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Social context, spatial structure and social network structure

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ABSTRACT

Frequently, social networks are studied in their own right with analyses devoid of contextual details. Yet contextual features – both social and spatial – can have impacts on the networks formed within them. This idea is explored with five empirical networks representing different contexts and the use of distinct modeling strategies. These strategies include network visualizations, QAP regression, exponential random graph models, blockmodeling and a combination of blockmodels with exponential random graph models within a single framework. We start with two empirical examples of networks inside organizations. The familiar Bank Wiring Room data show that the social organization (social context) and spatial arrangement of the room help account for the social relations formed there. The second example comes from a police academy where two designed arrangements, one social and one spatial, powerfully determine the relational social structures formed by recruits. The next example is an inter-organizational network that emerged as part of a response to a natural disaster where features of the improvised context helped account for the relations that formed between organizations participating in the search and rescue mission. We then consider an anthropological example of signed relations among sub-tribes in the New Guinea highlands where the physical geography is fixed. This is followed by a trading network off the Dalmatian coast where geography and physical conditions matter. Through these examples, we show that context matters by shaping the structure of networks that form and that a variety of network analytic tools can be mobilized to reveal how networks are shaped, in part, by social and spatial contexts. Implications for studying social networks are suggested.

1. Introduction

Social network data have been collected in many organizational, institutional and other settings. Often, both the social context and spatial organization of these settings are ignored. Fortunately, there are notable exceptions, including the study of village social structure and village network structure in Thailand reported by Entwisle et al. (2007) and the early Bank Wiring Room Study (Roethlisberger and Dickson, 1939; Homans, 1950). Our intent here is to suggest that social network analysis (SNA) can fruitfully examine how both context and spatial organization impact the network social structure(s) formed within them. In short, the 'place' where network data are collected is more than a research site and it is counterproductive to ignore this routinely. We examine five examples chosen to cover very different types of contexts and social network relations. In addition, because both contexts and networks differ, we doubt that one conceptualization of network phenomena and one modeling strategy will suffice across all contexts and all networks. The examples were chosen also to demonstrate the mobilization of different data analytic strategies.

The core concepts we use here are 'social network', 'social context' and 'spatial structure': (1) a *social network* is a set of social actors over whom one (or more) social relation(s) are defined (Wasserman and Faust, 1994); (2) the *social context* of a social network is made up of the human and symbolic features that are intrinsic to situations where social network data are collected; and (3) *spatial structure* consists of specific features of a context that are located explicitly in geographic space. This specification of social context and spatial structure is an analytical distinction that looks good on paper. Yet the boundary between them may be unclear in many empirical situations when contextual features are located in geographic space. The examples we use help sharpen this distinction empirically.[1] Throughout, our focus here is on *examining the impact of social context and spatial structure on social network*

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[1] Of course, spatial structure is an intrinsic part of a social context. However, geographic space merits attention in its own right in addition to other social features of a context.

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structure. This reflects a deliberate bias intended to counteract an implicit orientation of the field that social networks form in contexts and spatial structures that can be ignored when studying network phenomena. The social attributes of actors are *not* parts of network social contexts.

We restrict this inquiry further. Two broad frameworks can be distinguished. In one, *both* the network and context are dynamic with the potential for mutual influence over time. The research of Entwisle et al. (2007) exemplifies this domain. The second has the social context and spatial structure fixed and, while social networks form within them, there is little or no reciprocal impact on context and spatial structure. The Bank Wiring Room (BWR) represents this domain. We focus primarily on the latter for two reasons: (1) Exploring causal impacts is made a little easier empirically and (2) to concentrate on how context and spatial structure (partially) determine social structure. We also include three frequently used types of network ties: binary ties, valued ties and signed ties.

2. Example networks and their rationale for consideration

Our examples are chosen to include different actors, different social contexts and diverse geographical scales. The BWR study (Roethlisberger and Dickson, 1939) provides binary network data in a workplace having fixed work locations and imposed work group memberships. Conti and Doreian (2010) collected temporal data to study network formation and evolution in a police academy where there were contextual features and a fixed spatial structure. These temporal data are better suited to our argument having both valued and binary data. Both examples represent *designed* organizational contexts. Our substantive foundation for them is richer compared to the remaining three featuring contexts having larger geographical scales. We consider data from a search and rescue inter-organization network provided by Drabek et al. (1981) where we take a small step towards considering changes of social context and spatial structure. Next we consider Read's (1954) *signed* data for ties between sub-tribes in the highlands of New Guinea where approximate geographical locations were provided. Finally, we consider a trading network along the Dalmatian coast on the Eastern Adriatic (Milicic, 1993). In each example, we couple social network structures to social contexts and spatial structures. This coupling varies across the examples.

2.1. The Bank Wiring Room

The conceptual foundations for studying the impact of work environments are found in Homans (1950) and Feld (1981). Homans recognized that social activities are constrained and/or structured by the environments in which they occur. The work design couples work activities (behaviors) to interactions. This 'external system' comprises activities, interactions and sentiments (formed by group members) stemming directly from an organizational design (Homans, 1950, p. 90) *as social context*. This configuration is part of any group surviving within a structured environment. However, additional activities, interactions and behaviors, not strictly determined by the social context, also develop. This 'internal system' is the collection of activities, interactions and sentiments formed beyond those dictated by organizational design. Empirically, these two systems are coupled. Once a group establishes its external system, allowing it to survive in its organizational context, this arrangement develops beyond its utilitarian origin to an elaboration of group behavior in an internal system (Homans, 1950, p. 109). Working together to adapt to their environment leads a group to establish a set of inner dynamics paralleling those in its external system. As group members interact, as part of the external system, they develop sentiments towards one another. The internal system evolves and these practical interactions lead to personal sentiments. The nature of these general processes took a particular form in the BWR where the task flow was rigidly specified in the design of the room. Here, we tie parts of the external and internal systems explicitly to the design of the BWR and its spatial layout.[2] Distinguishing external and internal systems provides a powerful conceptual framework for coupling social contexts to social network structures in organizations.

The BWR had three work groups, each comprised of three wiremen connecting banks of terminals for telephone equipment and a solderman who soldered the wired connections. Two inspectors examined the constructed banks for quality control. Each wireman worked at two fixed adjacent benches and moved between them when a bank was completed. The soldering locations were also fixed. Wiremen and soldermen interacted in creating the equipment and both interacted with inspectors examining soldered banks. In response to these design features, sentiments towards others in the room developed forming part of the group's external system. The organization forbade workers from helping each other and trading jobs, yet both occurred in the BWR as part of the internal system. In these instances, proscribed activities and interactions occurred as a consequence of sentiments that included boredom with tasks and a desire to work with specific others. Non-work related chatter while tasks were completed, playing games during work time and breaks, as well conflicts over windows (being open or closed) were parts of the internal system. Friendships and animosities also formed as a part this internal system. The internal and external systems are coupled (Homans, 1950, p. 91). We emphasize the fixed physical features and the design of work activities of the BWR.

2.2. A police academy

Feld provides another foundation for coupling social structure contexts when he argues "in order to explain patterns in social networks, we need not look at causes of friendship but should concentrate our attention on those aspects of the extra network social structure that systematically produce patterns in a network (Feld, 1981, p. 1016)." His focus theory has roots in Homans' work and helps us understand the interrelationship between the formation of social networks and the other features of organizations. Work units, inspection units and work roles in the BWR are all relevant foci as parts of the 'extra network social structure'. The relevance of foci is clearer in the police academy and follows from Homans' argument that frequent interaction within the external system leads to sentiments of liking or approval within the group as part of the internal system. Conti and Doreian (2010) studied a police academy that constructed an important focus by placing of academy recruits in four squads. As described by Conti and Doreian (2010, p. 34):

> "The formation of squads was an integral part of the paramilitary phase. Each squad had a name, an elected leader who served as their direct contact in the departmental chain of command, and a flag that they carried while marching in formation or running. A strong sense of competition between the squads was encouraged. When one advanced more quickly through an ele-

[2] The 'Hawthorne studies' have been challenged in the literature (e.g. Carey, 1967; Jones, 1992) especially with regard to the so-called 'Hawthorne effect' established for production data for a small group of women. The analyses presented by Jones suggest strongly that there was no Hawthorne effect. However, whether or not there was such an effect is irrelevant for our use of the BWR data. These data pertain to a group of men studied much later in time by Roethlisberger and Dickson (1939). We pay no attention to the production data collected for these men. We focus on the link between the social organization of the BWR and the social relations formed therein.

ment of training, other squads expressed a strong motivation to catch up with the more successful squad. Conversely, when one squad had a disproportionate number of its members failing to meet the training standards, its members had a collective sense of shame. Also, punishments for rule violations were frequently distributed on a collective basis to those squads having detected violations committed by any member."

These squads had differential importance at different points during the academy. Police training moved through three distinct phases (Conti, 2009; Conti and Doreian, 2010). A *noncivilian phase* occurred first after recruits crossed the boundaries of their prior experiences. Much of this early training took place in a classroom. Once recruits had internalized the training structure and were able to comply with an interaction order of strict obedience to authority without incident, the curriculum moved to a *paramilitary phase.* During this phase, instruction focused primarily on firearms proficiency, motor vehicle pursuit, self-defense, providing medical assistance and physical fitness training. Squads became an intense focus for the recruits during this paramilitary phase. The final phase was an *anticipatory police phase* when separated skills such as firearms training and self-defense were united in building role playing scenarios that mimicked 'real life' police work and preparing for a final examination.

The academy imposed an arbitrary fixed seating arrangement, with a clear spatial structure, for lectures during the noncivilian phase. Training during the paramilitary phase occurred primarily in squads (social context). Both are designed features of the academy. Towards the end of the anticipatory police phase, instruction was confined to the same classroom where lectures were held. We couple the formation of social relations over time to the fixed context and fixed spatial structure.

2.3. Emergent interorganizational networks in response to natural disasters

Natural disasters strike human communities unpredictably, wreaking widespread damage and death. Normal behaviors, based on an area's social structure, are disrupted by events concentrated in time and space. Responding involves action by individuals and organizations. Responders converge to places in the immediate disaster area and contiguous areas (Fritz and Mathewson, 1957). They include specialist and non-specialist organizations with different organizational structures and mandates. At a minimum, their actions require coordination. Some responding organizations have institutionalized roles dealing with disruptive events. They include police departments, fire departments and emergency service providers. In contrast, other organizations may become coordinators in an emergent fashion that is contingent on the specifics of particular disasters. Both the routinized and emergent organizational actions have to be coordinated (Dynes and Aguirre, 1979). Much of this coordination takes the form of communication between pairs of responding organizations.

Considerable debate exists in the literature concerning the benefits of centralized versus decentralized coordination (Petrescu-Prahova and Butts, 2008) and the relative merits of different organizations adopting leadership roles. Centralized coordination across the entire network is one extreme while decentralized coordination in parts of the response network is the other. Dynes (2003) is an advocate of the importance and necessity of decentralized coordination while Auf der Heide (1989) points to centralized coordination being crucial for successful responses. Petrescu-Prahova and Butts (2008) argue that both views can be brought together by distinguishing global and local coordination processes within particular disaster responses.

Drabek et al. (1981) studied some natural disasters that struck communities in the United States. These included tornados, hurricanes and flash flooding. They also provided data on inter-organizational relations created by organizations in responding to disasters. Consistent with the above arguments, responding to a disaster creates an 'emergent multi-organizational network' (EMON) partially determined by local conditions and improvised actions. Although communities plan responses prior to a disaster, parts of the designed infrastructure can be destroyed when a disaster strikes. The basic communication structure was destroyed when a small tornado flipped a pleasure boat on a lake in Kansas. Fischer (1998) reports that disaster researchers have identified distinct phases. The first two of them are the 'impact phase' the 'immediate post-impact period'. We examine the structure of an emergent network during the immediate post-impact period in the Kansas SAR (Search and Rescue) mission with regard coordination.

2.4. Sub-tribes of pre-Agrarian human tribes and geographic location

To include *signed* social networks distributed in space, we turn to an example taken from the anthropological literature. Read (1954) studied the Gahuku-Gama whose society was composed of sub-tribes inhabiting an area in the highlands of New Guinea where "locality is of major importance in defining groups up to and including the sub-tribe (Read, 1954, p. 36)". Moreover, "warfare . . . is that activity which characterizes the tribes of the Gahuku-Gama as a whole and which differentiates them from other groups in other socio-demographic regions (Read, 1954, p. 39)". Villages of the Gahuku-Gama were distributed in a contiguous area where their warfare was conducted. The prevalence of war forms the social context and the spatial structure is the fixed village locations. Read distinguishes between conflict known as *hina* that was governed by rules for seeking redress for minor infractions and were settled amicably. In contrast, *rova* was a form of violence that was, so to speak, 'played for keeps'. Destruction of enemies and their property together with the need for vengeance meant that this form of warfare continued indefinitely. Read presented a network diagram showing positive alliance ties and negative enemy ties for the sub-tribes making up the Gahuku-Gama. He also provided a map of the area where these sub-tribes living in villages were located. Given the establishment of villages, the spatial structure of the New Guinea Highlands was fixed. Transportation was by foot with many villages within a short walking distance from each other. For Gahuku-Gama men waging war was an intense continual focus in the sense of Feld. Consistent with Homans' argument, social relations between sub-tribes involved both enmity and alliance ties with sentiments towards other sub-tribes and their members.

In Read's (1954) narrative, warfare was endemic and persistent so "the survival of each group depended, to a large extent, on the ability of members to maintain an essential balance [in terms of allies and enemies] in their political relations (Read, 1954, p. 43)." Read adds ". . . the Gahuka-Gama express their problem succinctly when they say 'the people in the center cannot live', the group that is surrounded by enemies faces extinction".

2.5. A Dalmatian coast trading network

Continuing our focus on larger scale geographic places, Milicic (1993) presented data on part of the Venetian trading network (for the 15th to 18th centuries) along the Dalmatian coast. Poor soil conditions meant many local populations on the Dalmatian coast, and on islands off the coast, could not fully support themselves. They were reliant on trading networks for some of their essential resources. Local exchanges of goods such as wheat, cheese, fish and wine occurred in this trading network. There were also non-local exchanges of items such as olive oil, salt, wood and dried fruit (from the Mediterranean) for items like iron, timber, animal skin, wool and cloth (from Northern Europe). The rugged coast inhibited trade over land and trading was conducted primarily over part of the Adriatic Sea off the Dalmatian coast. Milicic provided data on a trading network having 38 ports and places. The waters could be very rough during storms and the coast was infested by pirates. Together, these features generated a need for safe ports during storms and for overnight stays. Milicic agued that certain ports were advantaged because they occupied key locations on the Dalmatian trading network. They also had large enough natural and safe ports. The structure of the trading network was shaped by physical terrain, the geographic distances between ports in relation to sailing technology of the time and physical features of port. Advantaged coastal communities able to attract the most maritime traffic profited through trade, taxing goods passing through their ports and imposing fees. Further, these communities became larger, more complex and more stratified. We include this example in a speculative fashion and do so to present an alternative type of interpretation to one suggested by Hage and Harary (1996, pp. 180–194) regarding arguments that advantageous locations in trading networks determine societal attributes. While they may be correct regarding the trading network of the Torres Strait (between Australia and Papua-New Guinea), we offer an alternative interpretive account with this Dalmatian trading network and suggest attributes of places determined advantaged locations in the trading network.

3. Research methods

The network data we examine come from published documents or were collected by us. Details regarding the data collection efforts and the operationalization of the variables can be found in the source documents. Our concern is focused narrowly on *coupling observed network structure to features of the social context or spatial structure within which these networks were formed*. Because there are so many ways that contexts can affect the formation of social networks, we doubt that one method can cover them all. The five networks we consider here are chosen to use a variety of social network analytic (SNA) tools. Some are simple while other methods are quite complex. We provide no descriptive details of the tools for which technical documents can be consulted. Each method is *not* used for *every* example because the appropriateness of a tool depends on how social and spatial structure affects social structure. The SNA tools that we use are the following: (i) visual displays of networks; (ii) generalized blockmodeling (Doreian et al., 2005) building on traditional blockmodeling (Breiger et al., 1975); (iii) quadratic assignment (QAP) regression (Dekker et al., 2007); and (iv) exponential random graph (p*) models (Pattison and Wasserman, 1999; Robins et al., 2007; Wasserman and Pattison, 1996). We use Pajek (Batagelj and Mrvar, 1998) for visual displays and blockmodeling, Ucinet (Borgatti et al., 2002) for QAP and Pnet (Wang et al., 2006) for fitting p* models. We do not think that methods used here exhaust those useful for depicting links between contexts, spatial structures and social networks.

4. Empirical results

4.1. The Bank Wiring Room

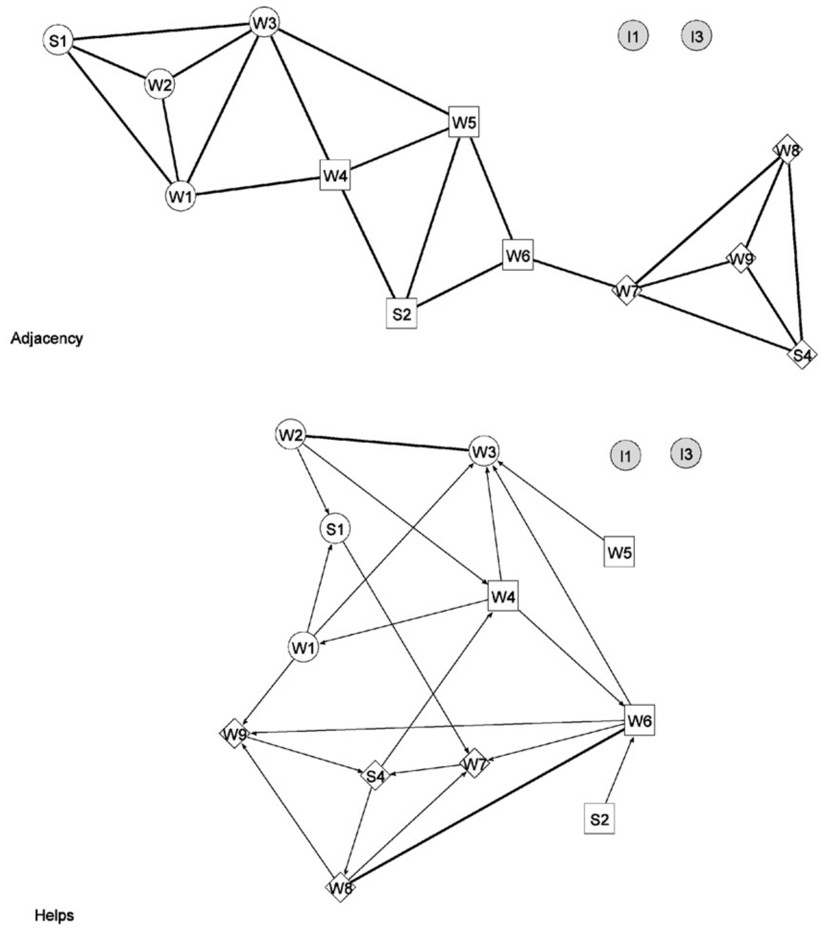
This particular data set is well known because of Homans' influence and these data were used in introducing blockmodeling. (See, for example, Breiger et al., 1975.) One blockmodeling result was a delineation of subgroups that corresponded with Homans' description of 'Clique A' and 'Clique B' as *the basic structure* of the room (together with some men not belonging to these subgroups). Given this accepted description, we ask a different question: Do the social and spatial arrangements of the room affect the formation of social relations (and hence blockmodel)? We employ the following social infrastructural features[3]: (i) fixed spatial adjacency (of work places of the room); (ii) work unit membership; (iii) inspection unit membership; and (iv) work role. Adjacency is shown in the top panel of Fig. 1. Work Units 1, 2 and 3 were comprised of {W1, W2, W3, and S1}, {W4, W5, W6, and S2} and {W7, W8, W9, and S4}, respectively. The two inspectors, I1 and I3, did not belong to any of the work groups. There were two inspection units, Inspection Unit 1 {I1, W1, W2, W3, S1, W4, W5, and S2} and Inspection Unit 2 {I3, W5, W6, S2, W7, W8, W9, and S4}. The work roles were wiremen, soldermen and inspectors. All four features are recorded as matrix arrays. The predicted social relations are: (a) helps; (b) friend; (c) game playing; (d) conflict over windows; and (e) antagonism. These were used as matrix arrays. While our general orienting hypotheses are [Context → Social Structure] and [Spatial structure → Social Structure], we do not rule out the possibility that the 'context' and 'spatial structure' are rivals for determining social network structure and need not be complementary in their effects.

While using adjacency (Fig. 1, top panel) for spatial structure is straightforward, there are options regarding variables representing context. One is to treat all membership units as identical in their impact and assume unit membership is all that matters. An alternative is to claim the units differ in their impacts: it matters to which unit individuals belong. We prefer the latter because all narratives concerning the BWR make it clear that these units differed regarding involvement in social relations. Throughout, we used QAP regression to assess the impact of context and spatial structure on social structure because data points in a network are interdependent. Many parametric statistical methods are, in principle, affected by the presence of network autocorrelation, and inference based on methods assuming interdependence can be compromised seriously. The permutation test used in QAP regression provides a more adequate foundation for inference.

Our approach was inductive so we are vulnerable to the charge of 'capitalizing on chance' when establishing links between relations. However, we adopted two guiding principles. Spatial adjacency was considered first for all relations (including conflict over windows and antagonism even though adjacency seemed unlikely to predict them). Adjacency could be a mechanism for generating positive and related ties like playing games together. It is also easier to help others in the same work role or adjacent workers. We examined bivariate relations between context and spatial structure and social relations. Second, because there is the risk of collinearity among the predictors, a risk realized in these data, we exercised caution and discarded all results showing tell-tale signs of collinearity.[4] Collinear predictor relations are not involved in the QAP regression results that we report. Also, with three work unit

[3] Two other features of the social infrastructure were recorded. One was proximity to the windows versus being away from the windows. It had no predictive value for any of the social relations including conflict over the windows. The conflict was over windows being open or closed. Sometimes, being near the window would be problematic while distance from the windows could be irksome at other times. In short, complaints could come from anywhere in the room. So location relative to windows had no predictive value for conflict over the windows. The second possible feature was 'front' versus 'back' (of the room) but this is redundant to work unit membership.

[4] As an additional check, ridge regression (Hoerl and Kennard, 1970) was used and the ridge traces were examined. These traces implied no changes regarding the selection of significant predictors for the QAP regressions.



Note: Plain circles represent members of Work Unit 1; squares represent members of Work Unit 2; diamonds represent members of Work Unit 3 and shaded circles represent inspectors.

Fig. 1. Adjacency and helps in the Bank Wiring Room.

matrices, only two can be entered in the same equation. Similarly, only one of two inspection unit matrices can be entered in an equation. In each result that we report, the omitted reference/category is the unit excluded from the estimated equation.

We use visual displays for depicting the social networks and report the QAP regressions. The following representation of vertices holds: plain ellipses represent members of Work Unit 1, boxes represent members of Work Unit 2 and diamonds represent members of Work Unit 3. Inspectors are shown in gray ellipses. Symmetric ties are represented by lines without arrowheads while directed ties have arrowheads. The only directed relation that we consider is helping.[5] The QAP regressions are in Table 1.

4.1.1. Helping

Helping ties are shown at the bottom of Fig. 1. Inspectors, consistent with their organizational role, never helped others. Only two reciprocated ties exist (between W2 and W3 and between W6 and W8). Otherwise, all helping ties are directed. The results are shown in Table 1A. Adjacency and Work Unit 2 account for only 15 percent of the variation of helping ties. The negative coefficient for the second work unit is consistent with the lower levels of helping within this unit compared to the other work units.

4.1.2. Friend

We show four symmetric BWR networks in Fig. 2. The QAP results are in Table 1 (panels B–E) for these four relations: friend; game playing, conflict over windows; and antagonism. To account for the variation in these four relations, we continue to use adjacency as spatial structure and combinations of the workplace items as indicators of social context. For four social relations, membership in work units is a predictor. However, different relationships are concentrated differently in different work units. It follows that when work units help account for the variation of social relations, no single work unit, or one specific combination of work units, has explanatory value for all social relations. Friend network ties (in Fig. 2 top left panel) are concentrated primarily in Work Units 1 and 3. The results shown in Table 1B are consistent with this: it is not surprising that the significant predictors are Work Units 1 and 3. The two positive coefficients can be interpreted as showing friendship levels were higher in these two work units. Of course, all ties not contained inside these two work groups cannot be accounted for with this equation. Work units account for 37 percent of the variation in the friend relational matrix.[6]

[5] We did not consider the job trading network because it was too sparse.

[6] We note that adjacency as the sole predictor accounts for 27 percent of the variation of friend ties. However, when the two work units and adjacency are used as predictors, adjacency is not significant with the explained variance rising modestly by 2 percent. The coefficients for the two work unit remain significant and positive

Table 1
QAP prediction equations for each social relation in the BWR.

Predictor	Unstandardized coefficient	Standardized coefficient	Permutation test *p*-value
A. Helps[a]			
Intercept	0.067	0	–
Adjacency	0.332	0.414	<0.001
Work Unit 2	−0.177	−0.130	0.017
B. Friend[b]			
Intercept	0.063	–	–
Work Unit 1	0.437	0.310	0.008
Work Unit 3	0.770	0.546	0.001
C. Games[c]			
Intercept	0.130	0	–
Adjacency	0.336	0.306	0.018
Work Unit 1	0.534	0.287	0.011
Work Unit 3	0.534	0.286	0.001
Inspection Unit 1[d]	0.269	0.182	0.038
D. Conflict over Windows[e]			
Intercept	0.139	0	–
Work Unit 2	0.361	0.424	0.047
Work Unit 3	0.694	0.220	0.005
E. Antagonism[f]			
Intercept	0.136	0	–
Inspection Unit 2[g]	0.664	0.511	0. 001

[a] $R^2 = 0.15$, $p < 0.001$, $N = 182$.
[b] $R^2 = 0.37$, $p < 0.001$, $N = 182$.
[c] $R^2 = 0.44$, $p < 0.001$, $N = 182$.
[d] Inspection Unit 1 without Work Unit 1
[e] $R^2 = 0.22$, $p = 0.002$, $N = 182$.
[f] $R^2 = 0.26$, $p = 0.002$, $N = 182$.
[g] Inspection Unit 2 without Work Group 3.

4.1.3. Game playing

Fig. 2 (bottom right panel) shows the game playing relation. The two isolates for game playing are the most disliked men in the room. All members of Work Units 1 and 3 are involved in game playing. Two members of Work Unit 2 are in the larger ‘cluster’ of game players and one joins with members of Work Unit 3. There is a bridge between the two denser clusters involving W5 and W7. We note that an inspector joined their game playing and members of Inspection Unit 1 played games together. Because Work Unit 1 is contained within Inspection Unit 1, Work Unit 3 is contained within Inspection Unit 2 and parts of Work Unit 2 are contained in both inspection units, some additional care is required when constructing predictor relations. If a work unit membership is represented by W_i and an Inspection Unit, I_j contains W_i, then the inspection unit used in the QAP regressions is ($I_j \backslash W_i$). The results reported in Table 1C show that adjacency is a strong predictor, as is (the modified) Inspection Unit 1 (as ($I_1 \backslash W_1$). Work Units 1 and 3 are predictive with higher levels of game playing within these units. These features of the designed environment account for 44 percent of the variation in game playing ties. There is a strong correspondence with the two cliques described by Homans and we argue that social context and spatial structure also accounts for much of the blockmodel description (Breiger et al., 1975). We note that adjacency by itself accounts for 36 percent of the variation of this social tie (see also Table 2).

4.1.4. Conflict over windows

As shown in Fig. 2 (top right panel), the men involved in this conflict are primarily from Work Units 2 and 3. Both inspectors and three members of Work Unit 1 stay out of these conflicts. The prediction equation is shown in Table 1D. Memberships in these units accounted for 22 percent of the variation in conflict ties. Again, adjacency, with these two work units included, is not significant. And, as the sole predictor, it accounts for only 5 percent of the variance. Its modest influence is eclipsed by membership in work units. Membership in Inspection Unit 2 ($I_2 \backslash W_3$), when used alone, is not significant.

4.1.5. Antagonism

Fig. 2 (bottom left panel) displays the antagonism ties of the BWR. As noted in Homans’ narrative, I3 and W5 are involved in the most antagonistic relations. It is clear also that most, but not all, of these ties are within Inspection Unit 2 ($I_2 \backslash W_3$). Consistent with this, the best prediction equation shown in Table 1E has this unit as the sole predictor and accounts for 22 percent of the variance of antagonism.

4.1.6. Summary of predicting the social relations in the Bank Wiring Room

Most of the QAP regressions using a single predictor show that both adjacency and social context have significant relations with the predicted social relations. (The one exception is that adjacency is not related to antagonism.) In general, the variation explained in the social relations cannot be neatly partitioned into two parts. Table 2 summarizes the predictive value, for the five social relations considered here, of three sets of contextual features: (i) adjacency alone; (ii) social context alone; and (iii) some combination of adjacency and social context. The specific items of social context, for each predicted relation, are those listed in the panels of Table 1. The third column presents a summary of the variance explained in the panels of Table 1 after both considering adjacency and social context. The final predictive values of organizational features are as follows: social context alone predicts friends, conflict over windows and antagonism and both adjacency and social context predict helping and game playing. The predictive utility ranges considerably from 44 percent explained variance for playing games to 15 percent for helping. There is sufficient support for our initial orienting hypotheses: both the context and spatial structure have an impact on social relations formed in the BWR.

but are lowered in value. The equation reported in Table 1 is preferable and work unit membership is the sole predictor of the friend ties.

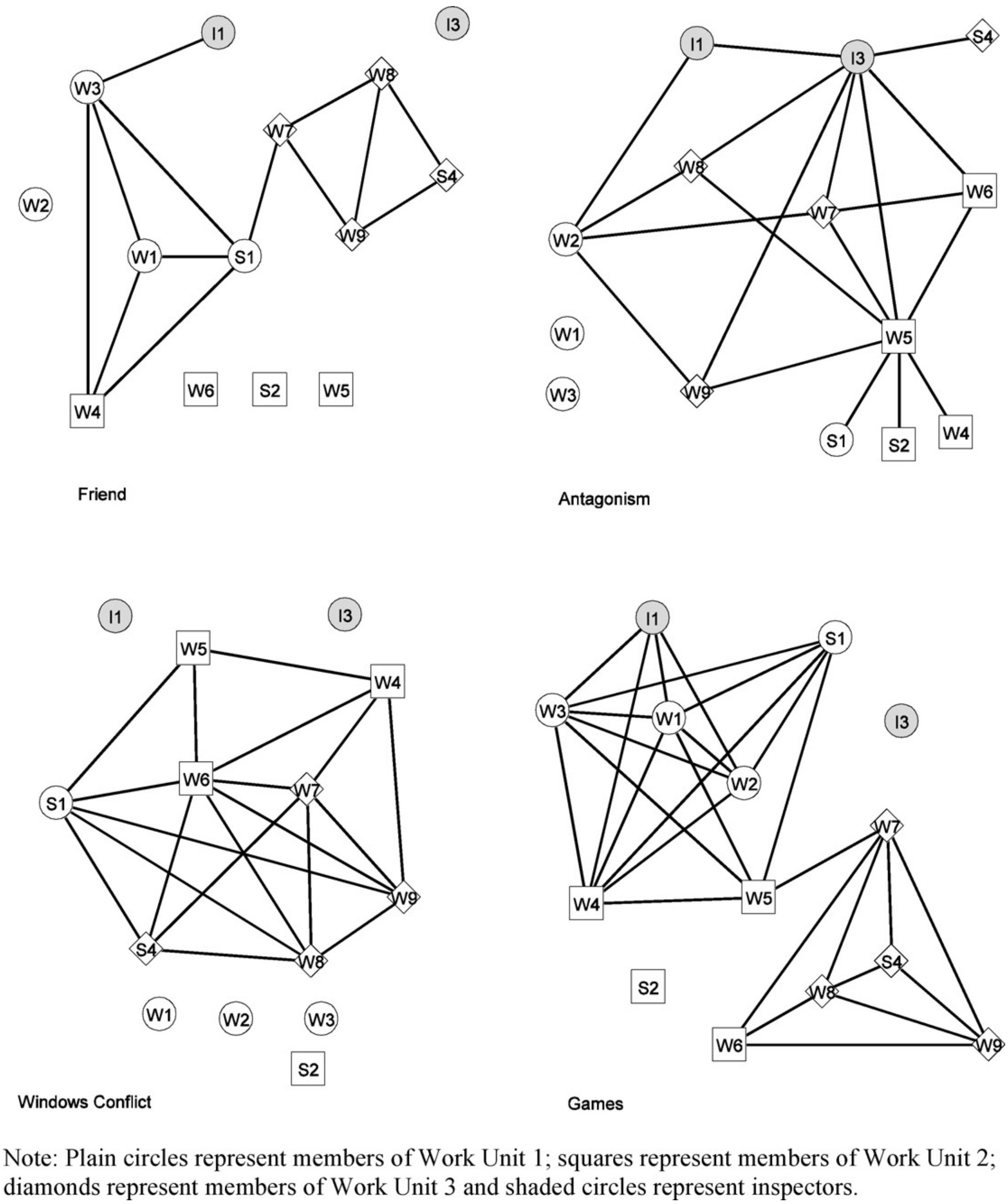


Fig. 2. Four symmetric relations in the Bank Wiring Room.

There are potential counter-arguments against our claim regarding the impact of context and spatial structure. One is that we have merely dressed up in equations observations made by other researchers about the incidence of these relationships. If we know that conflicts over windows occur among members within particular work groups, there is no surprise value in seeing this in our QAP regressions. The same holds true for membership in a particular inspection unit and antagonism. Even when accounting for 44 percent of the variance in game playing, the impact of particular work units and one inspection unit seems obvious. Even so, the point is that membership *does predict* some of the network structure. At a minimum, the approach presented here offers a way of *testing hypotheses* about the effects of unit membership that go beyond eye-balling network diagrams and constructing summaries. No systematic information was recorded about the psychological dispositions of the men in the BWR. We cannot rule out

Table 2
Summary of social infrastructure predicting social structure in the BWR.

Social structure relations	Variance explained by adjacency	Variance explained by social context	Explained variance overall
Helps	13%	5%	15% (adjacency and social context)
Friend	27%	37%	37% (social context alone)
Games	36%	39%	44% (adjacency and social context)
Windows Conflict	5%	22%	22% (social context alone)
Antagonism	0%	26%	26% (social context alone)

the possibility that Inspection Unit 2 happened to be populated by contentious individuals prone to disagreements or that agreeable men populated Work Unit 1. This suggests the value of having systematic attribute data for items in rival theories along with measures of social context. There were some surprises in the results that we report. We had anticipated that adjacency would play a greater role. Even so, adjacency and unit membership remain plausible mechanisms for the generation of social ties and do so in ways consistent with the insights of Homans and Feld.

There are also some specific features of the BWR that are beyond the reach of the approach we pursue here. Game playing was concentrated in two areas of the room defined by its design. Homans reports that different games were played in the two sub-groups and our estimated models do not differentiate game types. Also part of the record for the BWR is that the identified social groups – be they ‘Clique A’ and ‘Clique B’ or membership in units defined by the internal structure – had different production rates and reported rates differing from what they produced. We do not consider these internal group norms about preferred game playing and reporting work production.

Even though the data recorded by the observer in the room were collected over time, they were recorded for one point in time after things “had settled down”. While it is reasonable that these social relations would have causal impact on each other – for example, getting into arguments over the windows generalizing to general animosity towards others with whom the arguments were held – the essential cross-sectional nature of the recorded data preclude exploring this. We do not rule out the possibility that some relations have causal relevance for other social relations in ways that diminish the overall impact of the social infrastructure as reported here. This, however, would require genuine temporal data that are not available for the BWR. Such data are in the police recruit data reported by Conti and Doreian (2010).

4.2. Network evolution in a police academy

These data concern 68 police recruits who completed training at a mid-Western police academy in the US. Conti and Doreian (2010) studied network evolution among these recruits during their training to become certified police officers. Data were collected for four time points: T_0 (before the academy); T_1 (at the start of the non-civilian phase); T_2 (during the paramilitary phase) and T_3 (at the end of the anticipatory police phase). The predicted social relations are (i) social knowledge (of the recruits about each other) at T_1 and T_2 and (ii) friendship at T_3. As noted in Section 2.2, two design features of the academy – a fixed seating arrangement for the instruction of the entire cohort and squad membership for training not in a single classroom – were particularly salient. To explore the impact of these features we use spatial structure (adjacency[7]) and social context (squad membership) as primary predictor relationships. These are shown together in Fig. 3. The rows and columns have been permuted to place rows and columns for squad members together. The dashed lines extending beyond the matrix grid separate squads.

The friendship ties at T_3 (at the end of the training) are shown as a formatted array in Fig. 4. These ties are valued with stronger ties being darker in the matrix array. White squares represent null ties. The network is quite dense with denser patches of ties inside squads. Some of the ties outside squads are accounted for by the seating arrangement. Even at an early time point (T_1) there was the beginning of a clumping of social knowledge ties within the squads rather than between the squads. For each successive time point, the densest parts of the network were inside squads. While a visual examination of formatted arrays such as the one shown in Fig. 4 suggests that squad membership, as a designed feature, had an impact on the formation of social relations inside the academy, it does not provide a way of assessing this while controlling for other relations that are present. In particular, such a visual impression conveys little of the potential impact of the spatial structure imposed by a fixed seating arrangement.

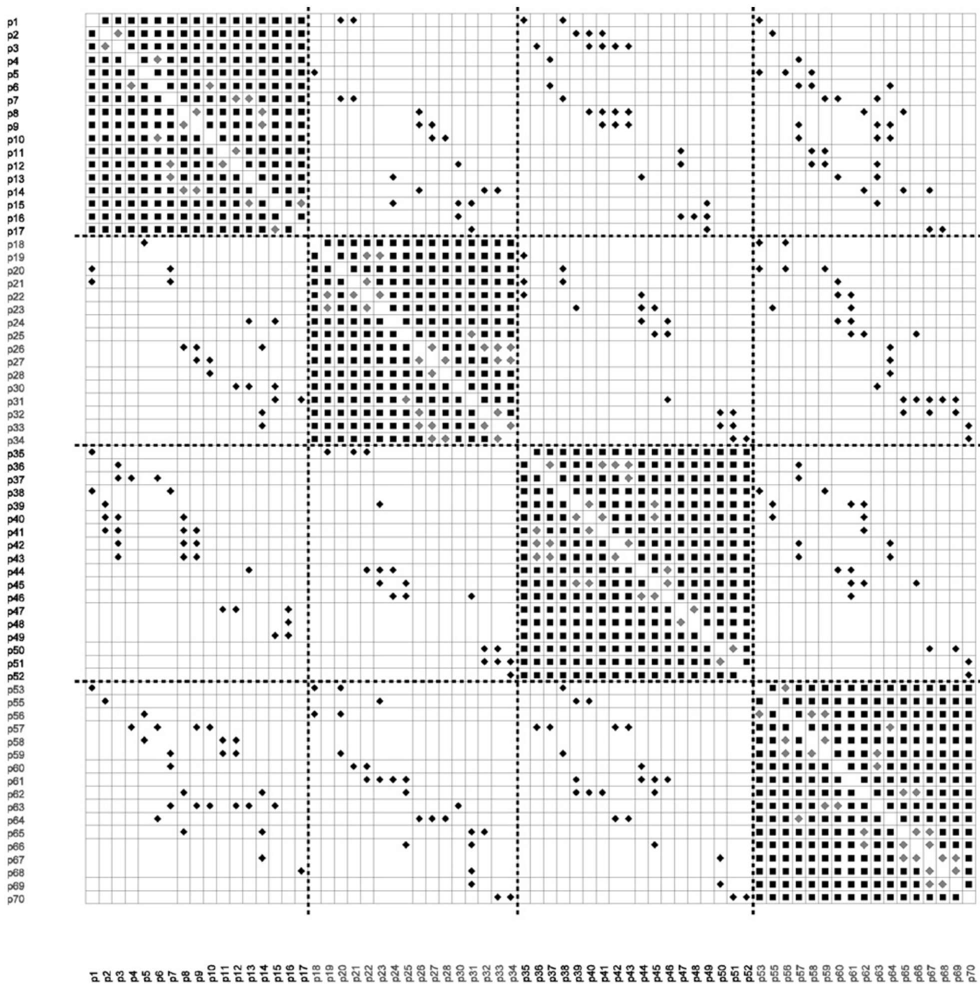
The simplest test to see whether or not the two social infrastructure variables have any predictive value for social knowledge and friendship uses QAP regressions in the same fashion as the BWR. These results shown in Table 3 are unequivocal. For *each* time point, adjacency (as spatial structure) and squad membership (as social context) are significant predictors of the social relations formed among the recruits. About 15 percent of the variation in social knowledge is explained at T_1. This rises to 30 percent at T_2 before dropping to 17 percent at T_3 for friendship ties. The unstandardized coefficient for adjacency declined slightly over time while the corresponding coefficient for squad membership increased dramatically. Both changes make sense. Data collection at T_2 occurred (by design) during the paramilitary phase when training occurred primarily in squads. The greater impact of squad membership reflects this change in instructional format. Both predictors are significant for predicting friendship at the end of the academy. While the change in the definition of the predicted variable at T_3 makes the interpretation of changes in magnitude problematic, there is no denying the predictive value of the social context and spatial structure for friendship at the last time point. Context is a more potent predictor of social relations than spatial structure.

This predictive value may not hold when a rival hypothesis is considered. Forming social ties is also an endogenous process where social knowledge at an earlier time point predicts to subsequent social knowledge and also to friendship at a later time. This includes pre-academy social knowledge for some pairs of recruits. Once started, the creation of social relations can continue in ways not totally conditioned by the context and spatial structure. Also, the academy had concerns about the historically difficult issue of race in law enforcement in the U.S. and worried that it could compromise the notion that, for police, ‘we are all blue.’ We used race also as a control and these results[8] are shown in Table 4.

The results in Table 4 show that both context and spatial structure retain predictive value at all three time points. However, their impacts diminish when the other social relational variables are included. The inclusion of race and pre-academy social knowledge increased the explained variance of social knowledge at T_1 from 15 percent to 23 percent (Table 4, top panel). The unstandardized coefficients for context and spatial structure drop slightly. From the standardized coefficients, squad membership remains the most potent predictor followed by pre-academy social knowledge. Race is a significant but modest predictor. For T_2 (Table 4, middle panel), including the additional variables means that 42 percent of the variation in social knowledge is accounted for. The unstandardized coefficient for adjacency drops further while that for squad membership increases. From the standardized coefficients at T_2, the most potent predictor remains squad membership followed by social knowledge at T_1. At T_3 (Table 4, bottom panel) the unstandardized coefficients for both infrastructure variables drop.

[7] Adjacency includes side-by-side across the lecture room and immediate in front-behind ties.

[8] Substantively, race was included in the original study design and the role of race has been reported extensively in Conti and Doreian (2010). For consistency, race is kept in these analyses but it is *not* intended as an operationalized part of the social context. When it is excluded for the QAP regressions the substantive results concerning the impact of context and spatial structure are unchanged. We keep race in the analyses reported here as a reminder that analyzing links between social structure and context, in general, is likely to include other variables.



Note: The diamonds denote seat adjacency and squares denote squad membership. The (lighter) diamonds inside the squads override squad membership for display purposes only: the diamonds inside the squads denote both squad membership and seat adjacency.

Fig. 3. Squad membership and seat adjacency for the police academy.

While they account for 17 percent of the variation in friendship by themselves, when used with the other variables the explained variation increases to 35 percent. The most potent predictors are social knowledge at prior time points in the academy.

In addition to providing a better account of relation formation during the academy, the inclusion of prior social variables as predictors confirms that relationship formation is an endogenous process and that the estimated impact of the social infrastructure is overstated when only infrastructure is considered. This implies that some of the impact of social infrastructure on social structure is over-estimated. In terms of the cumulative dynamics of social relations, it makes sense that the impact of social infrastructure will diminish over time. However, we suggest that while they may diminish, they do not disappear.

Table 3
Preliminary QAP regression results for a police academy.

Predictor	Unstandardized coefficient	Standardized coefficient	p-Value
Predicting Social Knowledge at T_1[a]			
Intercept	0.259	0.000	–
Seating adjacency	0.735	0.161	<0.001
Squad membership	1.079	0.355	<0.001
Predicting Social Knowledge at T_2[b]			
Intercept	0.626	0.000	–
Seating adjacency	0.648	0.111	<0.001
Squad membership	2.083	0.536	<0.001
Predicting Friendship at T_3[c]			
Intercept	0.724	0.000	–
Seating adjacency	0.586	0.107	<0.001
Squad membership	1.450	0.397	<0.001

[a] $R^2 = 0.15$, $p < 0.001$, $N = 4556$.
[b] $R^2 = 0.30$, $p < 0.001$, $N = 4556$.
[c] $R^2 = 0.17$, $p < 0.001$, $N = 4556$

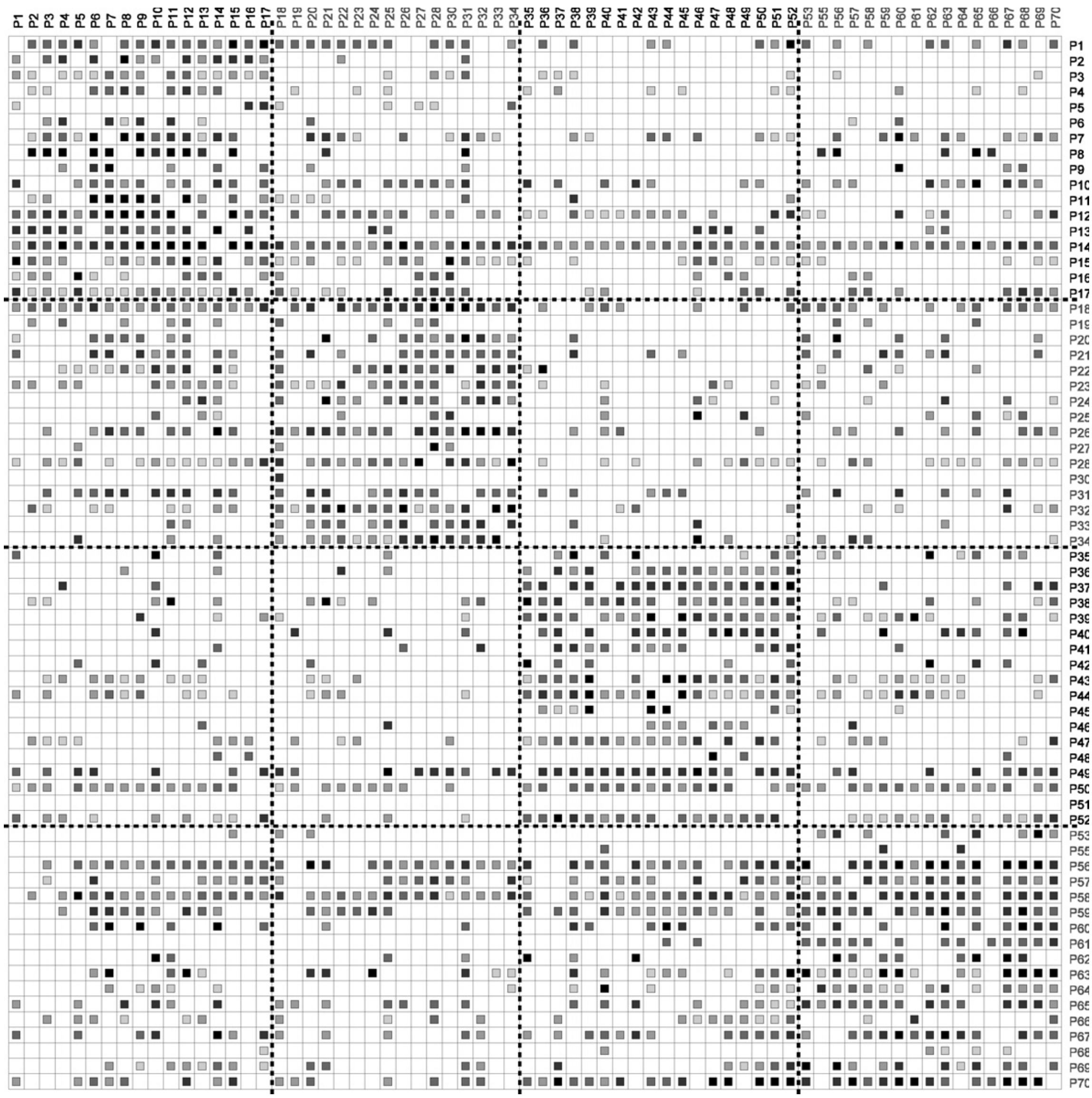


Fig. 4. Friendship relations at T_3 organized by squads.

4.3. An emergent multi-organizational SAR network

As noted in Section 2.3, coordination is essential for responding to disasters, with communication a crucial feature. The tornado that struck in Kansas destroyed the communication system in the affected county. Immediately after the disaster, there was ambiguity concerning the chain of command because the state park, located in a county, also contained a federal reservoir. Before the local sheriff took charge of the mission, he sought and obtained authorization from the County Attorney. We view this as a non-network element of the social context. Acting on the provided legal authority, the sheriff faced the problem of communicating with other organizations. The local unit of the state's highway patrol was the only organization with viable equipment for county-wide communication so the sheriff located his headquarters there. Utilizing this communication facility is another feature of the social context. Because this communication unit could be moved, its location was a spatial feature that was not fixed at the outset of the SAR effort. In the immediate post-impact period, the primary tasks were rescuing survivors and collecting bodies. Accordingly, the sheriff also placed his (new temporary) headquarters close to the location where survivors and bodies were taken. The latter was a fixed location in the state park where the Army Corps of Engineers base became the SAR morgue. The SAR communication data provided by Drabek et al. (1981) are shown in Fig. 5. These communications disproportionately involved the sheriff and the highway patrol unit and were conditioned by both the social context and the spatial structure around the communication center. Both were far more fluid than the fixed structures of the BWR and the police academy The shading ranges from black (continuous communication) through shades of gray to the least frequent level (once a day).

Our focus concerns both global and local coordination distinguished by Petrescu-Prahova and Butts (2006). If global coordination is important this implies that centralized coordination is present. Given the central location of the Sheriff in the communication equipment controlled by the Highway Patrol, it is reasonable to expect they will provide this coordination. An *idealized* form if this is shown in Fig. 6 where two organizations communicate with all other participating organizations. If this coordination is present, this ideal form will have predictive value. The result of a QAP bivariate regression is shown in the left panel of Table 5. The idealized structure, operationalizing global control, is a significant predic-

Table 4
Overtime quadratic assignment regression results for a police academy.

Predictor	Unstandardized coefficient	Standardized coefficient	p-Value
Predicting Social Knowledge at T_1[a]			
Intercept	0.116	0.000	–
Pre-Academy Social Knowledge	0.530	0.265	<0.001
Seating adjacency	0.695	0.152	<0.001
Squad membership	1.024	0.337	<0.001
Race	0.177	0.068	<0.001
Predicting Social Knowledge at T_2[b]			
Intercept	0.455	0.000	–
Pre-Academy Social Knowledge	0.260	0.102	<0.001
Social Knowledge at T_1	0.417	0.326	<0.001
Seating adjacency	0.322	0.055	<0.001
Squad membership	1.606	0.413	<0.001
Race	0.073	0.022	0.129
Predicting Friendship at T_3[c]			
Intercept	0.361	0.000	–
Pre-Academy Social Knowledge	0.127	0.053	0.001
Social Knowledge at T_1	0.159	0.132	0.000
Social Knowledge at T_2	0.394	0.420	0.000
Seating adjacency	0.201	0.037	0.004
Squad membership	0.442	0.121	0.000
Race	0.119	0.038	0.031

[a] $R^2 = 0.23$, $p < 0.001$, $N = 4556$.
[b] $R^2 = 0.42$, $p < 0.001$, $N = 4556$.
[c] $R^2 = 0.36$, $p < 0.001$, $N = 4556$

Table 5
One QAP regression and two ERG models for the Kansas SAR mission.

Predictor	Unstandardized coefficient	Standardized coefficient	Permutation test p-value
A. The QAP regression linking the ideal blockmodel to the observed communication structure[a]			
Intercept	0.917	0	–
Inspection Unit 2**	2.208	0.461	0.006

[a]$R^2 = 0.21$, $p = 0.003$, $N = 380$.

Parameter	ERGM only Parameter estimate (standard error)	ERGM plus Blockmodel Covariate Parameter estimate (standard error)
B. Two ERGM models for the observed communication structure		
Arc	−**3.250** (0.312)	−**3.279** (0.547)
Reciprocity	**1.592** (0.452)	**1.175** (0.484)
2-In-Star	**0.231** (0.023)	**0.227** (0.026)
3-Out-Star	**0.021** (0.005)	**0.019** (0.005)
Mixed-2-Star	−**0.108** (0.030)	−**0.088** (0.031)
AKT-T	**0.588** (0.207)	0.527 (0.279)
Blockmodel Covariate	– (–)	**0.846** (0.249)
Mahalanobis Distance	31.12	8.37

tor of communication and accounts for 21 percent of the variance. However, it is silent about local coordination.

We adopt a different modeling approach to capture local processes that could generate the communication network. Exponential random graph models (ergms) provide another way of modeling social networks (Wasserman and Pattison, 1996; Pattison and Wasserman, 1999). This approach assesses micro-level processes whose cumulative operation generates network structure. Table 5A shows the result from the QAP regression linking the actual communication structure (shown in Fig. 5) to the ideal core-periphery structure (shown in Fig. 6). Table 5B shows the results of estimating two ergm models (with the communication relationship matrix in binary form using all communication ties). On the left is a model with the following parameters: arcs, reciprocity, 2-in-stars, 3-out-stars, mixed 2-stars, alternating k-triangles. At face value, these local processes[9] appear to generate the communication network for the Kansas SAR.

Those considering a global prediction of the communication structure can argue that the result in Table 5A supports their position. Similarly, proponents of a decentralized view can argue that the local-process ergm supports their arguments. However, it would be useful to try and integrate both local and global coordination in a single model. In contrast to ergms, blockmodeling adopts a macro-level approach in describing the overall structure of the network in terms of macro-level processes. Doreian et al. (2009) proposed a way of combining these seemingly different approaches into a single flexible modeling framework. We adopt that framework here. On the right panel of Table 5B is another ergm with the same micro-level parameters and a covariate in the form of the matrix for the ideal core-periphery structure shown in Fig. 6.

The results are pertinent given our efforts to link the contextual structure of communication to the observed communication structure. The ergm by itself fits the data and all of the parameters are significant. The goodness of fit simulation shows that all of the observed features of the network do get reproduced, including the triad census. Mahalinobis distance has been proposed as a measure of overall fit (Wang et al., 2009) and its value for this estimated model is 31.1. By all of the fitting criteria, the set of

[9] A detailed interpretation of these parameters is quite lengthy and these details are tangential to our main point beyond noting that they represent micro-level processes.

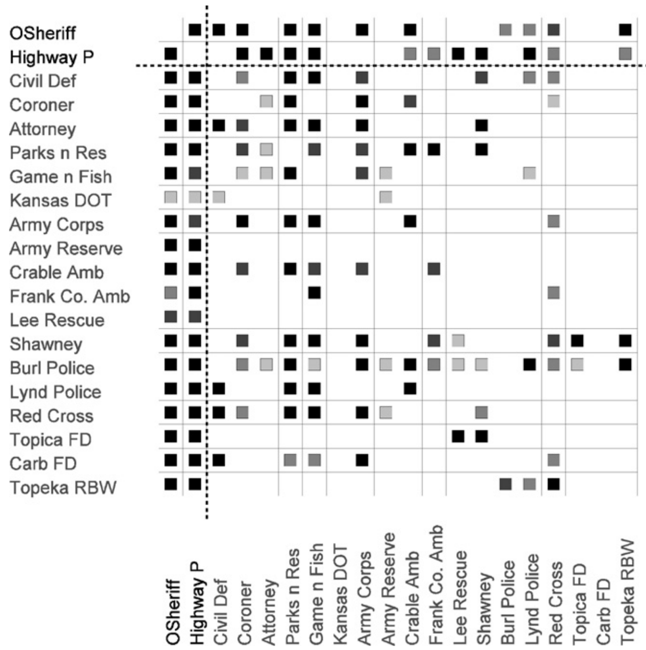


Fig. 5. Kansas SAR mission communication network as a matrix array.

micro-processes represented in the model is enough to account for the network's structure. Yet, when the matrix covariate for the ideal blockmodel is included, a different and more general model also fits. The numerical estimates of the micro-level parameters do not change much. (However, one of them is no longer significant.) More importantly, the covariate is significant and the Mahalinobis distance drops considerably to 8.4. We argue that the improvised communication contextual structure conditioned the communication patterns for the SAR mission as a form of global coordination. Yet, local coordination processes were operative also and are captured by the ergm parameters of the combined model.

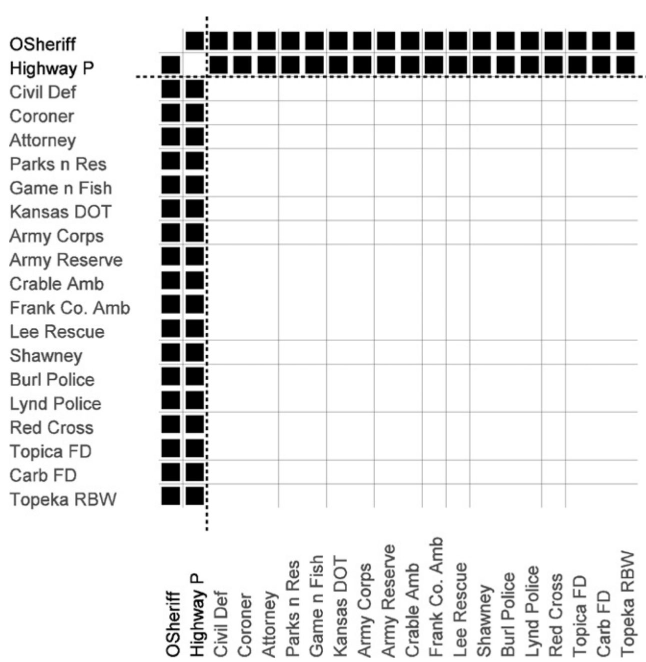
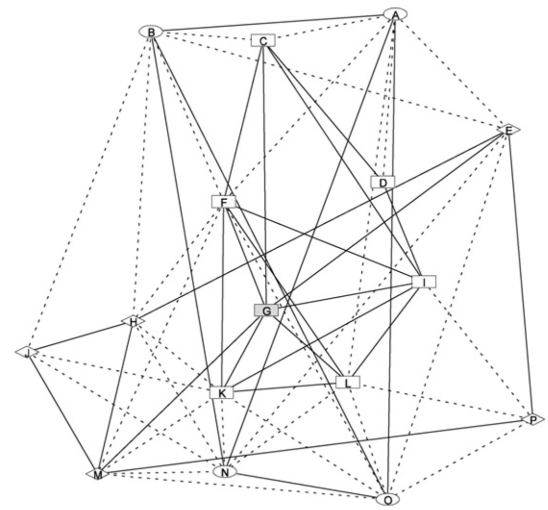


Fig. 6. Ideal center-periphery blockmodel for the Kansas SAR mission network.



Note: The shapes of the vertices denote clusters in the relaxed balance partition reported in Figure 8: Circles represent units in the first cluster, squares represent units in the second cluster; diamonds represent units in the third cluster and the shaded square represents the singleton in the final cluster.

Fig. 7. Relaxed balance partition for the sub-tribes of the Gahuku-Gama.

4.4. Geography and signed relations for the Gahuku-Gama

The signed alliance and enemy for ties among the sub-tribes of the Gahuku-Gama suggest the relevance of structural balance theory as presented by Heider (1946) and formalized by Cartwright and Harary (1956). Most, if not all, of the studies of signed networks within the framework of structural balance ignore the spatial locations of the units. Both Hage and Harary (1983) and Doreian et al. (2005) analyzed these data and paid no attention to the spatial locations of the sub-tribes. Instead, they focused on the 'ideal' blockmodel for a network fully consistent with structural balance having a distinctive form (Doreian and Mrvar, 1996). There are two types of blocks: (i) positive blocks containing only positive ties (with null ties allowed) and (ii) negative blocks having only negative ties (also with null ties allowed). Moreover, the positive blocks are on the main diagonal of the blockmodel and the negative blocks are off the main diagonal. Applied to the Gahuku-Gama network (Hage and Harary, 1983; Doreian et al., 2005) the unique best (optimal) partition had three clusters of sub-tribes. Some inconsistencies with (perfect) structural balance were present with positive ties (involving one sub-tribe) in negative blocks. This suggests that structural balance was not the only operative process. More importantly, as we show below, the spatial locations of sub-tribes mattered for the (generalized) blockmodel structure of this signed network.

Doreian and Mrvar (2009) proposed a generalization of structural balance where the positive and negative block types could appear anywhere in the blockmodel. This relaxed structural balance model or, more simply, relaxed balance model is a formal generalization of structural balance. Their modified algorithm for relaxed balance, which keeps the relocation algorithm and criterion function,[10] is implemented in Pajek (Batagelj and Mrvar, 1998). Fig. 7 shows the unique partition when one null block[11] is specified

[10] The criterion function that is minimized is $P(C) = \alpha N + (1 - \alpha)P$ where N is the number of negative ties in positive blocks and P is the number of positive ties in negative blocks and α (where $0 < \alpha < 1$) allows the two types of inconsistencies to be unequally weighted. Here $\alpha = 0.5$. When the value of the criterion function is zero, the signed blockmodel fits exactly.

[11] There is clearly a null block in Fig. 8 – actually two of them given the symmetry of the relation. When no null block was specified there are 8 equally well fitting partitions (with $P(C) = 0$). There is no way of choosing among them. However, spec-

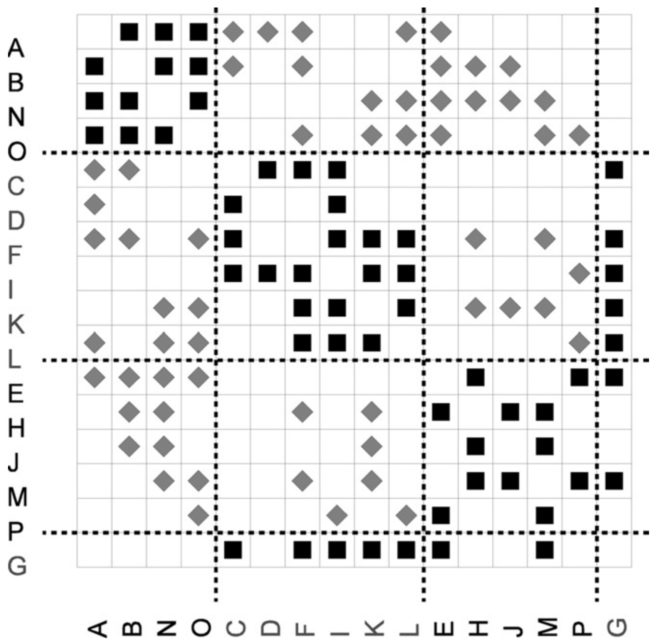


Fig. 8. Matrix array for the relaxed structural balance partition of the Gahuku-Gama network.

in a network diagram and as a formatted matrix (Fig. 8). This partition has no inconsistencies with relaxed structural balance and is a perfect fit. The sub-tribe G is a singleton in its own cluster and there are three other clusters of sub-tribes where there are positive ties within the clusters and negative ties to members of other clusters. Sub-tribe G has positive ties to members of two of the other clusters of sub-tribes.

The locations of the tribes in Fig. 7 correspond very closely to the locations shown in the map provided by Read (1954). This is important even though the diagram could be made clearer[12] (by moving vertices like G, C, N and O). However, location is particularly important – especially for G. Consider again G's location and the Gahuka-Gama claim that 'the people in the center cannot live'. G is in the middle of the geographical area inhabited by the Gahuka-Gama. Were it surrounded only by enemies, its chances of survival would be zero. We speculate that sub-tribe G needed to form positive ties with geographic neighbors in order to survive. Moreover, its uniqueness is not due to cultural differences between sub-tribes because there are none. Being located right in the geographic middle of an area where warfare is persistent suggests a need to form positive ties with enough immediate neighbors. And G has only positive ties to other sub-tribes. However, geography is not everything despite the compelling need for G to not be surrounded completely by enemies. Why G has positive ties with E and M but not with H does not have an obvious geographical rationale.

Given the locations of the sub-tribes, it is straightforward to compute the (approximate) *physical (i.e. geographic)* distance between pairs of sub-tribes having alliance and enemy ties in the Gahuka-Gama area. Using the non-parametric Mann-Whitney rank sum test, the null hypothesis that the geographical length of positive and negative ties are equal cannot be rejected ($p = 0.54$). The tie distance (in geographic space) within the central cluster of sub-tribes is less than the distances within the other two clusters shown in Figs. 7 and 8 ($p = 0.012$). That the alliance ties for the 'boundary clusters' – where the sub-tribes tend to be on the outer boundaries of the Gahuka-Gama's region – cover a longer geographical distance is suggestive of another impact of geography, especially as there is little warfare with similar units outside this boundary. Direct enemies are located short distances from them while long distances separate them from their allies.

4.5. A Dalmatian coast trading network

The Dalmatian coast trading network described in Section 2.5 is shown in Fig. 9. The network relations are direct sailing routes between places. Three port communities (Zadar, Hvar and Ragusa) are marked as gray vertices because they are distinctive as major cut vertices in this network. Consistent with this, they have the three highest betweenness scores. From the perspective of Hage and Harary (1983), it was their strategic location that conferred advantage on these three ports. Hvar was the primary focus of Milicic's (1993) account of strategic locations of ports in the trading network and the subsequent consequences for places enjoying a strategic location. However, we note that Zadar was the administrative center for Venice along the Dalmatian coast and Ragusa, now known as Dubrovnik, was a city state that remained unconquered until Napoleon's forces took it. At the time, all three ports became locations where wealth was transferred and accumulated. As a result, these ports became the largest, most complex and each developed an extensive stratification system. Indeed, Ragusa had a formal system of noble families (Krivošić, 1990; Batagelj, 1996). Here, we offer an alternative potential interpretation. Section 2.5 contains a description of adverse environmental features that created a need for safe overnight harbors. Hvar, Ragusa and Zadar had large enough natural harbor areas to shelter ships of the time. It is reasonable to argue that this attribute was the crucial factor. Note that this crucial attribute is a physical and not a social attribute. In this alternative account, advantageous locations were determined by a physical feature: having natural harbors to accommodate many ships, plus the goods and people they carried. Milicic points out that there was little to differentiate the places on this trading network initially in terms of their *material* resources. The ports enjoying favorable locations did so because of a physical attribute of their location. The structure of the network was conditioned by the environment and available transportation technologies. This includes the presence of major cut points of a network. So instead of arguing that cumulative advantage is driven by strategic network location, we argue that a particular attribute, *given the geographic context*, drove *both* the cumulative advantage and strategic location of specific places.

It is doubtful that the data needed to test which explanation has the most empirical support is in the historical record. This would require temporal data on sailing records, shipping technologies and ship speeds, initial port attributes and social organization over three centuries. Generalizing a data requirement from this claim, data are needed on social/natural contexts, spatial structures, social networks *and both social and physical attributes* over time.

5. Discussion and implications for studying social networks

Using five different networks, we have provided examples of how their social and spatial contexts impacted their structural forms. Two examples feature groups of individuals working inside formal organizations. The third example had data on communication among organizations responding to a natural disaster in geographic space. The fourth example has signed alliance and enmity ties for sub-tribes in the highlands of New Guinea and the

ifying one null block leads to the unique partition shown in Fig. 7 (which is one of the eight partitions when a null block is left out of the specification). It is the best partition.

[12] The network diagram of signed ties provided by Read does *not* have as good a correspondence. It was drawn to make the network diagram a little clearer. Doreian et al. (2005) produced a very similar network diagram. They also sought a clearer visualization of the network while diminishing the salience of geography.

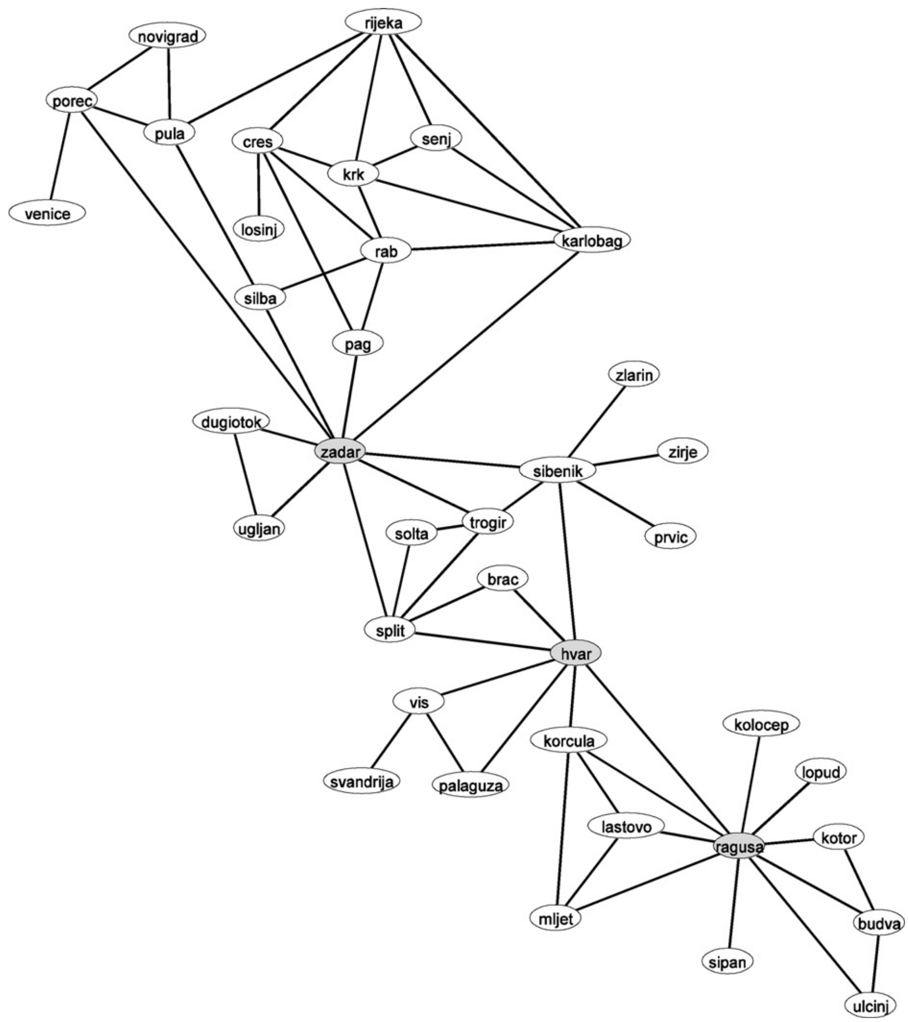


Fig. 9. Dalmatian coast trading network.

final example has places on a trading network. In each case, the ideas of social network(s), social context and spatial structure were operationalized. These examples vary greatly – but we doubt that we have come close to exhausting the ways in which the configuration of [social network, network context, and spatial structure] is present empirically. The basic point that we make is that it will be prudent to consider the orienting hypotheses that network context and spatial structure both condition the formation of social networks. The first three examples are more compelling than the last two examples because they were cast in terms of hypotheses that were tested. The last pair of examples were each more speculative with suggested ways in which context and location could affect network structure.

However, based on these examples, we cannot claim that infrastructure *always* affects the formation of networks and influences structural forms. The value of the Entwisle et al. (2007) study of the structure of networks formed in villages in Thailand and their social contexts lies in their examination of 51 networks. It follows that Entwisle and her colleagues have a sounder foundation for providing a strong and appropriate caution against the generalizability of interpretations about the generation of network structure based on a single network. This caution also applies to the five networks considered here. However, these five networks come from very different empirical domains and have very different social actors and network processes. Yet, all show or suggest the impact of social contextual features on the details of network formation, albeit in different ways.

The first implication of the analyses presented here is that studies of social networks that ignore the contexts of these networks are fraught with hazard. The second implication builds on the first and shows that we need to be clear about how contexts and spatial structures have impacts on network structures. Third, using a variety of network modeling tools will be useful if not essential.[13] Given that different aspects of the social infrastructure had different impacts on the social relations in the Bank Wiring Room, a blanket statement that 'social contexts affects network structure' can be no more than a starting point for examining the relation between the two. A fourth implication, made clear in the analyses of network in the police academy, is that we need to consider both the impact of the context *and* endogenous processes of network formation in studying the formation and structures of social networks. A fifth implication is that, even though we considered only fixed contexts having impacts on network formation, it will be necessary to examine reciprocal processes linking change in both infrastructure

[13] The study of the initial response to the World Trade Center disaster by Bevc et al. (2009) employed geographical tools in the form of quadrant analysis and nearest neighborhood analysis. While many network analysts do not use these tools they are relevant for studying network phenomena.

and social structure. The Kansas SAR example suggests that spatial locations that are fixed are not the only spatial locations that matter. The Dalmatian coast trading network formed over the course of centuries and we do not have much information about the processes that created the trading ties and the emergence of particular ports. Sixth, to tackle all of these problems will require the collection of temporal data for network structure, network contexts and actor attributes. The data of the police academy come closest to temporal data needed. However, its social context remained fixed over time. More generally, we need to allow for changing social and spatial contexts to examine the reciprocal effects of infrastructure and social structure. Finally, we may need a general theory of how networks, social contexts and spatial arrangements affect each other over time. Regarding the last point, Allen and Henn (2006) discuss how to design[14] work (and other) environments to realize not only organizational objectives but also to create good working environments for people. It would be nice if SNA can contribute to such efforts.

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[14] One reviewer directed out attention to this book, one that contains formatted network diagrams (Allen and Henn, 2006, p. 55) of exactly the sort generated by pajek and present in our Figs. 3 and 4.