local commerce, or high-quality institutions may be required to leave the local vicinity of the neighborhood to engage in some everyday tasks. Consequently, routine activity spaces of residents may evolve idiosyncratically (leading to fewer opportunities for contact) as residents find work, schooling, or shopping opportunities potentially well outside the neighborhood. Others may simply not engage in as many nonhome activities (Furstenberg et al. 1999). Both scenarios yield lower potential for public contact and sparser structures of intersection between residents. In contrast, local neighborhood environments that present a wide variety of options for employment, commerce, education, and other amenities will tend to bring residents together in shared activity locations more extensively. Moreover, the availability of attractive destinations for conventional routine activities is likely to lead to more widespread joint use of streets and other interstitial public outdoor places as residents travel between locations (Browning and Soller 2014).

Public contact is necessary for the emergence of *public familiarity*—mutual recognition in public space. In Jacobs's approach, higher levels of public contact are assumed to lead to mutual recognition and varying levels of passive to active engagement (Grannis 2009) in public space. Few studies have directly assessed this hypothesis, but Blokland and Nast (2014) find that survey-reported regular use of a neighborhood shopping district in two proximate Berlin neighborhoods was associated with public familiarity (e.g., talking to unknown others in public). Jacobs acknowledges that more active ties of mutual acquaintanceship may result from these encounters but emphasizes the benefits of widespread, nominal public interactions. Specifically, she argues that casual, superficial public contacts and the resulting familiarity yield, in the aggregate, a "web of public respect and trust" (Jacobs 1961, p. 56), indicating that the network of intersecting people and places in the context of routine activity is consequential for neighborhood collective trust.

Extant research offers evidence in support of the core claim that increased familiarity breeds trust. Research on organizations in urban contexts points to the role of shared involvements and the resulting (even quite weak) familiarity in producing trust. In his "organizational embeddedness" approach, Small (2009) argues that local organizations bring individuals together, providing the spatial basis for interaction (Oldenburg 1989; Blau and Schwartz 1997). In turn, repeated public interaction establishes a foundation for mutual trust—a finding rooted in a robust literature in social psychology (Lawler and Yoon 1993; Lawler 2001). Small's analysis of mothers' involvement in an urban child care center shows that public contact in the context of center involvement provided sufficient information and familiarity among mothers to encourage trust, despite relationships that involved little more than face-to-face recognition. In turn, mothers (some of whom barely knew one another) could be relied upon for high-stakes mutual support, such as caring for one another's children in an emergency.

Small's analysis focuses specifically on contact in the context of organizational involvements. Although many urban encounters occur in organizational contexts (e.g., stores, schools, churches), public trust may also follow from contact and associated familiarity in nonorganizational contexts. Jacobs's model emphasizes public contact in the context of conventional routine activity as a condition for the emergence of public trust. Mutual observation and public interaction among neighborhood residents who cue their participation in everyday (often organizationally anchored) activities, such as employment and family-related tasks, are likely to provide an interactional context under which familiarity yields place-based trust. Blokland and Nast (2014), for instance, find that weak forms of survey-reported public familiarity in the context of a local shopping district fostered trust that others would intervene on the respondent's behalf in the case of a threat. Moreover, although Small is focused on relational rather than community-level trust, the prevalence of such informal exchanges among neighborhood residents (rooted not only in organizationally based interactions but in less formal public encounters as well) is likely to concatenate, with implications for generalized trust.

Finally, public contact and familiarity also may serve as the basis upon which mutually supportive exchange networks emerge within urban neighborhoods. Again, Small's analysis provides qualitative evidence in support of the claim that weak contacts may yield social support benefits. Exchange networks rooted in weaker contact may provide a broad base of potential social support opportunities and are not encumbered by the demands (and potential conflicts) associated with greater intimacy (Jacobs 1961; Browning et al. 2004). To date, however, no study has examined the role of public contact potential—as captured by actual information on the routine activities patterns of urban residents—in promoting beneficial aspects of neighborhood social organization.

THE STRUCTURE OF SHARED ROUTINES AS AN ECOLOGICAL NETWORK

We formalize Jacobs's notion of public contact employing the concept of an *ecological ("eco-") network*. Econetworks can be understood as the set of links among neighborhood residents through shared routine activity locations. Econetworks are instances of two-mode or affiliation networks (Robins and Alexander 2004) in which actors are tied indirectly through another node set (in the econetwork case, locations). Here we formalize the notion of public contact potential through specifying an econetwork linking actors when their routine activity locations are near one another in space under the assumption that proximity constitutes an ecological precondition for contact. Conceptualizing public contact potential employing an econetwork approach sheds light not only the impact of quantitative increases in the extent of shared routines but also on the role of *distinct econetwork structures* in promoting neighborhood social organization.

We focus on two key dimensions of econetwork structure capturing theoretically relevant precursors to Jacobs's web of public familiarity and trust— the *extensity* and *intensity* of shared exposures. The extensity of econetwork exposure refers to the breadth of ties across all neighborhood households, while intensity measures the degree to which household dyads are characterized by ties through multiple locations. These structural dimensions of econetworks may have both shared and divergent implications for neighborhood interaction patterns and the assessment of social climates.

First, we anticipate that econetwork extensity will be linked with generalized trust and associated prosocial normative orientations with respect to informal social control (collective efficacy) and the intergenerational support of youth. The larger the proportion of neighbors encountered in conventional routine activities, the greater the likelihood that trust will generalize to neighborhood residents as a whole. Extensity captures any instance of a shared routine activity location among residents and may therefore involve only the most nominal familiarity. Yet the breadth of such familiarity across the econetwork may be a particularly important foundation for the emergence of a generalized sense of trust. The number of more involved social network ties one can maintain is inherently limited (Roberts et al. 2009) and is likely to be an insufficient basis for evaluating the trustworthiness of neighborhood residents as a whole. Consequently, evidence of the behavioral reliability of neighborhood residents whom one does not know personally but who otherwise become familiar while engaging in daily routines provides an important independent source of information shaping perceptions of trust. In turn, shared expectations for prosocial action—including norms regarding the social support and supervision of children in public space—are more likely to emerge in contexts characterized by ongoing, conventional, routine activity-based encounters.

A second econetwork structural characteristic potentially relevant for neighborhood social organization is econetwork intensity—or the extent to which residents who share one location also share other locations. High-intensity econetwork structures foster increased public contact among any given set of two neighbors, increasing the likelihood of mutual recognition and public familiarity. Trust and shared expectations for prosocial action may be more efficiently promoted when residents encounter each other at multiple locations as the trust developed at one location where familiar neighbors are encountered spreads to other locations where those same neighbors are observed. High-intensity econetwork structures are also more likely to involve residents who have contact at both residential locations proximate to their home (e.g., at a nearby convenience store) as well as more distal institutional locations (e.g., a school in the local district). Linkage of residents sharing "street neighborhood" routines and institutional involvements may be important for building trust and neighborhood mobilization capacity beyond the confines of immediate residential environments (Grannis 2009).

Multiple shared locations and the associated enhanced public familiarity may be particularly important in facilitating social interaction and exchange (Curley 2010; Gehl 2011). Frequent encounters across multiple locations enhance the sense of a common routine activity pattern and may increase the likelihood of active engagement (i.e., superficial verbal interaction). In turn, these active engagements in public space may ultimately lead to network-based social support activities, such as advice giving and favor exchange (Small 2009). In this view, econetwork structures characterized by higher levels of intensity encourage the development of social interaction and exchange independent of preexisting levels of friendship or family ties within the neighborhood.

Public contact in routine activity spaces is likely to inform perceptions of both neighbors as a social collectivity (e.g., the trustworthiness of the people who are my neighbors) as well as the set of locations that constitute the neighborhood spatial community (e.g., the trustworthiness of the local places neighbors share as part of their daily routines). The spatial community of a neighborhood encompasses routine activity locations that may or may not fall within the boundaries of neighborhood units as typically employed in urban research (e.g., a grocery store shared by two residents of the same census tract that is located in a different but proximate tract). Encounters with publicly familiar neighbors at locations outside neighborhood boundaries may enhance the sense of trust attributed to the neighborhood spatial community as a whole. Thus, it is important to consider not only the role of shared locations within an administratively defined boundary but also the potential for public contact across the larger set of shared routine activity locations. As the distance of shared routines locations from the residential neighborhood increases, however, their impact on neighborhood social organization may diminish.

Finally, a resident's structural location within the econetwork may play an important role in understanding variation in assessments of neighborhood social organization among residents of the same neighborhood. Extant research has offered evidence of substantial within-neighborhood variability in perceptions of collective efficacy, intergenerational closure, and exchange networks among urban residents (on the order of 60%–80%; Sampson et al. 1997, 1999; Mujahid et al. 2007). To date, explanations of within-neighborhood variation in neighborhood evaluations (e.g., collective efficacy [Sampson et al. 1997]) largely have focused on resident and household-level attributes, such as demographic and socioeconomic background. In contrast, the econetwork approach described here acknowledges the potential for variation in a resident's spatial exposures and his or her resulting econetwork position to explain within-neighborhood variability in social organization perceptions.

The individual position of a resident in the neighborhood econetwork is, by definition, a relational construct that cannot be understood without reference to the behavior of other residents as they engage in routine activities. Encounters with neighbors will be limited if nonhome routine activities are confined to location settings that are not shared by other residents. Because activity spaces vary in their characteristics at the resident level within neighborhoods, econetwork positions likely will vary as well, with potentially important consequences for experiences of the neighborhood social climate. We expect that residents who exhibit higher levels of econetwork extensity— that is, who share locations with a relatively larger proportion of their neighbors—will perceive higher levels of neighborhood social organization.

Research has not yet examined the contribution of econetwork structure to neighborhood social processes. Recent efforts to measure neighborhood-level social networks have offered important evidence of the potential for social network structures to vary across contexts and influence sociologically relevant outcomes. In one of the few efforts to map entire social networks at the community level, Entwisle et al. (2007) demonstrate that network structures vary meaningfully across villages in Thailand and partially explain village-level variability in the ability to locate and interview former residents. Hipp and colleagues (2013) simulate network ties within neighborhoods using a spatial interaction function (Butts et al. 2012). Generating measures of neighborhood social network structure from simulated data, Hipp et al. find evidence of network structure effects on crime rates in five cities. These approaches represent important advances in integrating network and contextual approaches. The econetwork approach, however, is not intended to proxy the actual network of established social ties but to capture the potential for contact in public space through uncovering the structure of shared routine activities. In the only extant empirical evaluation of econetwork effects, Browning, Soller, and Jackson (2015) examine the cross-sectional link between a measure of econetwork intensity and adolescent risk behavior. They find that higher-intensity econetworks exert a protective effect on delinquency and substance use. The direct effect of econetwork structure on dimensions of neighborhood social organization, however, has not been investigated.

In summary, a focus on the econetwork origins of neighborhood social organization incorporates recognition of the potentially productive role of weak forms of interaction rooted in ongoing intersection in public space. The emphasis on variability in space use across neighborhoods is a heretofore neglected neighborhood dynamic that may nevertheless have significant implications for neighborhood social organization. Using unique, longitudinal data on the routine activity locations of Los Angeles residents, we describe our approach to the measurement of ecological network structure and examine the consequences of econetwork variability for neighborhood social organization. Specifically, we examine (1) the extent to which measures of econetwork structure predict changes in social organization over time, above and beyond a wide range of potential confounders; (2) the potential for measures of econetwork extensity and intensity to differentially influence changes in dimensions of social organization (with intensity exhibiting more pronounced effects on social network interaction and exchange); and (3) the extent to which individual positions within neighborhood-based econetworks explain within-neighborhood variability in changes in social organization.

DATA AND MEASURES

Our analysis combines data from waves 1 and 2 of the Los Angeles Family and Neighborhood Survey (L.A.FANS) and the 2000 decennial census. The first wave of L.A.FANS was conducted between 2000 and 2001 and is based on a stratified random sample of residents within 65 census tracts in Los Angeles County. The sample covers the entire income range, but high-poverty tracts were oversampled. Within each selected tract, roughly 39 households were randomly selected; households with children were oversampled. Within each household a randomly selected adult (RSA) was interviewed. If children under age 17 lived in the household, then the primary caregiver (PCG; RSAs may also serve as PCGs), a randomly selected child (RSC), and one of the child's siblings (if present) also were interviewed. The second wave of L.A.FANS was conducted between 2006 and 2008. Our sample for the analysis of social organization outcomes consists of all RSA respondents who did not attrite or move between waves ($N = 682–687$; the number of respondents slightly varies across outcomes due to missing data on the dependent variables). We apply the 2000 census data to the 1990 tract boundaries because the L.A.FANS sampling design is based on 1990 boundaries.[2] Consistent with the L.A.FANS sampling strategy, we use census tracts to approximate neighborhood boundaries.

DEPENDENT VARIABLES

We measure the association between neighborhood- and household- centered measures of econetwork structure and three dependent variables that capture various neighborhood processes. All dependent variables are change scores—that is, the mean of the scale items at wave 1 subtracted from the mean of the scale items at wave 2—based on responses obtained from RSAs at both waves of L.A.FANS. Following Sampson et al. (1997), we constructed a *collective efficacy* measure using information from two scales—social cohesion and informal social control—administered as part of the community survey. The social cohesion scale is based on items measuring respondents' level of agreement (on a five-point scale) with the following statements: (1) "People around here are willing to help their neighbors," (2) "This is a close-knit neighborhood," (3) "People in this neighborhood can be trusted,"

[2]See Peterson et al. (2007) for information on crosswalk procedures.

(4) “People in this neighborhood generally don’t get along with each other,” and (5) “People in this neighborhood do not share the same values.” We reverse coded the last two items. The informal social control scale is constructed from respondent assessments of the likelihood that their neighbors could be counted on to intervene if (1) “Children were skipping school and hanging out on a street corner,” (2) “Children were spraypainting graffiti on a local building,” or (3) children were “showing disrespect to an adult.” Responses were given on a five-point scale (wave 1 α for the combined collective efficacy scale = .73; wave 2 α = .78).

Intergenerational closure includes five items that assess RSAs’ perceptions of the presence of bonds between neighborhood adults and children: (1) “Parents in this neighborhood know their children’s friends,” (2) “Adults in this neighborhood know who the local children are,” (3) “There are adults in this neighborhood that children can look up to,” (4) “Parents in this neighborhood generally know each other,” and (5) “You can count on adults in this neighborhood to watch out that children are safe and do not get in trouble.” The respondent’s level of agreement was reported on a five-point scale. By design, this scale captures aspects of adult-child social ties as well as expectations for active support and informal social control of local youth by neighborhood adults (wave 1 α = .75; wave 2 α = .76; Sampson et al. 1999). Finally, *social network interaction/exchange* is measured with responses to questions asking the respondent how often neighbors (1) do favors for each other, (2) watch each other’s property, and (3) ask each other for advice. Responses were given on a four-point scale (wave 1 α = .70; wave 2 α = .75).

INDEPENDENT VARIABLES

Econetwork Measures

We construct neighborhood-level and household-centered measures of econetwork structural characteristics that we hypothesize are associated with our dependent variables. The econetworks examined in our study are based on geographic coordinates of nonhome routine activity locations for household members as reported by RSAs and by PCGs on behalf of the RSCs at wave 1 of L.A.FANS. We use nonhome activity locations of RSAs and RSCs to construct neighborhood econetworks for each L.A.FANS tract. For each tract, we construct distinct network measures, and ties within each network are possible only among residents of the same tract. Activities include grocery shopping, health care, a place other than home or work where the RSA spends the most time, school, employment, religious services, relatives’ homes, child care, and places other than home where the child spends the night. Households report an average of 5.04 nonhome activities that also have corresponding valid latitude/longitude coordinates.

To construct two-mode networks, we first partition the collection of all activity locations into distinct activity *clusters* based on proximity in geographic space.[3] Specifically, we use a *k*-means clustering algorithm, which is an iterative procedure that finds the *k* distinct subsets/clusters of activity locations that minimize the within-cluster sum of squared distances

[3]We exclude locations with invalid latitude/longitude coordinates, as well as locations outside California as they are unlikely to be part of the respondents’ daily routines.

between the locations and the cluster centroid (mean of the locations within the cluster) for a prescribed value of k (Kanungo et al. 2002).

We employ the cluster solution based on $k = 2{,}500$; this number of clusters minimized the median within-cluster distance between routine activity location latitude/longitude coordinates (38 meters at the 50th percentile) while also allowing for detection of colocation within the network.[4] On average, each cluster contained 2.14 unique activity locations (min = 1, max = 12).

Neighborhood Econetwork Measures

Econetwork measures operationalize the two key dimensions of intensity and extensity of econetwork linkage. To measure *econetwork intensity*, we employ the two-mode clustering coefficient C presented by Robins and Alexander (2004). The coefficient C takes as its denominator the number of 3-paths (L_3) that occur in a two-mode network. In our study, 3-paths occur when two households are connected through a shared activity cluster (see panel B, fig. 1). The numerator ($4 \times C_4$) represents four times the number of 3-paths that are closed by being part of a 4-cycle (C_4), that is, a relation where two households are connected through two distinct activity clusters. C_4 is multiplied by 4 because every C_4 configuration contains four L_3 configurations. This measure captures overall tendencies for 3-paths to become closed 4-cycles and is formally defined as

$$C = \frac{4 \times C_4}{L_3}.$$

This measure ranges between 0 and 1, with 1 indicating that all 3-paths in the network are closed (i.e., are 4-cycles). On average, the proportion of 3-paths within an econetwork that are closed is .08, with a standard deviation of .03.

To capture *econetwork extensity*, we measure the proportion of all possible dyadic ties in the projected econetwork that are realized for each household, aggregated to the neighborhood level (see below for a more detailed discussion of the household-level measure). The projected network consists of ties between households (as opposed to household-location ties) wherein ties exist if households share a location. On average, the proportion of other L.A.FANS sampled households to which a given household is tied is .39, with a standard deviation of .13. This proportion-based measure facilitates comparisons across tracts/networks (Entwisle et al. 2007).[5] We further address the issue of network comparison with additional tests in the sensitivity tests section below.

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[4]Limiting the distance between activity location points that define a cluster would enhance precision but reduce the capacity to detect network ties. On the other hand, very large average distances between locations will result in crude approximations of activity clusters. We opt for an approach that balances these objectives. We also note that within-cluster distances between activity locations vary (e.g., at the 75th percentile, the median within-cluster distance between routine activity location latitude/longitude coordinates is 317 meters; at the 95th percentile, it is 602 meters). Clusters with the largest distances between points tend to be located in lower-density areas on the periphery of metropolitan Los Angeles, where shared spaces may plausibly involve larger physical areas. Nevertheless, we examined the effects of clustering solutions based on $k = 2{,}000$ and $k = 3{,}000$, with comparable results. Use of block groups to cluster locations also resulted in negligible differences in the effects of econetwork structural characteristics.

[5]The econetwork measures were generated using the following R packages: igraph, biGraph, and tnet (Csardi and Nepusz 2006; Opsahl 2009; Vogt and Mestres 2011).

Household Econetwork Extensity

Our measure of *household extensity* captures individual econetwork members' tendencies to overlap in activity clusters with other members when engaging in routine activities. To measure household extensity, we first created binary projections for each econetwork. This yielded 65 symmetric matrices, which indicate whether a given household is tied to another econetwork household (0 = no, 1 = yes). The household extensity measure is defined as the proportion of other households in the projected econetwork to which a given household is connected (through any activity location), minus the neighborhood-level extensity estimate. Note that the neighborhood-level version of this measure is the tract-level mean of the household proportions, while the household measure is deviated from the tract mean (resulting in an average score near zero).

Figure 2 visualizes two actual L.A.FANS econetworks for the purposes of illustration. For each census tract, the two-mode (household and location ties) and one-mode projected (households tied to each other through any location) networks are presented. In the two-mode network for tract A, the shaded nodes (circles = households, squares = nodes) are instances of 4-cycles (a set of closed 3-paths) capturing intensity in the network. Because the two households we highlight are tied through at least one location, they are given a direct tie in the one-mode projected network for census tract A (the highlighted circles). For tract B, we select the two household nodes in the network with the lowest (.029) and highest (.529) household extensity values (i.e., the proportion of all other households in the sampled network to which these individual households are tied through any location). The high-extensity household is tied to a high proportion of other households in the network because it is connected to a number of relatively central locations (these households are also highlighted in the one-mode projected network). Overall, tract A exhibits higher values of both intensity and extensity. Differences in the level of extensity are particularly visible through the onemode projected networks.

One concern about our approach to the measurement of econetwork structure is that we base our measures on a sample of households from Los Angeles tracts rather than on the population econetworks from these tracts. We address the potential for bias in our measures of econetwork extensity and intensity due to the node-based sampling design in appendix B. In short, we find that sampling from various plausible simulated population econetworks with levels of extensity and intensity comparable to those observed in the L.A.FANS study results produces reasonable estimates of econetwork extensity and intensity.

Individual- and Neighborhood-Level Controls

Individual-level attributes that might influence respondents' neighborhood perceptions were included in the analysis. Demographic controls include sex, race, age, and immigrant generation. *Male* sex is captured by a dummy variable. *Race* is represented using three dummy variables that indicate whether the respondent is white, black, or other (Latino is the omitted reference group). *Age* is a continuous variable that is measured in years. *Immigrant generation* is measured by two dummy variables that capture whether a respondent is second generation or third or later generation (first generation is the omitted reference group). The *educational level* of respondents is a linear measure capturing grade completed through high school degree (beyond high school, unit changes in the variable correspond to some vocational school, vocational school degree, some college, college degree) and ranged from 0 to 19 (categorical versions of the education variable yielded comparable results). We also control for *residential tenure*, which indicates whether the respondent has lived in the neighborhood for two or more years.

Marital status is measured with two dummy variables that assess whether a respondent is *single* or *cohabiting* (married is the omitted reference group). Two ordinal variables measure *family in neighborhood* and *friends in neighborhood*. Each variable ranges from 1 (none live in the respondent's neighborhood) to 4 (most or all live in the respondent's neighborhood). Finally, dummy variables are used to measure whether a respondent *is a parent* as well as whether they are *currently employed* or not.

At the neighborhood level we control for a range of characteristics using 2000 census data cross-walked to 1990 tract boundaries and L.A.FANS neighborhood assessments. *Concentrated disadvantage* is the weighted least-squares score from a factor analysis of the following six items (Johnson and Wichern 2002): (1) the poverty rate, (2) percentage of residents employed in the secondary labor sector, (3) percentage of households headed by a female, (4) unemployment rate among adults ages 16–64, (5) percentage of residents employed in managerial/professional occupations (reverse coded), and (6) percentage of residents who are college graduates (reverse coded). *Residential instability* is measured with the standardized percentage of residents age five and older who have moved in the past five years. *Immigrant concentration* is the mean of the standardized percentages of the tract population who are (1) foreign born and who (2) do not speak English well or at all (among those age five and older). We also include *population density* per square mile and the *percent black* in the neighborhood.

To capture conditions that may deter the use of neighborhood space and influence neighborhood assessments, we include a measure of neighborhood *social disorder*. The social disorder scale was based on interviewer assessments of the presence of adults loitering, congregating, or hanging out; prostitutes; people selling illegal drugs; people drinking alcohol; drunk/intoxicated people; and homeless people on each block face (i.e., one side of the street for a given block; Jones, Pebley, and Sastry 2011). The scale was constructed based on a three-level Rasch model with disorder items at level 1, block face at level 2 (controlling time of day the block face was observed— evening or morning versus afternoon), and census tract at level 3 (Raudenbush and Sampson 1999). The final scale score is the tract-level empirical Bayes residual from the level 3 model (multilevel reliability = .88).

Additional Controls

Additional measures that might affect both neighborhood perceptions and the network measures themselves also are included. The closer sampled respondents' home locations are to each other, the more likely they are to share the same activity locations. To account for this, *distance to other respondents* is captured by the average Euclidean distance from a respondent's home location coordinates to the home locations of other respondents in the neighborhood. *Distance to activity clusters* is the average distance between a respondent's home location and the activity clusters to which he or she belongs (computed in kilometers using latitude and longitude coordinates). We control the *total number of activity locations* at the household level and the *total number of clusters* at the neighborhood level. These measures are included to ensure that any observed econetwork effects are due to the structure of routine activity interconnection rather than the household- or neighborhood-level tendency to engage in more or fewer activities overall. The total number of clusters at the neighborhood level is highly correlated with both econetwork structural measures (see the discussion of sensitivity tests below for the role of network size in complicating comparisons of network structural effects). Finally, we include a measure of *perceived neighborhood safety* (1 = fairly/completely safe; 0 = somewhat/extremely dangerous).[6]

ANALYTIC STRATEGY

We include measures of wave 1 econetwork structural characteristics and controls (including wave 1 measures of the dependent variables) in multilevel models of change in social organization assessments between waves.[7] We consider econetwork level intensity and extensity in separate models owing to the high correlation between the two measures ($r > .60$). Our analytic sample includes only respondents who did not move (or attrite) between waves in order to capture a sample of respondents who provide longitudinal social organization assessments on the same location. By restricting the sample to respondents who did not move, however, the analyses are potentially vulnerable to selection bias. Accordingly, we present the results of multilevel models employing inverse probability weights (IPW) based on the propensity both to move and to attrite between waves. Specifically, we fit logistic regression models of the probability of moving and attrition between waves and divided the product of the unadjusted probabilities of these two outcomes by the covariate-adjusted product to construct stabilized IPW for each RSA (Robins, Hernán, and Brumback 2000).[8] This approach downweights respondents who exhibit higher propensities to experience the conditions actually observed for those respondents with respect to moving between waves and wave 2 follow-up. In contrast, respondents who exhibit low probabilities of experiencing the conditions actually observed for them are up-weighted in the analysis (Sharkey and Sampson 2010). We employed multiple imputation to address missing data (approximately 10%; Royston 2004). Results of weighted, multilevel models of the social organization outcomes combine results from 10 multiply imputed data sets.

We present a sequence of seven models for each outcome. Model 1 includes baseline covariates without econetwork measures. Models 2–4 estimate the effect of neighborhood-level econetwork intensity, neighborhood-level econetwork extensity, and household-level econetwork extensity, respectively. Models 5–7 report the results of models comparable to models 2–4 with the addition of important potential predictors of local public space use and

[6]The L.A.FANS also provides a number of land use variables with which public contact potential may be confounded (Peterson et al. 2007). We included measures of the number of businesses, social service organizations, and religious organizations separately and jointly in addition to the controls presented in tables 2–4. Effects of econetworks are virtually unchanged in these models.

[7]These models are mathematically equivalent to the residualized gain score approach (modeling wave 2 outcomes including the lagged dependent variable as a covariate.

[8]A description of the additional variables used in the weighting models and a summary of the results from the logistic regression models on moving and attrition can be found in tables A1 and A2.

shared routines with which econetwork effects may be confounded—reported friends and family in the neighborhood, perceived safety, and neighborhood-level social disorder.

RESULTS

Table 1 presents descriptive statistics for all variables in the analyses. Reflecting the demographics of Los Angeles, the sample is predominantly Latino (54%), with smaller proportions white (31%), black (8%), and Asian or other race/ethnicity (7%). Change scores for the dependent variables in the analysis are consistently negative, indicating that neighborhood social climate assessments declined over the two waves of the study.

Two-level hierarchical linear models (households nested in neighborhoods) of collective efficacy change are presented in table 2. Model 1 includes only the individual and neighborhood structural control variables (neighborhood disorder, friends and family in the neighborhood, and perceived safety are included in models 5–7). Wave 1 collective efficacy is negatively associated with the collective efficacy change score (at the conventional significance level), as is white (vs. Latino) race/ethnicity, cohabiting (vs. married), and being a parent. The effects of neighborhood-level variables do not reach significance in model 1.[9]

Models 2–4 add measures of econetwork structure. Introducing the measure of econetwork intensity in model 2 results in a positive and significant effect on the collective efficacy change score. The effects of control variables change only modestly across models in table 2; however, we do note that the marginally significant negative effect of percent black on collective efficacy change in model 1 is reduced by some 20% in magnitude with the introduction of econetwork intensity in model 2. Model 3 replaces neighborhood intensity with neighborhood extensity, the coefficient for which also is positively associated with the outcome. Finally, model 4 adds household extensity (group-mean centered) to model 3. Contrary to our hypothesis that within-neighborhood econetwork variability in extensity affects change in collective efficacy assessments, we observe no evidence of household econetwork extensity effects in this model. Models 5–7 reproduce models 2–4, adding measures of friend and family network ties, perceived safety, and neighborhood disorder to assess the robustness of the econetwork effects to these potential confounders. Both friends in the neighborhood and perceived safety are powerfully positively associated with the collective efficacy change score. Family members in the neighborhood and neighborhood social disorder, however, are not significantly associated with the outcome. The magnitude and significance of the econetwork measures remain essentially unchanged in these additional models.

[9]Neighborhood-level controls are, in some cases, highly correlated and should be interpreted with caution (see table A3 for correlations among neighborhood predictors in the analysis). We opted for the more conservative approach of incorporating a wide range of neighborhood controls in order to reduce bias in the estimates of econetwork effects. Although beyond the scope of the current analysis, theoretical and empirical treatment of the neighborhood-level determinants of differential econetwork structure is a key question for future research. In addition, the very high correlation between immigrant concentration and concentrated disadvantage and the relatively low correlation between concentrated disadvantage and %black highlights the distinctive character of Los Angeles by comparison with other frequently studied cities such as Chicago. Future research on the role of econetworks should extend to areas characterized by varying neighborhood race/ethnic and socioeconomic status distributions. It should be noted, however, that the distribution of social organization outcomes across Los Angeles and Chicago (the two major U.S. cities on which comparable neighborhood social organization data have been collected) is quite similar.

Models of change in intergenerational closure between L.A.FANS waves are presented in table 3. Model 1 independent variables are identical to those included in model 1 of table 2 with the exception that wave 1 collective efficacy is replaced with wave 1 intergenerational closure. Wave 1 intergenerational closure is negatively associated with change in intergenerational closure between waves, as is white race/ethnicity, being single (vs. married), being a parent, and education level. Neighborhood control variables do not achieve significance in these models.

Introduction of econetwork intensity in model 2 results in a positive and significant effect, consistent with results for collective efficacy change. The effects of control variables remain comparable to those observed in model 1. Models 3 and 4 include neighborhood and household-level econetwork extensity. Both variables are positive predictors of intergenerational closure change. The positive effect of household extensity in model 4 indicates that within-neighborhood variability in the extent of econetwork ties to other neighborhood residents is an independent predictor of change in intergenerational closure assessments. Models 5–7 introduce friend and family network measures, perceived safety, and neighborhood social disorder. In model 5, the coefficients for the number of friends in the neighborhood and perceived safety are positive and significant. The effects of econetwork measures remain statistically significant and comparable in magnitude in these models (in the case of econetwork intensity, the coefficient increases somewhat).

Finally, table 4 presents the results for social interaction/exchange. In model 1, wave 1 social interaction/exchange and both black and white (vs. Latino) race/ethnicity negatively predict change in this outcome between waves. Again, none of the neighborhood control variables achieve significance at the conventional level. Model 2 shows neighborhood intensity to once again be a positive and significant predictor. But in models 3 and 4, neither neighborhood nor household extensity is found to significantly influence change in social interaction/exchange. Thus, models of the social interaction/exchange change scores offer evidence of positive econetwork intensity effects but no evidence of econetwork extensity effects on this outcome.[10] Models 5–7 again introduce friend and family network measures, perceived safety, and neighborhood social disorder, with friends in the neighborhood and perceived safety positively predicting change in social interaction/exchange. The effect of econetwork intensity remains unchanged in these models.

We observe significant effects of a measure of number of friends in the neighborhood for all three outcomes, consistent with the long-standing urban sociological emphasis on the role of strong, informal ties in generating positive neighborhood assessments (Kasarda and Janowitz 1974). Accordingly, we compared standardized coefficients for the effects of econetwork intensity and the measure of the proportion of friends in the neighborhood to offer a useful benchmark to assess the relevance of econetwork effects for neighborhood social organization outcomes. In model 5 from table 2, a comparison of the standardized coefficient for *friends in neighborhood* (.07) with that of *econetwork intensity* (.10) as well as analogous comparisons for change in intergenerational closure (friends in neighborhood: .

[10]We also examined the hypothesis that econetwork structural characteristics exhibit nonlinear effects on social organization outcomes (e.g., tapering off beyond a threshold). We found no evidence of nonlinearity in the effects of either extensity or intensity.

09; intensity: .08) and social interaction/exchange (friends in neighborhood: .07; intensity: .10) reveal a consistent pattern. The positive effects of econetwork intensity—which capture weak forms of place-based interaction potential—on assessments of neighborhood social organization are, at a minimum, comparable to those exhibited by the extent of neighborhood-based close friendships, a classically emphasized variable in urban community studies.[11]

SENSITIVITY TESTS

Effects of Econetwork Characteristics When Constructed Using Variable Specifications of Routine Activity Boundaries

The results presented in tables 2–4 are agnostic with respect to the location of spatial intersection among neighbors, raising the question of whether shared routines occurring outside the boundary of the neighborhood are differentially effective in yielding beneficial social organization. To address this question, we constructed econetworks based on ties occurring within varying boundary specifications, specifically, two, three, four, and five or more miles from the residential tract centroid. With respect to econetwork extensity, the results revealed little variation in the significance of effects on social organizational outcomes across local network definitions. For econetwork intensity, coefficient estimates for networks based on *smaller* radii fell marginally outside of the conventional significance level, but the strength of the association increased with increasing radii. These results may be due to the relative infrequency of household ties through multiple locations, rendering the estimation of intensity levels more difficult when the boundaries of econetwork ties are limited. Accordingly, we interpret these tests as offering little evidence that ties through more distal locations are less effective for generating social organization than more proximate shared routines. However, it is possible that encountering neighbors through both a local and a distal location makes the latter more salient, just as encountering one with whom a membership of some kind is shared in a context that is removed from the typical setting yields a greater sense of attachment (e.g., shared nationality is more powerful when discovered in a distant country). Tests of interaction effects between econetwork characteristics and the average distance between activity locations and the tract centroid (at the neighborhood level) and the average distance between the home and activity locations (at the individual level) also offered no evidence of significant declines in the impact of econetworks as activity location distances increased.

Alternative Approaches to Comparing Econetwork Structure across Networks

When assessing the effects of network structural characteristics across multiple networks, the comparability of measures may become problematic if networks vary in size and density.[12] Accordingly, we investigated the association between alternative measures of both intensity and extensity and neighborhood social organization outcomes. Specifically, we

[11]In the cross section, intensity is not associated with social organization outcomes at conventional levels of significance, while extensity is associated with all three outcomes at the neighborhood level and both intergenerational closure and collective efficacy in within-neighborhood models of econetwork position effects. These results suggest the possibility of lagged effects of intensity and more powerful contemporaneous impact of extensity. However, given the high potential for endogeneity in the cross-sectional results (levels of collective efficacy, intergenerational closure, and social network interaction and exchange are likely to influence the extent of econetwork contact among neighbors), we chose to emphasize the more rigorous analyses of change.

constructed econetwork measures that capture the deviation of each econetwork structural feature from what is expected by chance, given the number of individuals, location clusters, and ties in the network. Subtracting simulated mean values based on 1,000 random networks from the observed mean levels of intensity/extensity and dividing by the standard deviations generated from the simulated network distributions yield standardized econetwork measures for comparison across multiple networks. Estimates of the effects of these alternative measures of econetwork structure yielded comparable results to those presented in tables 2–4. We chose to report the proportion-based measures for ease of interpretation.

Analyses of Movers

Although the results of our analyses are robust to a range of potential alternative explanations, we cannot rule out the possibility that some unmeasured household characteristic explains the tendency both to colocate with neighbors and positively evaluate neighborhood environments. Were this to be the case, however, we would likely observe an association between econetwork structural measures and neighborhood social organizational outcomes for movers as well as nonmovers, under the assumption that the bias characterizing econetwork effects comparably afflicts estimates for both groups. We reproduced analyses of models of econetwork effects presented in tables 2–4 for movers and found no evidence of association between econetwork structural characteristics and social organization outcomes.

DISCUSSION

Chicago school theorists recognized the implications of urban mobility patterns in the early stages of the discipline's emergence. McKenzie (1921), for instance, highlighted the role of streetcars and automobiles in expanding the radius of everyday activity beyond the boundaries of traditionally understood neighborhoods, with implications for neighborhood integration. These early insights suggested the potentially significant role of spatial variability in activity routines in setting the ecological conditions for the emergence of neighborhood social organization. Nevertheless, incorporation of daily exposure and mobility patterns into sociologically inspired theoretical models of neighborhood functioning remained limited throughout the 20th century (Matthews and Yang 2013). The most recent wave of neighborhood research—a veritable explosion of empirical analyses examining neighborhood effects on an unprecedented range of outcomes—largely has ignored the actual spatial exposures of residents, with the exception of schools (Arum 2000; Teitler and Weiss 2000; but see Krivo et al. 2013; Jones and Pebley 2014; Jackson et al. 2015; Sharp, Denney, and Kimbro 2015). The continued neglect of spatial exposures in theoretical and empirical work on neighborhoods no doubt is due, in part, to the lack of available data in large-scale social surveys commonly employed for neighborhood research. The collection of activity space data in the L.A.FANS represents an important step forward, providing an opportunity to link basic features of everyday routine activity patterns to other aspects of neighborhood experience.

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[12]Models presented in tables 2–4 include the number of locations in the econetwork as a control as one strategy to address the network comparison problem. In no case was this variable a significant predictor of neighborhood social organization change. Moreover, the effects of econetwork measures were comparable in models with or without controls for the total number of locations.

Our emphasis on the role of econetworks in fostering various aspects of neighborhood social organization integrates classic and contemporary social disorganization and social ecological approaches to challenge the (ironically) aspatial explication of mechanisms accounting for neighborhood social organization. Specifically, we articulate a model linking structures of activity space overlap to everyday public contact, public familiarity, trust, and prosocial normative orientations. We contrast this focus on the productive role of weak, place-based interactions rooted in routine conventional activity to the long-standing emphasis on significantly closer ties as the basis for effective neighborhood social organization (Bursik and Grasmick 1993).

The current analysis had three major objectives. First, we investigated whether aggregate aspects of activity space intersection as captured by structural characteristics of ecological networks were associated with social organizational outcomes longitudinally. This relatively conservative approach exploits unique data from L.A.FANS capturing changes in assessments of neighborhood functioning between two waves. Evidence from multilevel models indicates that neighborhoods with greater econetwork intensity (the extent to which household dyads encounter one another through multiple locations in the econetwork) exhibit higher levels of collective efficacy, intergenerational closure, and social network interaction and exchange. Similarly, neighborhood extensity (the average proportion of all households in the neighborhood to which a given household is tied through any routine activity location) is positively associated with collective efficacy and intergenerational closure. These effects were observed above and beyond a host of neighborhood- and individual-level controls, including the extent of kin and friend ties within the neighborhood. The findings indicate that econetwork characteristics—a heretofore neglected dimension of neighborhood network structure—independently contribute to changes in neighborhood social organization over time.

Second, we considered hypotheses about the relative importance of distinct dimensions of econetwork structure. Econetwork extensity was positively associated with both collective efficacy and intergenerational closure, indicating that broad-based, but likely weaker, exposures to other households through conventional routine activities foster generalized trust and prosocial expectations regarding neighborhood-based conduct. Because econetwork intensity involves household ties through multiple locations, we hypothesized that intensity would be more powerfully associated with the formation of actual social network ties than would extensity. Our expectation regarding the link between intensity and network ties was borne out; higher intensity was associated with increases in neighbor network interaction/exchange, while extensity was not associated with this outcome. Like extensity, however, intensity exhibited relatively powerful associations with measures of collective efficacy and intergenerational closure. Thus, intensity appears to be productive both for generalized trust and prosocial norms as well as supportive neighbor-based network interactions. Given the relatively high correlation between intensity and extensity, we were unable to simultaneously estimate their effects on social organization outcomes; however, these findings point to the possibility of distinct social organizational implications of different econetwork structures.

Finally, we considered the hypothesis that within-neighborhood variability in neighborhood social organization assessments could be explained by relative household-level econetwork position. The substantial within-neighborhood variability in neighborhood social organization typically has been explained in reference to individual-level characteristics thought to influence the social psychology of neighborhood evaluations (Sampson et al. 1997, 1999). Within-econetwork position, however, cannot be understood as an isolated individual- or household-level feature. Network position depends, in part, on the behavior of other households and therefore must be understood as an inherently relational characteristic. Although we did not find evidence of group-mean-centered household-level extensity effects on collective efficacy or social interaction/exchange, levels of reported intergenerational closure were higher among households that were more embedded in their econetworks relative to other households in the neighborhood. Although observed for only one outcome, this finding suggests that econetwork position may be relevant for understanding variability across people (and, potentially, locations) in social organization perceptions.

The econetwork approach to urban social climate redirects attention to the spatial dynamics of activity patterns in urban neighborhoods and the role of activity space structures in producing the ecological preconditions for the emergence of neighborhood social organization. Jacobs’s (1961) essential insight—that interactions in public space are a key ingredient of functional urban neighborhoods—was obscured in the decades following her seminal work, as survey research yielded data on urban residents abstracted from the spatial context of everyday routines. The use of residential location as a proxy for shared exposures emerged as an antidote to the exclusive reliance on survey data in the resurgence of neighborhood effects research since the late 1980s. Yet this approach has continued to dominate neighborhood effects research, despite Jacobs’s emphasis on the crucial role of nonhome activity patterns for understanding neighborhood dynamics. Although our approach remains circumscribed by a reliance on census tract boundaries to identify neighborhoods, the incorporation of relatively rich information on activity space exposures sheds light on the substantial variability in, and consequences of, public contact potential.

More generally, the econetwork concept holds substantial promise for advancing research on the impact of spatial contexts on well-being—both with respect to theory development and methodological concerns. First, the notion of shared exposure is fundamental to a number of prominent theoretical approaches in the neighborhood effects literature. Wilson (1987, 1996), for instance, has argued that consequential “role modeling” processes occur through exposures of youth—potentially in public space—to adults engaged in activities associated with education and regular employment. Similarly, Sampson (2006) suggests that the extent to which routine activities of adults and children overlap has implications for the social control capacity of urban neighborhoods. Both mechanisms point to the importance of information on urban ecological networks. Beyond knowledge of econetwork structure as a whole, these hypotheses suggest the importance of information on the extent of age homophily or heterophily (e.g., intergenerational) in shared routines as well. For instance, existing approaches to measuring adult-child interaction at the neighborhood level (e.g., the ratio of adults to children in a census tract) fall dramatically short by comparison with information that could be obtained through econetwork data.

Racial and ethnic segregation within activity spaces is also a critically important research direction to which the econetwork approach could add substantial insight. Housing policy and research have heavily emphasized the benefits of mixed-income neighborhoods under the assumption that "social mixing" will follow from residential proximity. Although survey research on the development of social networks in mixed-income communities calls the social mixing hypothesis into question (Kleit 2005), research on the extent of shared routines among neighbors (employing activity space data) has yet to emerge. To the extent that Wilson's emphasis on shared exposures is important, research has neglected a potentially important dynamic within mixed-race and mixed-income communities.

In addition to the composition of econetworks with respect to people, research on the composition of locations is needed as well. Locations of intersection within econetworks may vary substantially with respect to land use characteristics and associated activity patterns, potentially conditioning the impact of shared routines on neighborhood social organization. Jacobs's (1961) emphasis on diversity of uses is relevant here—locations that combine multiple and diverse destinations may tend to bring neighborhood residents into regular contact who might not otherwise encounter one another. On the other hand, homogeneity of use may yield higher levels of contact and enhance trust. Decomposition of econetworks with respect to the characteristics of shared locations will be an important next step in addressing the conditions under which shared routines yield the greatest benefits to neighborhood social organization. Ultimately, greater insight into both the causes and consequences of econetwork structure and composition will have implications for the ongoing policy discussion regarding optimal urban neighborhood design.

Finally, the econetwork concept raises a number of questions relevant to the ongoing and seemingly intractable debate regarding the appropriate unit of analysis to capture "neighborhood." With Sharkey and Faber (2014), we view the search for the "correct" neighborhood operationalization as fruitless, favoring an approach that tailors the unit of analysis chosen to the research question and theoretical orientation of the project at hand. Yet understanding neighborhoods as units of exposure (as most theoretical approaches within the neighborhood effects literature do) suggests the importance of taking the actual structure of shared exposure seriously. Capturing patterns of shared exposure employing ecological networks holds the potential to identify clusters of people and locations that tend to intersect at higher rates—these "ecological communities" may be important contextual units in their own right.

While these analyses offer the first investigation of econetwork effects on neighborhood social organization, they are nevertheless limited in a number of respects. First, the L.A.FANS provides an extensive but not complete representation of the activity spaces of Los Angeles residents. Second, the activity space data did not offer detailed information on the timing and duration of routine activity exposures. Third, the activity location clusters employed were relatively large and varied in size. Defining econetwork ties based on closer proximity within clusters would enhance the probability of public contact; however, clustering solutions based on very small distances between activity locations produced few clusters, complicating econetwork estimation. Fourth, the possibility of selection bias in the estimates of econetwork effects on social organization outcomes due to reliance on the sample of respondents who did not move or attrite between waves remains a concern. We employed an inverse probability weighting approach based on rich models of the propensity to move and attrite and examined the impact of econetworks on movers (finding no associations with social organizational outcomes). Nevertheless, selection bias cannot be entirely ruled out. Finally, we expected to find that econetwork characteristics involving more distal locations on average would likely yield weaker associations with neighborhood social organization outcomes. We found no evidence of this pattern. However, richer data on a larger number of neighborhoods (with more variability in activity location distributions) would offer additional insight into how activity location distance influences neighborhood social climate perceptions.

Future investigations of econetwork influences on neighborhood and individual well-being will benefit from data resources that capture patterns of mobility and intersection in urban space. These sources of information are increasingly affordable additions to traditional social survey data collection efforts. Capitalizing on recent advances in GPS technology and the availability of smartphone-based methods of spatial tracking will offer an opportunity for more fine-grained estimates of exposures (Browning and Soller 2014). In addition to GPS tracking, incorporation of ecological momentary assessment technologies (Shiffman, Stone, and Hufford 2007) through mobile devices will substantially expand the capacity to investigate everyday neighborhood experiences and their implications for community as well as individual health and well-being (Palmer et al. 2013). In combination with more sophisticated theoretical attention to the role of activity space exposures, these novel data collection approaches will yield significance advances in research on urban community life.

APPENDIX A

TABLE A1

Description of Additional Variables Used for Selection Models of Wave 2 Sample Retention and Did Not Move

Variable	Variable Type	Variable Description
Neighborhood satisfaction	Dummy	How satisfied are you with neighborhood? 1 = very satisfied
Been robbed	Dummy	Has household been robbed in this neighborhood? 1 = yes
Social disadvantage	Continuous	Social disorder scale
Physical disadvantage	Continuous	Physical disorder scale (e.g., presence of vacant lots, graffiti, etc.)
Food scarcity	Dummy	Ever a time when didn’t have food in the past 12 months? 1 = yes
Organization participation	Continuous	Number of organizations participate in
Number of moves before 14	Continuous	Number of moves before fourteenth birthday
Lived with both parents	Dummy	Lived with both parents from birth to age 14? 1 = yes
Born in California	Dummy	Born in California? 1 = yes
Currently in school	Dummy	Currently in school? 1 = yes
Plan to move	Dummy	Plan to move in the next 2 years? 1 = yes
TANF benefits	Dummy	Received TANF benefits currently or in the past 2 years? 1 = yes
Self-rated health	Ordinal	Self-rated health? 1 = excellent health, 5 = poor health
Smoker	Dummy	Do you smoke? 1 = yes

Variable	Variable Type	Variable Description
Number of drinks	Continuous	Number of days drank in the past 30 days
Overweight	Dummy	Doctor told you that you have excess weight? 1 = yes

TABLE A2

Logistic Regression: Wave 2 Sample Retention and Did Not Move

	In Wave 2 Sample (*N* = 2,263)		Did Not Move (*N* = 1,064)	
	Coefficient	**SE**	**Coefficient**	**SE**
Analysis variables:[a]				
Male	−.24*	.10	−.08	.16
Age	.01*	.00	.04**	.01
Black	−.41+	.21	−.40	.35
White	−.30+	.17	−.22	.28
Asian/other race/ethnicity	−.11	.19	−.71*	.31
Cohabitating	−.13	.16	.15	.26
Single	−.25*	.11	−.45*	.17
Parent	.38**	.13	−.26	.23
Years of schooling	.02	.02	.01	.02
Residential tenure	.26*	.11	.80**	.17
Currently employed	.16	.11	−.10	.17
Second generation	.15	.19	−.30	.31
Third generation	.37*	.18	.08	.31
Distance to other respondents	−2.40	3.43	2.25	6.39
Distance to activity clusters	−.22	.24	−.73	.46
Family in neighborhood	−.09	.07	−.02	.10
Friends in neighborhood	.10	.06	.02	.10
Perceived neighborhood safety	−.02	.12	−.10	.18
Total household number of locations	−.00**	.00	−.00	.01
Total number of clusters	.11	.03	.00	.05
Concentrated disadvantage	−.24*	.11	−.20	.18
Residential instability	.05	.07	−.49**	.12
Immigrant concentration	−.10	.13	.67**	.21
Population density	.00	.00	−.00	.00
%black	−.91	.75	2.55*	1.21
Collective efficacy	−.09	.07	.03	.16
Intergenerational closure	−.02	.09	.18	.16
Social interaction/exchange	.21**	.07	.13	.10
Additional variables:				
Neighborhood satisfaction	.00	.13	.02	.20
Been robbed	.13	.10	−.29+	.15
Social disadvantage	.16*	.08	.17	.13

	In Wave 2 Sample (N = 2,263)		Did Not Move (N = 1,064)	
	Coefficient	SE	Coefficient	SE
Physical disadvantage	.22 [*]	.11	−.34 [+]	.18
Food scarcity	−.33	.22	.01	.37
Organization participation	.10 [*]	.04	.05	.07
Number of moves before 14	−.02	.02	.04	.03
Lived with both parents	−.06	.10	.06	.16
Born in California	.04	.15	.10	.24
Currently in school	−.05	.15	.62 [*]	.24
Plan to move	−.13	.10	−.70 [**]	.17
TANF benefits	.40 [*]	.18	.08	.27
Self-rated health	−.02	.05	−.18 [*]	.08
Smoker	−.13	.13	.01	.21
Number of drinks	.02 [*]	.00	−.01	.01
Overweight	−.10	.13	.01	.20
Intercept	−1.19 [+]		−.92	

[a] We also considered weights based on selection models with varying combinations of the econetwork measures, with negligible changes to the results reported in tables 2–4 in the text.

[+] $P < .10$, two-tailed tests.

[*] $P < .05$.

[**] $P < .01$.

TABLE A3

Correlation Matrix of Neighborhood-Level Variables

	Concentrated Disadvantage	Immigrant Concentration	Residential Instability	Population Density	Percent Black	Social Disorder	Econetwork Extensity	Econetwork Intensity	Number of Activity Locations
Concentrated disadvantage	…								
Immigrant concentration	.84	…							
Residential instability	.50	.61	…						
Population density	.53	.71	.66	…					
%black	.27	−.07	.04	.02	…				
Social disorder	.78	.69	.52	.61	.42	…			
Econetwork extensity	−.02	.07	−.01	−.01	−.27	.04	…		
Econetwork intensity	.25	.34	.09	.12	−.29	.19	.61	…	
Number of activity locations	−.25	−.38	−.19	−.23	.44	−.05	−.41	−.53	…

APPENDIX B Ecological Network Sampling

Our empirical investigation of the impact of ecological network structure on neighborhood social organization is based on ecological network measures derived from a probability sample of households in Los Angeles County. Unlike design-based inference for population parameters—where sample summary statistics are estimators of the corresponding population summary statistics, possibly after adjustment (e.g., weighting, finite population correction)—network measures derived from a probability sample of nodes (households) are potentially problematic as estimators of their population network counterparts. As discussed by Handcock and Gile (2010), this phenomenon arises from the fact that sampling probabilities of the units of analysis (dyads) in network analyses are in most cases not readily derived from the sampling probabilities of nodes, which come from the study design. Thus, we do not have guarantees that L.A.FANS-based ecological network measures are appropriate estimators of their full population counterparts, even for large sample sizes (numbers of nodes).

To address whether this issue is a potential weakness of our empirical findings, we performed a Monte Carlo simulation study. In this study, we generated a series of synthetic population ecological networks and sampled from them in a manner consistent with the L.A.FANS design (i.e., random sampling of households and constructing ecological networks from the sampled nodes). From our simulation study, described in detail below, we conclude that the ecological network statistics used in our empirical analyses (extensity and intensity) can be used as estimators of their population counterparts. Nevertheless, we do not necessarily anticipate these findings to hold for other ecological network measures.

To perform our simulation study, we began by simulating population ecological networks. Since common network models such as exponential random graph models (Frank and Strauss 1986; Snijders et al. 2006) are not designed to generate realistic bipartite graphs with spatially referent nodes such as ecological networks, we instead employed an intuitive origin/destination network generative model to construct population ecological networks. In our model, we suppose that there are some "global" locations/activities to which a large proportion of the population is drawn (and we allow the level of attraction to vary among these locations) as well as some "local" locations/activities to which only certain groups of individuals are drawn. Intuitively, the global locations could be places like a downtown city center or a popular mall, while the locally attractive locations might represent places like a neighborhood grocery store or a smaller business district.

More formally, this model can be described as follows: suppose that the population of N_a households may visit N_e distinct locations. Let $\boldsymbol{Y}$ be the $N_a \times N_e$ incidence matrix, where $Y_{ij} = 1$ if household i visits location j and $Y_{ij} = 0$ otherwise. Let A_G be a partition of the N_a households into G groups. Then,

$$P\left(Y_{ij}=1 \middle| i \in Ag\right)=p_j^G+p_{gj}^L \quad \forall\, g\ =1,\ldots G,$$

where p_j^G is the (global) probability that any household visits location j and p_{gj}^L is the (local) probability that any member of Ag visits location j.

To construct our synthetic ecological networks, we assume that there are two levels of globally attractive locations, say p_{g_1} and p_{g_2}, so that the vector of global attractiveness for all locations, $\boldsymbol{p}^G$, is some permutation of

$$\{p_{g_1}\mathbf{1}_{k_{g_1}}, p_{g_2}\mathbf{1}_{k_{g_2}}, \mathbf{0}_{N_e}-k_{g_1}-k_{g_2}\},$$

where $\mathbf{1}_k$ is the k-dimensional unity vector, and we allow the total number of globally attractive locations, $K_G = k_{g_1} + k_{g_2}$, to vary as well. Further, we assume that the local attraction probability is constant, that is, $p_{gj}^L = p^L$, for all g = 1, G and j = 1,…, N_e. Also, each partition of the actors, A_g, is assumed to have only one location that is locally attractive.

We set N_a = 1,000 to roughly match the household population of a typical Los Angeles County census tract and let N_e = 1,000 be the number of possible activity locations. We also set the number of groups to be G = 25 and the number of globally attractive locations to be K_G = 5, with $k_{g_1} = 4$ weakly attractive and $k_{g_2} = 1$ strongly attractive global locations.

Our choices for G, $k_{g_1}$and k_{g_2} are empirically justified. First, it is reasonable to assume that there are many more locally attractive locations than globally attractive ones, that is, that G > K_G. Second, these parameter values were chosen in order to achieve values of extensity and intensity that are similar to those observed in the L.A.FANS data. In figure B1, we provide the distribution of extensity and intensity across the 65 observed networks as well as the distribution of these statistics for the eight simulated population networks that we examine here. The numbering of the simulated population networks in figure B1 matches the indices in table B1, described below. Note that the distributions of extensity and intensity across the observed and simulated networks are similar.

According to Sastry, Pebley, and Zonta (2002), 25.48% of grocery shopping, church visits, work, and health care facilities that L.A.FANS sample residents typically use are within a 15-minute walk from their home. Based on this observation, we set p^L = 0.25 and vary the remaining set of model parameters, the strong and weak levels of global attractiveness,

$$\{p_{g_1}, p_{g_2}\},$$

in order to obtain various levels of extensity and intensity in our simulated population econetworks. Intuitively, as global locations become more attractive, individuals are more likely to be connected to one another, and this is highly correlated to the extensity and intensity measure. Empirically, we observe that p_{g_1} appears to more strongly influence intensity, while p_{g_2} appears to have a stronger effect on the extensity in the population econetwork. A summary of the parameter settings implemented here is available in table B1.

From each of the eight synthetic population econetworks, we sample 1,000 sets of 39 individuals (average number of households per tract in L.A.FANS) and construct the sample ecological network for these individuals. For each of these sampled networks, we compute intensity as well as mean extensity on the projected one-mode network.

In table B1, across a variety of parameter settings, we provide the value of extensity and intensity calculated on the simulated population econetwork as well as the mean and standard deviation of these statistics when calculated on the sampled networks. As a measure of estimator performance, we also provide the mean squared error. In figures B2 and B3, we provide histograms of these statistics across the 1,000 sample econetworks where the parameter setting is indicated in the top right of the plots and the value of the statistic computed on the large simulated network is displayed as a vertical red line.

From our simulation study, we find that across a wide range of levels of population extensity and intensity, estimates of these measures based on sampled nodes (households) perform reasonably well. On average, the measures calculated on sample networks closely match the observed statistic computed on the population econetwork. Further, the variance of the sample-based statistics is not unduly large. Based on these simulations, we chose to rely on our sample-based estimates of extensity and intensity. We note, however, that our findings may not apply to other measures of econetwork structure such as centrality and clustering.

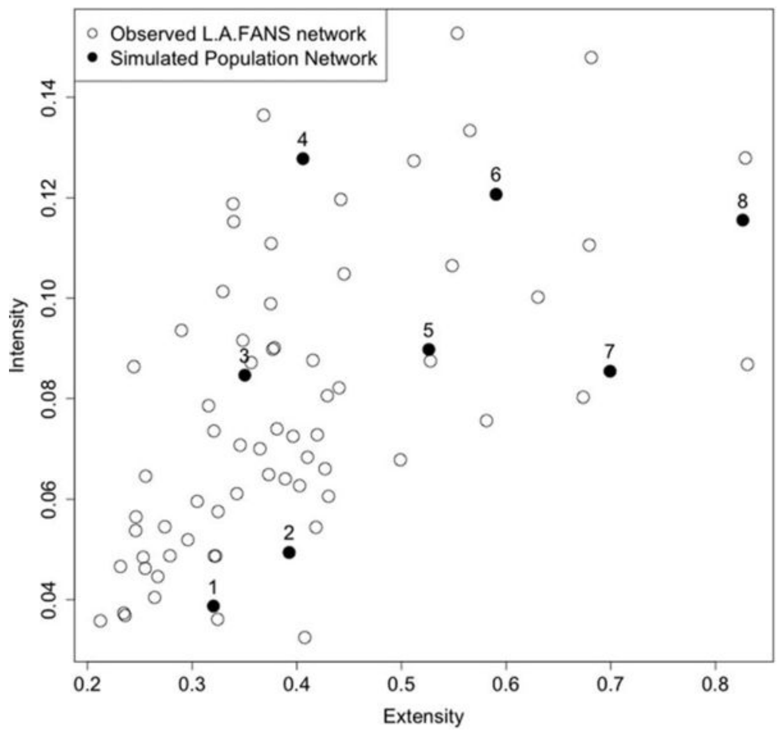

Fig. B1.

Scatterplot of intensity versus extensity for the 65 L.A.FANS econetworks (open circles) and for the eight simulated population networks (closed circles).

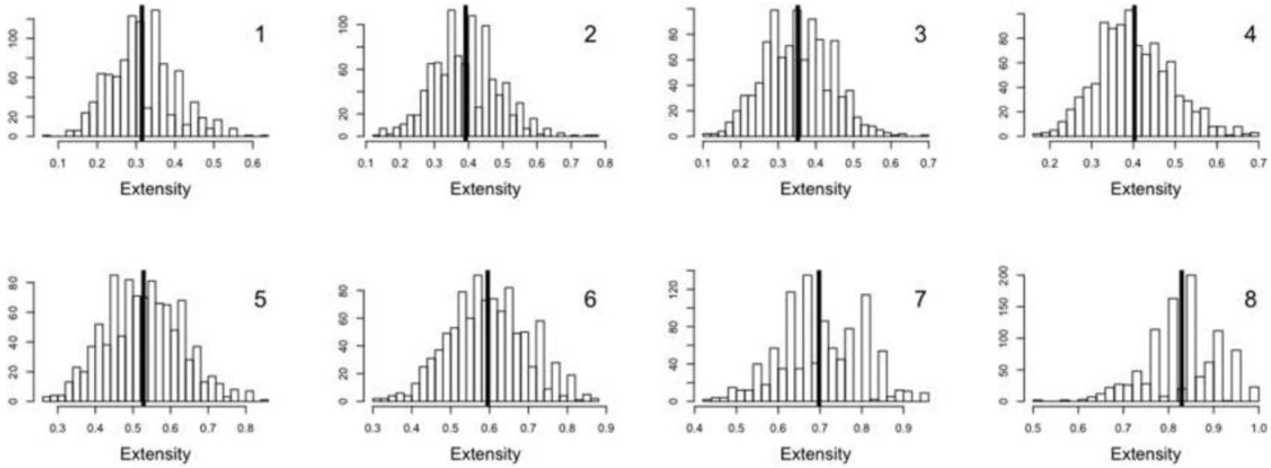

Fig. B2.

Extensity: histograms of sample-based extensity across the eight synthetic population econetworks. The black vertical line denotes the population extensity level.

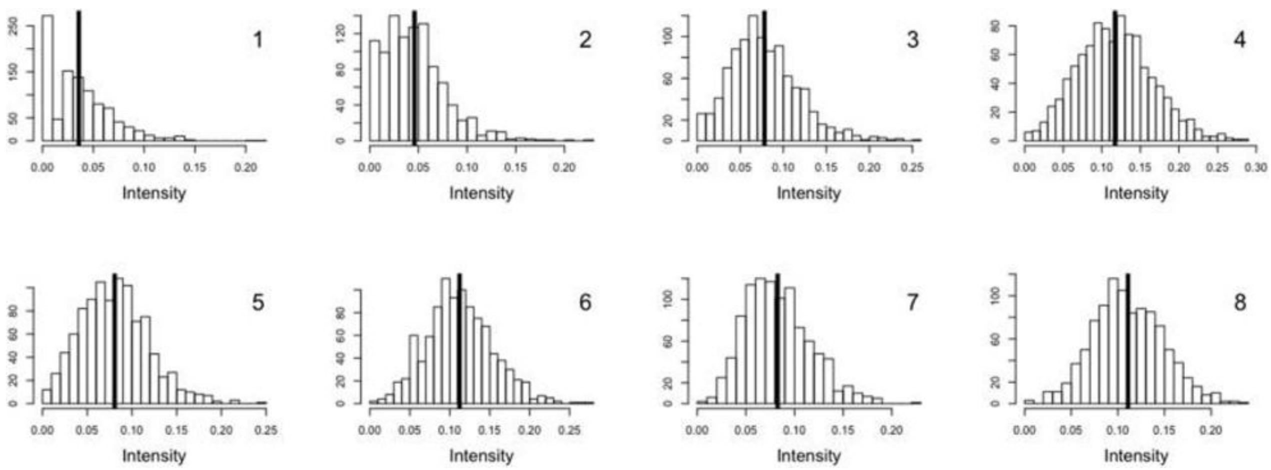

Fig. B3.

Intensity: histograms of sample-based intensity across the eight synthetic population econetworks. The black vertical line denotes the population intensity level.

TABLE B1

Comparison of Extensity and Intensity Values between the Simulated Population Econetwork and Sampled Econetworks

		Statistics				Performance Mean Squared Error		Parameter Settings	
Simulation Number	**Network**	**Extensity**		**Intensity**				p_{g_1}	p_{g_2}
1	Population	.3203		.0397					
	Samples	.3151	(.0839)	.0358	(.0319)	.0071	.0010	.040	.550
2	Population	.3927		.0504					
	Samples	.3914	(.0957)	.0459	(.0325)	.0091	.0011	.050	.600

		Statistics						Parameter Settings	
Simulation Number	Network	Extensity		Intensity		Performance Mean Squared Error		p_{g_1}	p_{g_2}
	Population	.3502		.0857					
3	Samples	.3502	(.0894)	.0780	(.0404)	.0080	.0017	.075	.600
	Population	.4058		.1288					
4	Samples	.4024	(.0889)	.1172	(.0490)	.0079	.0025	.100	.625
	Population	.5261		.0908					
5	Samples	.5282	(.1014)	.0807	(.0380)	.0103	.0015	.075	.700
	Population	.5904		.1217					
6	Samples	.5952	(.0994)	.1122	(.0418)	.0099	.0018	.100	.750
	Population	.6992		.0865					
7	Samples	.6976	(.0985)	.0826	(.0335)	.0097	.0011	.075	.850
	Population	.8261		.1165					
8	Samples	.8290	(.0820)	.1108	(.0377)	.0067	.0015	.100	.900

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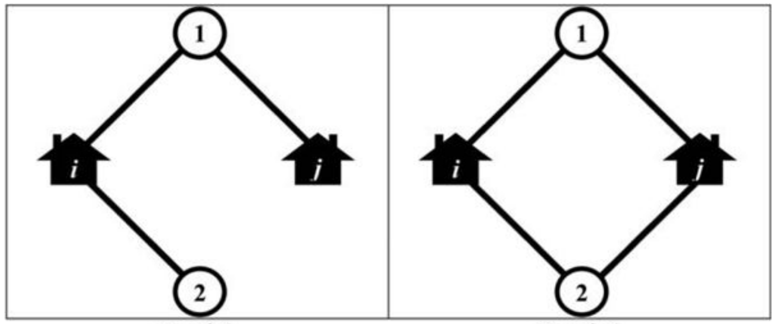

Fig. 1.
Illustration of open versus closed 4-path.

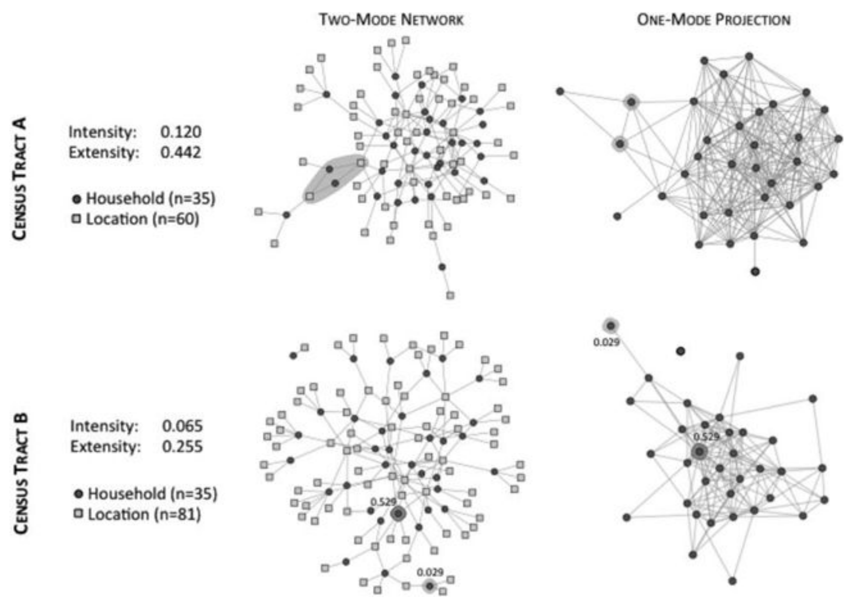

Fig. 2.

Two-mode and one-mode projected econetworks for two L.A.FANS census tracts. For tract A, we highlight an instance of intensity in the two-mode network and again highlight the involved individuals in the one-mode projected network. For tract B, we highlight the individuals with the highest and lowest (nonzero) extensity values in both networks.

TABLE 1

Descriptive Statistics from the L.A.FANS

	Mean	SD	*N*
Dependent variables:			
Collective efficacy change score	−.08	.63	687
Intergenerational closure change score	−.02	.66	687
Social interaction/exchange change score	−.09	.84	682
Independent/household variables:			
Wave 1 collective efficacy	3.59	.67	688
Wave 1 intergenerational closure	3.67	.64	688
Wave 1 social interaction/exchange	2.82	.78	686
Male	.40	…	692
Age	43.10	13.49	692
Latino (reference)	.54	…	692
Black	.08	…	
White	.31	…	
Asian/other race/ethnicity	.07	…	
Married (reference)	.61	…	692
Cohabiting	.08	…	
Single	.31	…	
Parent	.77	…	692
Years of schooling	12.71	4.53	681
Residential tenure	.83	…	684
Currently employed	.67	…	692
First generation (reference)	.50	…	692
Second generation	.13	…	692
Third generation	.37	…	692
Distance to other respondents	.01	.01	671
Distance to activity clusters	.19	.20	677
Family in neighborhood	1.47	.70	687
Friends in neighborhood	1.98	.77	687
Total household number of locations	4.53	1.72	685
Perceived neighborhood safety	.72	…	683
Neighborhood variables:			
Concentrated disadvantage	.00	1.26	65
Residential instability	.00	.88	65
Immigrant concentration	.00	1.10	65
Population density	14,836.16	10,462.03	65
%black	.08	.10	65
Social disorder	.00	1.23	65
Total number of clusters	84.92	17.30	65
Econetwork measures:			

	Mean	SD	*N*
Neighborhood intensity	.08	.03	65
Neighborhood extensity	.39	.13	65
Household extensity (centered around neighborhood mean)	.01	.19	685

TABLE 2

Multilevel Regression Models of Change in Collective Efficacy between L.A.FANS Waves (N = 687)

	Model													
	1		2		3		4		5		6		7	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Individual/household measures:														
Wave 1 collective efficacy	−.56**	.03	−.56**	.03	−.57**	.03	−.57**	.03	−.62**	.04	−.63**	.04	−.63**	.04
Male	.00	.04	.00	.04	.00	.04	.00	.04	−.01	.04	.00	.04	.00	.04
Age	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Black	−.13	.09	−.15	.10	−.14	.10	−.14	.09	−.17^{+}	.09	−.15^{+}	.09	−.15^{+}	.09
White	−.22**	.07	−.23**	.08	−.24**	.08	−.24**	.08	−.22**	.08	−.23**	.08	−.23**	.08
Asian/other race/ethnicity	−.01	.07	−.02	.07	−.01	.07	−.01	.08	.01	.07	.01	.07	.01	.08
Cohabiting	−.20*	.09	−.18*	.09	−.19*	.09	−.19*	.09	−.17^{+}	.09	.18*	.09	−.18*	.09
Single	−.06	.06	−.06	.06	−.07	.06	−.07	.06	−.07	.06	−.08	.06	−.09	.06
Parent	−.10*	.06	−.11^{+}	.05	−.12*	.06	−.12*	.05	−.09^{+}	.05	−.10^{+}	.05	−.10*	.05
Years of schooling	−.01^{+}	.01	−.02^{+}	.01	−.01^{+}	.01	−.01^{+}	.01	−.01^{+}	.01	−.01^{+}	.01	−.01^{+}	.01
Residential tenure	−.01	.05	−.01	.05	−.01	.05	−.01	.05	−.01	.05	−01	.05	−.01	.05
Currently employed	−.02	.04	−.02	.04	−.02	.04	−.02	.04	−.02	.04	−.03	.04	−.03	.04
Second generation	.09	.08	.09	.07	.08	.08	.08	.08	.08	.08	.07	.08	.07	.08
Third generation	.12^{+}	.07	.13^{+}	.07	.13^{+}	.07	.13^{+}	.07	.13*	.07	.12^{+}	.07	.12^{+}	.07
Distance to other respondents	.29	1.33	.03	1.22	.12	1.20	.15	1.20	−.65	1.24	−.46	1.23	−.44	1.23
Distance to activity clusters	.02	.09	.07	.08	.04	.08	.04	.08	.06	.08	.03	.09	.03	.09
Total household number of locations	.00	.02	.00	.02	.00	.02	.00	.02	.00	.02	.00	.02	.00	.02
Family in neighborhood	…	…	…	…	…	…	…	…	−.03	.03	−.02	.03	−.02	.03
Friends in neighborhood	…	…	…	…	…	…	…	…	.09**	.03	.09**	.03	.09**	.03
Perceived neighborhood safety	…	…	…	…	…	…	…	…	.17**	.06	.17**	.06	.17**	.06
Neighborhood-level measures:														
Concentrated disadvantage	−.09	.07	−.11^{+}	.06	−.10	.06	−.10^{+}	.06	−.11^{+}	.06	−.09	.07	−.09	.07
Residential instability	−.09^{+}	.05	−.08^{+}	.04	−.09*	.04	−.09*	.04	−.07	.04	−.08^{+}	.04	−.08^{+}	.04

	Model													
	1		2		3		4		5		6		7	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Immigrant concentration	−.02	.07	−.02	.07	−.01	.07	−.01	.07	−.01	.06	−.01	.07	.01	.07
Population density	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
% black	−.76^{+}	.43	−.62	.38	−.68	.41	−.67	.41	−.31	.39	−.38	.43	−.38	.43
Total number of clusters	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Social disorder	…	…	…	…	…	…	…	…	−.02	.04	−.02	.04	.02	.04
Econetwork measures:														
Neighborhood intensity	…	…	2.73**	.97	…	…	…	…	3.21**	1.14	…	…	…	…
Neighborhood extensity	…	…	…	…	.62**	.18	.62**	.18	…	…	.66**	.19	.67**	.19
Household extensitv	…	…	…	…	…	…	.10	.12	…	…	…	…	.08	.11
Intercept	2.26**	.19	2.01**	.21	2.02**	.21	2.04**	.20	1.94**	.22	1.97**	.21	1.99**	.20
Neighborhood variance component	.01		.00		.00		.00		.01		.00		.00	
Household variance component	.26		.26		.26		.26		.25		.25		.25	

$^{+}P < .10$, two-tailed tests.

$^{*}P < .05$.

$^{**}P < .01$.

TABLE 3

Multilevel Regression Models of Change in Intergenerational Closure between L.A.FANS Waves (N = 687)

	Model													
	1		2		3		4		5		6		7	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Individual/household measures:														
Wave 1 intergenerational closure	$-.61^{**}$	.04	$-.63^{**}$	.04	$-.63^{**}$	.04	$-.64^{**}$	.04	$-.68^{**}$	.04	$-.68^{**}$	.04	$-.68^{**}$	.04
Male	.04	.04	.04	.04	.04	.04	.04	.04	.04	.04	.04	.04	.04	.04
Age	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Black	$-.17^{+}$	.10	$-.18^{+}$	.10	$-.18^{+}$	.10	−.16	.10	$-.18^{+}$	.10	−.16	.10	−.15	.10
White	$-.21^{**}$	.06	$-.21^{**}$	.06	$-.22^{**}$	.06	$-.23^{**}$	.06	$-.20^{**}$	.06	$-.20^{**}$	.06	$-.21^{**}$	.06
Asian/other race/ethnicity	−.08	.08	−.08	.08	−.08	.08	−.09	.09	−.06	.09	−.05	.09	−.06	.09
Cohabiting	$-.17^{+}$	.09	$-.17^{+}$	.09	$-.17^{+}$	.10	$-.18^{+}$	.10	−.15	.10	$-.16^{+}$	.10	$-.17^{+}$	.10
Single	$-.12^{*}$	.05	$-.12^{*}$	.05	$-.12^{*}$	.05	$-.12^{*}$	.05	$-.12^{**}$	.05	$-.13^{**}$	.05	$-.14^{**}$	.04
Parent	$-.15^{*}$	.06	$-.15^{*}$	.06	$-.16^{*}$	.06	$-.17^{**}$	.07	$-.12^{*}$	.06	$-.13^{*}$	.06	$-.14^{*}$	.06
Years of schooling	$-.02^{*}$	.01	$-.02^{*}$	.01	$-.02^{*}$	.01	$-.01^{*}$	.01	$-.02^{*}$	.01	$-.02^{*}$	.01	$-.01^{*}$	.01
Residential tenure	.02	.06	.01	.06	.01	.06	.01	.06	.01	.05	.01	.06	.01	.05
Currently employed	−.02	.05	−.02	.05	−.02	.05	−.02	.05	−.02	.05	−.02	.05	−.02	.05
Second generation	.08	.08	.07	.07	.07	.08	.06	.08	.07	.07	.08	.07	.07	.08
Third generation	.04	.06	.05	.06	.04	.06	.05	.07	.05	.06	.05	.06	.05	.06
Distance to other respondents	1.16	1.16	.92	1.08	1.04	1.11	1.13	1.13	.44	1.14	.59	1.17	.67	1.19
Distance to activity clusters	−.13	.09	−.09	.09	−.12	.09	−.11	.09	−.09	.09	−.12	.09	−.12	.09
Total household number of locations	$.03^{+}$	.01	$.03^{*}$	.01	$.03^{*}$	.01	.02	.01	$.02^{+}$	.01	$.02^{+}$	.01	.02	.01
Family in neighborhood	…	…	…	…	…	…	…	…	−.02	.03	−.01	.03	−.02	.03
Friends in neighborhood	…	…	…	…	…	…	…	…	$.12^{**}$	.02	$.12^{**}$	.02	$.11^{**}$	.02
Perceived neighborhood safety	…	…	…	…	…	…	…	…	$.12^{*}$	.06	$.11^{+}$	.06	$.11^{+}$	.06
Neighborhood-level measures:														
Concentrated disadvantage	−.07	.07	−.09	.07	−.07	.07	−.07	.07	−.06	.07	−.05	.07	−.05	.07
Residential instability	−.04	.07	−.03	.04	−.04	.04	−.04	.04	−.02	.04	−.03	.04	−.03	.04
Immigrant concentration	.02	.08	.02	.07	.02	.07	.02	.07	.04	.07	.04	.07	.04	.07

	Model													
	1		2		3		4		5		6		7	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Population density	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
%black	−.42	.43	−.31	.42	−.38	.42	−.37	.42	−.01	.42	−.14	.41	−.14	.41
Total number of clusters	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Social disorder	…	…	…	…	…	…	…	…	−.04	.05	−.03	.04	−.03	.04
Econetwork measures:														
Neighborhood intensity	…	…	2.13*	.87	…	…	…	…	2.60**	.99	…	…	…	…
Neighborhood extensity	…	…	…	…	.33*	.15	.34*	.15	…	…	.35*	.16	.36*	.16
Household extensity	…	…	…	…	…	…	.28*	.12	…	…	…	…	.24*	.12
Intercept	2.79**	.26	2.61**	.27	2.67**	.27	2.70**	.27	2.45**	.27	2.53**	.26	2.58**	.26
Neighborhood variance component	.00		.00		.00		.00		.00		.00		.00	
Household variance component	.27		.28		.28		.27		.27		.27		.27	

+ $P < .10$, two-tailed tests.

* $P < .05$.

** $P < .01$.

TABLE 4

Multilevel Regression Models of Change in Social Network Interaction/Exchange between L.A.FANS Waves ($N = 682$)

	Model													
	1		2		3		4		5		6		7	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Individual/household measures:														
Wave 1 social network intergenerational/exchange	−.53**	.04	−.54**	.04	−.53**	.04	−.54**	.04	−.57**	.05	−.57**	.05	−.57**	.05
Male	−.05	.06	−.05	.06	−.05	.06	−.05	.06	−.06	.06	−.05	.06	−.06	.06
Age	−.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Black	−44**	.14	−.46**	.14	−.45**	.14	−.43**	.14	−.48**	.14	−.46**	.14	−.45**	.14
White	−.24**	.09	−.26**	.10	−.25**	.09	−.26**	.09	−.24*	.10	−.24*	.09	−.25**	.09
Asian/other race/ethnicity	−.09	.14	−.10	.14	−.09	.14	−.09	.14	−.09	.14	−.07	.14	−.08	.14
Cohabiting	−.03	.13	−.03	.13	−.03	.13	−.04	.13	−.01	.13	−.02	.13	−.03	.13
Single	−.11	.07	−.10	.07	−.11	.07	−.11	.07	−.11^{+}	.07	−.12^{+}	.07	−.12^{+}	.06
Parent	−.02	.08	−.01	.07	−.03	.08	−.04	.08	.01	.08	.00	.08	−.01	.08
Years of schooling	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	−.01	.01	.01	.01
Residential tenure	.11	.09	.11	.09	.11	.09	.11	.09	.12	.09	.12	.09	.11	.09
Currently employed	.05	.07	.05	.07	.05	.07	.05	.07	.03	.07	.03	.07	.04	.07
Second generation	−.20^{+}	.11	−.21^{+}	.11	−.20^{+}	.11	−.22^{+}	.12	−.23*	.11	−.23*	.11	−.23*	.11
Third generation	.03	.10	.04	.11	.03	.11	.03	.11	.03	.10	.02	.10	.02	.11
Distance to other respondents	2.28	1.56	1.99	1.51	2.22	1.56	2.29	1.56	1.49	1.49	1.71	1.61)	1.79	1.61
Distance to activity clusters	−.10	.13	−.05	.12	−.09	.13	−.09	.13	−.06	.12	−.11	.13	−.11	.13
Total household number of locations	.00	.02	.00	.02	.00	.02	−.01	.02	.00	.02	.00	.00	.00	.00
Family in neighborhood	…	…	…	…	…	…	…	…	−.04	.05	−.03	.05	−.03	.05
Friends in neighborhood	…	…	…	…	…	…	…	…	.09*	.04	.09*	.04	.09*	.04
Perceived neighborhood safety	…	…	…	…	…	…	…	…	.22*	.09	.20*	.08	.20*	.08
Neighborhood-level measures:														
Concentrated disadvantage	−.05	.07	−.06	.06	−.05	.07	−.05	.07	−.02	.07	−.01	.07	−.01	.07
Residential instability	−.03	.05	−.02	.04	−.03	.05	−.03	.04	.00	.04	−.01	.05	−.01	.04
Immigrant concentration	−.01	.08	.00	.07	−.01	.07	−.01	.07	.04	.08	.03	.08	.03	.08

	Model													
	1		2		3		4		5		6		7	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Population density	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
%black	−.26	.41	−.13	.42	−.24	.42	−.24	.41	.45	.49)	.18	.48	.18	.47
Total number of clusters	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Social disorder	…	…	…	…	…	…	…	…	−.07^{+}	.04	−.05	.04	−.05	.04
Econetwork measures:														
Neighborhood intensity	…	…	2.27*	1.16	…	…	…	…	3.30*	1.28	…	…	…	…
Neighborhood extensity	…	…	…	…	.13	.32	.14	.31	…	…	.20	.33	.21	.32
Household extensity	…	…	…	…	…	…	.25	.21	…	…	…	…	.21	.21
Intercept	1.60**	.25	1.41**	.29	1.55**	.28	1.58**	.28	1.15**	.30	1.35**	.30	1.39**	.30
Neighborhood variance component	.00		.00		.00		.00		.00		.00		.00	
Household variance component	.49		.48		.49		.48		.47		.48		.47	

$^{+}$ $P < .10$, two-tailed tests.

* $P < .05$.

** $P < .01$.