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Building the Community: Endogenous Network Formation, Homophily and Prosocial Sorting Among Therapeutic Community Residents

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Abstract

Background: Researchers have begun to consider the ways in which social networks influence therapeutic community (TC) treatment outcomes. However, there are few studies of the way in which the social networks of TC residents develop over the course of treatment.

Methodology: We used a Temporal Exponential Random Graph Model (TERGM) to analyze changes in social networks totaling 320,387 peer affirmations exchanged between residents in three correctional TCs, one of which serves men and two of which serve both men and women. The networks were analyzed within weekly and monthly time-frames.

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Contributors

Keith Warren worked on conceptualizing the model and hypotheses and did most of the writing on the manuscript.

Benjamin Campbell ran all of the statistical models—in the case of this analysis that was far from a trivial task—and made authorial contributions in the network theory and methodology sections.

Skyler Cranmer is one of the original designers of the TERGM, the statistical model used in this analysis. He supervised Benjamin Campbell in running the statistical models and contributed to the introduction, statistical analysis, results and conclusions sections.

Nathan Doogan contributed to the conceptualization of the statistical model and consulted on the database, which he was primarily responsible for setting up.

George De Leon reviewed the article from the point of view of TC clinical theory—he is generally considered to be the leading expert in the world—and has been important to the overall conceptualization of the model and interpretation of the results.

Mackenzie Weiler reviewed several versions of the article, providing feedback and editorial support, and did extensive checking of statistics during the revision phase.

Fiona Doherty was active in discussion of the revisions and did extensive editorial and formatting work on the revised manuscript.

Conflict of Interest

No conflict of interest declared.

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Results: Within a weekly time-frame residents tended to close triads. Residents who were not previously connected tended not to affirm the same peers. Residents showed homophily by entry cohort. Other results were inconsistent across TC units. Within a monthly time-frame participants showed homophily by graduation status. They showed the same patterns of triadic closure when connected, tendency not to affirm the same peers when not connected and homophily by cohort entry time as in a weekly time frame.

Conclusions: TCs leverage three human tendencies to bring about change. The first is the tendency of cooperators to work together, in this case in seeking graduation. The second is the tendency of people to build clusters. The third is homophily, in this case by cohort entry time. Consistent with TC clinical theory, residents spread affirmations to a variety of peers when they have no previous connection. This suggests that residents balance network clustering with a concern for the community as a whole.

Keywords

Therapeutic communities; Social networks; Network formation; Substance abuse; Mutual Aid; Cooperation in groups; Emergence

1. Introduction

Mutual aid between residents forms the basis of substance abuse treatment in therapeutic communities (TCs) (DeLeon, 2000; Pearce and Pickard, 2013); clinical staff work to foster the development of a community among the residents, which in turn becomes the method of treatment (De Leon, 2000; Perfas, 2012; Yates et al., 2017). TCs appear to help their residents achieve and maintain sobriety (De Leon, 2010; Magor-Blatch et al., 2014; Vanderplasschen et al., 2013). But evidence of clinical effectiveness does not directly demonstrate that the community of peers is the method of treatment, nor does it offer clues that could lead to more effective use of the community. Researchers have therefore begun to focus on peer interactions. Several studies have found that supportive peer interaction and an orderly unit atmosphere predict graduation, an important proximal predictor of long-term success (Mandell et al., 2008; Carr and Ball, 2014; Condelli and Hubbard, 1994; De Leon et al., 1982; Hubbard et al., 2003; Jensen and Kane, 2012; Toumbourou et al., 1998).

Investigation into the mechanisms of social network formation within TCs can illuminate the way in which a helpful community of peers develops (Kreager et al., 2018). Doogan & Warren (2017a; 2017b) have found evidence of interactions that are known to foster cooperation in large groups, including reciprocity and generalized reciprocity (Rand & Nowak, 2013). Campbell et al. (2018) found that TC residents were more likely to graduate when peers who also eventually graduated formally affirmed them for prosocial behaviors. Social networks vary and each TC's network will be unique. But understanding common features of these networks could open the door to improving outcomes by intervening to strengthen the community (Yates et al., 2017).

Here we model how TC residents organize themselves into cooperative groups. At least two mechanisms seem likely. First, social reinforcement – by which we mean a base of supporting connections that go beyond the direct ties to a particular actor – is a key element of community building (Wellman and Frank, 2001). To operationalize this concept, consider a TC resident A, who has connections to two other residents B and C. Social support theory predicts that resident A will have stronger social support if B and C are connected to each other than if they are not, and B and C are more likely to influence A if they are also connected to each other (Coleman, 1988). Clusters or cliques tend to be composed of many sets of closed triads (Kadushin, 2012; Wasserman and Faust, 1994). Indeed, the tendency for the friend of a friend to be a friend is a microprocess that tends to lead to emergent clustering at the network level.

Second, both theory and experiments demonstrate that cooperation in groups arises when individuals can choose to connect with peers who are willing to work together toward a mutual goal, a mechanism known variously as spatial selection (the term we use hereafter), network cooperation, or correlation between individuals (Rand and Nowak, 2013; Skyrms, 2014; Skyrms and Pemantle, 2009). This is not surprising—many college students choose their partners for group projects on this principle—but it suggests that successful TC residents, those who graduate from the program, should be more likely to connect with peers who also graduate. The finding of Campbell et al. (2018) that affirmation by peers who ultimately graduate predicts graduation in TCs is suggestive of this process. We therefore hypothesize that residents who eventually graduate will be more likely to connect with peers who graduate.

2. Methods

2.1 Data

Data were gathered from clinical records kept at three freestanding minimum security correctional facilities run as TCs. All residents were felony offenders; specific offenses included burglary, robbery, domestic violence and drug possession. All TCs had a maximum length of stay of six months. Facility 1 included two male units of eighty beds each and one female unit of eighty beds. This facility drew from a mixed urban and rural catchment area of six counties. Facility 2 included one male unit of sixty-four beds and drew from a rural catchment area of five counties. Facility 3 drew from a rural and suburban catchment area of eight counties. It included one male unit of ninety beds and one female unit of sixteen beds. The female unit was established roughly six years after the male unit.

The facilities were run with a conscious attempt at fidelity to TC principles as codified in De Leon (2000) and Harvey (2005). One such principle is that TC residents engage in ongoing peer feedback. This regime of mutual monitoring includes affirming peers who show prosocial behaviors such as supporting others or doing good work on a job crew (De Leon, 2000). Such positive reinforcement is known to be beneficial in the treatment of criminal offenders (Bonta and Andrews, 2016). An affirmation therefore constitutes a cooperative act aimed at helping a peer by reinforcing prosocial behavior and as such is basic to TC treatment (De Leon, 2000; Warren et al., 2007). Affirmations are common; one study found that residents gave a mean of 70.57 peer affirmations over a six month TC stay (Warren et al., 2007).

To monitor fidelity these programs kept an electronic record of written resident peer affirmations for prosocial behavior. In order to give a written affirmation, a resident would fill out a form that included his or her own name as the sender of the affirmation, a peer as the receiver of the affirmation, the date and the content of the affirmation. A committee of senior residents and staff would then vet the affirmation for legitimacy. For example, if a resident affirmed a peer for job performance that was actually poor, the affirmation would be disallowed. The affirmation would then be read aloud to the community, either at morning meeting or during a meal, and subsequently be entered into a computer database. This format delayed the delivery of the affirmation in those cases in which residents did not also immediately verbally affirm peers. But it was hoped that the public context of the resulting affirmation would counterbalance the delay (Lattal, 2010), and research suggests that public affirmations can influence behavior over a time period of several weeks (Warren, Doogan, De Leon, Phillips, Moody & Hodge, 2013). In this analysis we treat the resulting sequence of records as a social network. When resident A affirms resident B a directed connection is established between the two.

The number of affirmations that residents exchanged varied considerably from facility to facility. Facility 1 collected a total of 64,629 affirmations from 1226 female residents (52.71 per resident) and 28,278 affirmations from 1365 male residents (20.71 per resident). Facility 2 collected a total of 57,784 affirmations from 1128 male residents (51.23 per resident). Facility 3 collected a total of 10,375 affirmations from 76 female residents (136.51 affirmations per resident) and 144,021 affirmations from 1852 male residents (77.77 affirmations per resident). For purposes of analysis we summed the affirmations into weekly and monthly networks. In doing so we ignored the actual number of times that A affirmed B; that is, there is one arrow going from A to B regardless of the number of actual affirmations that occurred during the weekly or monthly period.

In addition to the network itself, facilities kept data on admission dates, age of residents, race of residents and whether or not residents successfully graduated. Successful graduation marked completion of residents' correctional sentence and their release back into the community. For purposes of this analysis, race is treated as European-American (white) vs. all other groups, including Latino, African American and Asian.

2.2 Statistical Analysis

Conventional regression analysis assumes that observations in a data set do not influence each other once we have conditioned on some set of variables. More formally, regression analysis assumes that the error terms in any regression model are independently identically distributed (i.i.d.) (Cranmer et al, 2012; Cranmer et al., 2017). This is obviously problematic in any analysis of TC data, since TC clinical practice is based on the interactions between individuals. It is even more problematic if we want to understand exactly how individuals in the programs interact. For instance, it's quite common for individuals in social networks to arrange themselves in triads, groups of three people who all know and like each other (Wasserman and Faust, 1994). But this implies that if Resident A has pre-existing ties with Residents B and C, then Residents B and C are likely to form a tie between them in order to complete the triad (Wasserman and Faust, 1994). The ties in the triad therefore depend on other ties.

Temporal Exponential Random Graph Models (TERGMs) are longitudinal models of network evolution that model factors that drive individuals to form relations, be they individual, dyadic, or system-wide factors (Hanneke et al., 2010; Cranmer and Desmarais, 2011; Cranmer et al., 2017; Leifeld et al., 2018). TERGMs do this by examining the prevalence of these features relative to a “random” network with the same size of the observed network (Erdös and Rényi, 1959). Conventionally, these “random” networks would be simulated, and these simulations would be repeated until parameter estimates stabilize (Snijders, 2002; Hunter et al., 2008; Krivitsky and Handcock, 2014; Leifeld et al., 2018). However, by conditioning upon previously observed networks, TERGMs can efficiently be estimated through bootstrapping over other slices of the same network to produce unbiased estimates without relying upon computationally expensive and often intractable approaches such as Markov Chain Monte Carlo (Desmarais and Cranmer, 2010; Cranmer and Desmarais, 2011; Desmarais and Cranmer, 2012; Leifeld et al., 2018). TERGMs are capable of simultaneously modeling the relationship between individual attributes, relational attributes, and network structure.

We test two hypotheses. The first operationalizes the concept of social support via the “friend of a friend is a friend” mechanism; residents will tend to close triads, which can lead to supportive and mutually influential clusters (Centola, 2010; Coleman, 1988; Wellman & Frank, 2001). That is, if residents A and B had exchanged affirmations, and residents B and C had exchanged affirmations, we would expect for residents A and C to exchange affirmations as well. In order to test this hypothesis, we use the geometrically weighted edgewise shared partners (GWESP) statistic. This statistic measures the number of common connections two actors in a focal pair have, and it decreases the additional weight of triadic ties beyond the first so as to improve model stability (the GWESP parameter for governing this decrease was set at .5) (Snijders et al., 2006; Robins et al., 2007; Hunter et al., 2008).

The second hypothesis is that of spatial selection. In the TC context, we expect residents who eventually graduate to preferentially exchange affirmations with peers who also eventually graduate. This would suggest that graduates were clustering in cooperative groups and mutually supporting each other’s recovery. TERGM models this as homophily, a tendency for future graduates to interact more with each other (McPherson et al., 2001). Because it would be possible for future graduates to preferentially exchange affirmations without future nongraduates doing the same (or vice versa), we tested each group separately using a mixing model.

TERGMs can analyze homophily in continuous and categorical variables. In continuous variables, homophily is measured by the absolute value of the difference between individuals. For these variables, like age or difference in time of arrival, a positive relationship indicates heterophily, that individuals who are further apart are more likely to interact. A negative relationship indicates homophily, that individuals who are further apart in age are less likely to interact. For categorical or binary variables, TERGMs analyze homophily through matching categorical values. For these binary variables, such as graduation or race, positive effects indicate homophily, that individuals who are of the same race or graduation status are more likely to interact. A negative coefficient would indicate heterophily, that individuals who are of different graduation status or race are likely to interact.

We control for racial homophily, which is common in American correctional institutions (Schaefer et al., 2017; Trammell, 2009). Race is discrete, so positive parameter values indicate homophily. We control for homophily by age (Schaefer et al, 2017), and by entrance cohort, which occurs in TCs (Doogan and Warren, 2017a; Doogan and Warren, 2017b) as well as the broader correctional population (Schaefer et al., 2017). Age and cohort homophily are continuous, so negative values indicate homophily.

Finally, we control for two endogenous social network structures. The number of edges effectively plays the role of the intercept term in a standard regression model, and is nearly always included in an Exponential-family Random Graph Model (Hunter et al., 2008). We also include the number of triads in which two participants who are not connected mutually connect to a third actor. We once again used a geometrically weighted statistic, in this case the geometrically weighted dyadwise shared partners (GWDSP) statistic (Snijders et al., 2006; Robins et al., 2007). We expect that the parameter estimate for this variable will be negative after controlling for GWESP, since TC residents are expected to spread affirmations to a variety of peers (De Leon, 2000).[1] We test the hypotheses in one week and one calendar month time frames separately for each facility and for men and women, resulting in a total of ten analyses.

3. Results

Table 1 gives descriptive statistics. In part because of the rural catchment area of Facilities 2 and 3, and the partially rural catchment area of Facility 1, the percentage of European-Americans among the residents was quite high, ranging from 58% to 91%. The graduation rates for the facilities are also very high, ranging from 75% to 84%. This may reflect the time limited nature of the programs, or it may mean that the social networks that developed among the residents improved program retention.

Results of the TERGM model with a weekly time frame can be found in Table 2.[2] The edges statistic was higher for the female units, indicating that women are more active overall in sending affirmations. This is consistent with previous social network literature (Taylor et al, 2000).

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[1]Reciprocity is not included in the model because the values are sufficiently high that inclusion produces complete separation and nonconvergence in the model. (Using the Statnet grecip, monthly reciprocity was measured at .92 for Facility 1 men, .73 for Facility 1 women, .84 for Facility 2, .85 for Facility 3 men and ..70 for Facility 3 women.) This meant that we had two choices. We could have symmetrized the matrix, creating a set of undirected connections and thereby abolishing reciprocity by fiat. Or we could keep the direction of the network edges and not control for reciprocity. In either case we found that residents formed triads, tended to connect with different peers apart from triads, and showed homophily by graduation status and cohort in all of the facilities, but use of the directed network allowed for use of the mixing model. We therefore used the directed network and did not include reciprocity. Results of the analysis of the symmetrized network are available upon request.

[2]All models, in both Tables 2 and 3, simulate networks that approximate observed networks, indicating good model fit.

Hypothesis 1, that residents would show a tendency toward triadic closure, is supported with positive and statistically significant values of the GWESP statistic for all facilities. All units show negative and statistically significant values of GWDSP (the tendency for an unconnected focal pair of actors not to have many ties in common). Thus, when residents are not connected in the network, they tend not to affirm the same peers. Rather, they spread the affirmations around.

Hypothesis 2, that future graduates will demonstrate spatial selection by preferentially exchanging affirmations with other future graduates, yields inconsistent results, with male residents in Facility 3 who eventually graduated showing this preference ($\beta = 0.06$, 95% CI = 0.04, 0.09), and residents who did not eventually graduate showing a tendency to avoid affirming each other in Facility 1 ($\beta = -0.14$, 95% CI = −0.32, −0.01 for men and $\beta = -0.12$, 95% CI = −0.20, −0.04 for women). In two cases, models did not converge when we included the difference in age as a homophily term, but there was homophily by age in the three units for which the term could be included. Homophily by race is found in four of the five units, but not in the Facility 3 female unit. This anomalous finding is likely because this unit was much smaller than the others and very heavily white. We find homophily by entrance time in all units.

Results of the TERGM within a monthly time frame can be found in Table 3. Again, the edge statistic is higher for the female units. As in the weekly time frame, hypothesis 1 is supported; all units show a tendency toward triadic closure, with positive and statistically significant values of GWESP. GWDSP is again negative in all units, and more so in the female units. With respect to Hypothesis 2, we find that eventual graduates tend to affirm each other in Facility 1 and Facility 3 for both men and women. However, eventual nongraduates tend not to affirm each other. For Facility 2 at the monthly level, a model cannot be estimated using a term that separates homophily for eventual graduates and nongraduates. This is due to a perfect (or nearly-perfect) separation problem; people who do not go on to graduate almost never affirm those who also do not go on to graduate, or people who do go on to graduate only affirm those who also graduate. As an alternative, we use a node-match term that allows us to look at homophily, but aggregates these relationships. This term is less susceptible to separation as there is more potential for variability. (*We label this by placing the term "Preferential Affirmation by Graduation Status" in the cell where preferential affirmation for nongraduates would otherwise be reported.)* This term demonstrates clear evidence of homophily by graduation status ($\beta = 0.13$, 95% CI = .07, .18). Homophily by age and race are not significant in the Facility 3 women's unit, apparently because of its small size and heavily European-American composition, but were significant in all other units in which they could be modeled. Homophily by cohort is statistically significant for men and women in all facilities.

4. Discussion

This analysis reveals multiple factors that influence the formation of social networks in TCs. TC residents who affirm each other are more likely to affirm a common peer, thereby self-organizing into triadic clusters. On the other hand, if they do not affirm each other, they are less likely to affirm a common peer. Eventual program graduates tend to affirm each other in all analyses in a monthly time frame, while eventual program nongraduates tend not to affirm each other. Homophily by entrance date occurs in all analyses.

Time frame plays a complex role in this and in previous studies. Analysis of affirmations within a daily time frame finds no particular tendency toward triadic closure and a tendency to concentrate affirmations on particular peers (Doogan & Warren, 2017a). In this study graduates preferentially affirm each other within a monthly time frame but not within a weekly time frame. One explanation for the role of time in detecting triad formation is that the networks grow denser as the time frame grows longer. It is also possible that in shorter time frames the actual prosocial incidents that residents affirm are more influential, whereas in longer time frames relationships between peers are more influential. So, in a daily time frame receiving an affirmation may bring enough attention so that others notice and also affirm the individual, while in longer time frames a process of consciously balancing affirmations between closer and less familiar peers may assert itself. Clinicians and researchers may see quite different patterns over different time frames.

The data in this study come from a small number of minimum-security correctional facilities that, in terms of racial composition, are atypical of the American prison system as a whole. The facilities also have graduation rates that are substantially higher than those of most TCs (Malivert et al., 2012). Nevertheless, this study offers a number of useful insights into TC clinical theory and practice. Most obviously, it adds to the accumulating evidence that TCs leverage deep-seated human impulses to connect and cooperate with others in order to foster a self-organizing community of recovering individuals. Cooperation in any group depends on spatial selection, the ability of individuals who want to cooperate to find each other and create strong ties (Gallo and Yan, 2015; Rand and Nowak, 2013; Skyrms, 2004). Since graduation is an important predictor of success following TC treatment (Malivert et al., 2012), a preference among eventual TC graduates to connect with peers who also eventual graduate strongly suggests that this process of cooperative residents connecting and working together helps to drive success in TCs (see also Campbell et al., 2018). The analyses also find that future nongraduates are more likely to affirm graduates than each other. This suggests that they are not connecting with each other in such a way as to undermine treatment. Rather, graduates appear to be shunning peers who do not eventually graduate, perhaps because they have decided that the latter are not seriously motivated to succeed. This would be consistent with qualitative literature on TCs; for instance, Miller et al. (2006) find that TC residents judge peers in this way.

Transitive triads are ubiquitous in human social networks (Easley and Kleinberg, 2010; Kadushin, 2012; Prell, 2012; Wasserman and Faust, 1994). In this case, transitivity indicates that connected residents agree on which peers should be affirmed, a sign that they have learned a common body of program knowledge and values. Further, both theory and empirical evidence suggest that triads and clusters of triads are effective in setting norms and providing social support (Centola, 2010; Coleman, 1988; Wellman and Frank, 2001). Since the exchange of feedback in triads is likely to be more influential than the exchange in dyads, triadic structure may be an important factor in bringing about changes in behavior and identity that are thought to underlie TC outcomes (Best et al., 2014).

The TC clinical literature cautions that small groups can also serve to undermine treatment—the norms set within any cluster do not need to be prosocial (De Leon, 2000; Kreager et al., 2018). Therefore, while it is reasonable to assume that preferential exchange of affirmations among eventual graduates indicates cooperation toward a prosocial goal, we cannot assume the same thing about triad formation. In fact, empirical analyses of network clustering as a predictor of outcomes shows both positive and negative relationships to outcomes, depending on the facility that is analyzed (Campbell et al., 2019; Warren et al., In review).

The negative GWDSP coefficients we find in all programs suggest that when residents are not connected they tend to spread affirmations around, rather than concentrating them on one peer. This is what TC clinical theory would suggest should happen—residents ought to show concern for all peers in the facility (De Leon, 2000; Kreager et al., 2018). In these TCs, therefore, there is a tendency toward clustering, but there is also a balancing tendency to support peers beyond one's own cluster.

Homophily by cohort status is also apparent in all analyses (and previous studies (Doogan & Warren 2017a, 2017b)); residents who go through the same process at the same time interact more with each other over the course of treatment. This raises the possibility that TCs could counteract other forms of homophily by consciously admitting mixed groups of residents at roughly the same time.

5. Conclusions

At least three factors—transitive triad formation, preferential connection of future graduates to other future graduates, and homophily by cohort status—lead to clustering across these TCs. This suggests that a clinical and research agenda could be built around ways in which to foster clinically useful, prosocial clusters of TC residents.

A question that this study leaves unanswered is whether affirmations play an active role in network formation or whether they simply follow a previously existing set of relationships. While theoretical work on cooperative network formation suggest that an active role is possible (Skyrms and Pemantle, 2009), and previous research demonstrates that residents react to peer affirmations within a time frame of a few days (Doogan & Warren, 2017a), further studies will be required for a full understanding of the role of affirmations in fostering group cooperation.

Future graduates tend to interact with each other, while future nongraduates tend not to interact with other nongraduates. This suggests that nongraduates suffer from comparative isolation rather than the formation of subgroups that undermine treatment. Ways might be found to more effectively embed these residents in the community, such as assigning them to work positions in which they are exposed to more central network members or projects that require groups of residents to work together (Aslan, 2016).

Finally, there is the overarching question of how TC residents choose the peers with whom they connect. Homophily by cohort suggests that shared experience plays a role. Beyond this, what draws graduates together? What are the characteristics of nongraduates that keep graduates from connecting with them? How do residents decide who is motivated to change, and what motivates residents to connect to peers (De Leon & Jainchill, 1986; Miller, Sees and Brown, 2006)? Interventions that arose from these lines of research would respect the clinical primacy of the community structure of TCs (De Leon, 2000; Yates et al., 2017), along with the self-organizing nature of the community, in which residents give rise to a social network by reacting to peers.

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References

Albert R, Barabási AL, 2002 Statistical mechanics of complex networks. Rev. Mod. Phys 74, 47–97. 10.1103/RevModPhys.74.47

Aslan, 2016 A qualitative evaluation of the Phoenix Futures recovery through nature program: A therapeutic intervention for substance misuse. J. Groups Addict. Recover 11, 93–108. 10.1080/1556035X.2015.1110741

Aslan L, Parkman TJ, Skagerlind N, 2016 An evaluation of the mutual aid facilitation sessions pilot program, “You do the MAFS.” J. Groups Addict. Recovery 11, 109–124. 10.1080/1556035X.2016.1153441

Bell, 1994 Connection in therapeutic communities. Int. J. Addict 29, 525–543. 10.3109/10826089409047398 [PubMed: 8188445]

Best D, Lubman DI, Savic M, Wilson A, Dingle G, Alexander Haslam S, Haslam C, Jetten J, 2014 Social and transitional identity: exploring social networks and their significance in a therapeutic community setting. Ther. Communities 35, 10–20. 10.1108/TC-04-2013-0007

Birkeland S, Cappelen AW, Sørensen EØ, Tungodden B, 2014 An experimental study of prosocial motivation among criminals. Exp. Econ 17, 501–511. 10.1007/s10683-013-9380-x

Campbell BW, Cranmer S, Doogan N, Warren K, 2019 Relationship between network clustering in a therapeutic community and reincarceration following discharge. J. Subst. Abuse Treat 97, 14–20. 10.1016/j.jsat.2018.10.008 [PubMed: 30577895]

Campbell BW, Cranmer S, Harvey C, Warren K, 2018 Therapeutic community graduates cluster together in social networks: Evidence for spatial selection as a cooperative mechanism in therapeutic communities. Addict. Behav 79, 74–80. 10.1016/j.addbeh.2017.12.003 [PubMed: 29253660]

Carr WA, Ball SA, 2014 Predictors and treatment outcomes of perceived ward atmosphere among therapeutic community residents. J. Subst. Abuse Treat 46, 567–573. 10.1016/j.jsat.2014.01.003 [PubMed: 24560437]

Centola, 2010 The spread of behavior in an online social network experiment. Science. 329, 1194–1197. 10.1126/science.1185231 [PubMed: 20813952]

Condelli WS, Hubbard RL, 1994 Relationship between time spent in treatment and client outcomes from therapeutic communities. J. Subst. Abuse Treat 11, 25–33. 10.1016/0740-5472(94)90061-2 [PubMed: 8201630]

Cranmer SJ, Desmarais BA, 2011 Inferential network analysis with exponential random graph models. Polit. Anal 19, 66–86. 10.1093/pan/mpq037

Cranmer SJ, Desmarais BA, Menninga EJ, 2012 Complex dependencies in the alliance network. Confl. Manag. Peace Sci, 29, 279–313. 10.1177/0738894212443446

Cranmer SJ, Leifeld P, McClurg SD, Rolfe M, 2017 Navigating the range of statistical tools for inferential network analysis. Am. J. Pol. Sci. 61, 237–251. 10.1111/ajps.12263

De Leon, 2000 The therapeutic community: theory, model, and method. Springer Pub, New York.

De Leon, 2010 Is the therapeutic community an evidence-based treatment? What the evidence says. Ther. Communities 31, 104.

De Leon G, Jainchill N, 1986 Circumstance, motivation, readiness and suitability as correlates of treatment tenure, J Psychoactive Drugs, 18:3, 203–208. DOI: 10.1080/02791072.1986.10472348 [PubMed: 3772644]

De Leon G, Wexler HK, Jainchill N, 1982 The therapeutic community: Success and improvement rates 5 years after treatment. Int. J. Addict 17, 703–747. 10.3109/10826088209053012 [PubMed: 7107092]

Desmarais BA, Cranmer SJ, 2012 Statistical mechanics of networks: Estimation and uncertainty. Physica. A 39, 1865–1876. 10.1016/j.physa.2011.10.018

Desmarais BA, Cranmer SJ, 2010 Consistent confidence intervals for maximum pseudolikelihood estimators. Proceedings of the Neural Information Processing Systems 2010 Workshop on Computational Social Science and the Wisdom of Crowds.

Doogan NJ, Warren K, 2017a A network of helping: Generalized reciprocity and cooperative behavior in response to peer and staff affirmations and corrections among therapeutic community residents. Addict. Res. Theory 25, 243–250. 10.1080/16066359.2016.1249864 [PubMed: 29151825]

Doogan NJ, Warren KL, 2017b Saving My Life: Dynamics of Peer and Staff Corrections Among Therapeutic Community Residents. Subst. Use Misuse. 52, 1429–1438. 10.1080/10826084.2017.1284236 [PubMed: 28467267]

Easley D, Kleinberg J, 2010 Networks, crowds, and markets: Reasoning about a highly connected world. Cambridge University Press, Cambridge.

Erdős P, Rényi A, 1959 On Random Graphs. I. Publicationes Mathematicae, 6, 290–297.

Gallo E, Yan C, 2015 The effects of reputational and social knowledge on cooperation. Proc. Natl. Acad. Sci. U.S.A 201415883. 10.1073/pnas.1415883112

Gampa A, Linley JV, Roe B, Warren KL, 2018 Generosity, fairness, trust and time: the performance of therapeutic community residents in economics experiments. Ther Communities. 39, 98–107. 10.1108/TC-06-2017-0017

Hanneke S, Fu W, Xing EP, 2010 Discrete temporal models of social networks. Electron. J. Stat 4, 585–605. 10.1214/09-EJS548

Harvey, 2005 Why we do what we do: Rationale and theoretical applications for therapeutic community activities in Ohio. Columbus, Ohio: Ohio Department of Alcohol and Drug Addiction Services.

Hubbard RL, Craddock SG, Anderson J, 2003 Overview of 5-year followup outcomes in the drug abuse treatment outcome studies (DATOS). J. Subst. Abuse Treat 25, 125–134. 10.1016/S0740-5472(03)00130-2 [PubMed: 14670518]

Hunter DR, Handcock MS, Butts CT, Goodreau SM, Morris M, 2008 Ergm: a package to fit, simulate and diagnose exponential-family models for networks. J. Stat. Softw 24, 1–29. 10.18637/jss.v024.i03 [PubMed: 18612375]

Jensen EL, Kane SL, 2012 The effects of therapeutic community on recidivism up to four years after release from prison: a multisite study. Crim. Justice Behav 39, 1075–1087. 10.1177/0093854812442331

Kadushin, 2012 Understanding social networks: Theories, concepts, and findings. Oxford University Press, New York.

Khadjavi M, Lange A, 2013 Prisoners and their dilemma. J. Econ. Behav. Organ 92, 163–175. 10.1016/j.jebo.2013.05.015

Kreager D, Bouchard M, De Leon G, Schaefer D, Soyer M, Young J, Zajac G, 2018 A Life Course and Networks Approach to Understanding Prison Therapeutic Communities. In Social networks and the life course: integrating the development of human lives and social relational networks. Springer Berlin Heidelberg, New York, NY.

Krivitsky PN, Handcock MS, 2014 A separable model for dynamic networks. J. R. Stat. Soc. Series B. Stat. Methodol 76, 29–46. 10.1111/rssb.12014 [PubMed: 24443639]

Lattal KA, 2010 Delayed reinforcement of operant behavior. J. Exp. Anal. Behav, 93, 129–139. [PubMed: 20676272]

Leifeld P, Cranmer SJ, Desmarais BA, 2018 Temporal exponential random graph models with btergm : estimation and bootstrap confidence intervals J. Stat. Softw 83, 1–36. 10.18637/jss.v083.i06

Magor-Blatch L, Bhullar N, Thomson B, Thorsteinsson E, 2014 A systematic review of studies examining effectiveness of therapeutic communities. Ther. Communities 35, 168–184. 10.1108/TC-07-2013-0024

Malivert M, Fatséas M, Denis C, Langlois E, Auriacombe M, 2012 Effectiveness of therapeutic communities: a systematic review. Eur. Addict Res 18, 1–11. 10.1159/000331007 [PubMed: 21997500]

Mandell W, Edelen MO, Wenzel SL, Dahl J, Ebener P, 2008 Do dimensions of therapeutic community treatment predict retention and outcomes? J. Subst. Abuse Treat 35, 223–231. 10.1016/j.jsat.2007.10.004 [PubMed: 18248942]

McPherson M, Smith-Lovin L, Cook JM, 2001 Birds of a feather: homophily in social networks. Annu. Rev. Sociol 27, 415–444. 10.1146/annurev.soc.27.1.415

Miller S, Sees C, Brown J. 2006 Key aspects of psychological change in residents of a prison therapeutic community: a focus group approach. How J Crime Justice. 45, 116–128. 10.1111/j.1468-2311.2006.00409.x

Pearce S, Pickard H, 2013 How therapeutic communities work: Specific factors related to positive outcome. Int. J. Soc. Psychiatry 59, 636–645. 10.1177/0020764012450992 [PubMed: 22820178]

Perfas, 2012 Deconstructing the therapeutic community: A practice guide for addiction professionals. Hexagram Publishing, Red Hook, NY.

Prell, 2012 Social network analysis: history, theory & methodology. SAGE, Los Angeles; London.

Rand DG, Nowak MA, 2013 Human cooperation. Trends Cogn. Sci 17, 413–425. 10.1016/j.tics.2013.06.003 [PubMed: 23856025]

Robins G, Snijders T, Wang P, Handcock M, Pattison P, 2007 Recent developments in exponential random graph (P*) models for social networks. Soc. Networks 29, 192–215. 10.1016/j.socnet.2006.08.003

Schaefer DR, Bouchard M, Young JTN, Kreager DA, 2017 Friends in locked places: An investigation of prison inmate network structure. Soc. Networks 51, 88–103. 10.1016/j.socnet.2016.12.006 [PubMed: 28983147]

Skyrms, 2004 The stag hunt and the evolution of social structure. Cambridge University Press, Cambridge, UK ; New York.

Skyrms, 2014 Social Dynamics. Oxford University Press, Oxford.

Skyrms B & Pemantle R, 2009 A dynamic model of social network formation. Adaptive Networks: Theory, Models and Applications, 231–251.

Snijders, 2002 Markov chain Monte Carlo estimation of exponential random graph models. J. Soc. Struct 3, 1–40.

Snijders TAB, Pattison PE, Robins GL, Handcock MS, 2006 New specifications for exponential random graph models. Sociol. Methodol 36, 99–153. 10.1111/j.1467-9531.2006.00176.x

Taylor SE, Klein LC, Lewis BP, Gruenewald TL, Gurung RAR, & Updegraff JA 2000 Biobehavioral responses to stress in females: Tend-and-befriend, not fight-or-flight. Psychol. Rev, 107(3), 411–429. 10.1037/0033-295x.107.3.411 [PubMed: 10941275]

Toumbourou JW, Hamilton M, Fallon B, 1998 Treatment level progress and time spent in treatment in the prediction of outcomes following drug-free therapeutic community treatment. Addiction. 93, 1051–1064. 10.1046/j.1360-0443.1998.937105110.x [PubMed: 9744136]

Trammell, 2009 Values, rules, and keeping the peace: how men describe order and the inmate code in California prisons. Deviant Behav. 30, 746–771. 10.1080/01639620902854662

Vanderplasschen W, Colpaert K, Autrique M, Rapp RC, Pearce S, Broekaert E, Vandevelde S, 2013 Therapeutic communities for addictions: A review of their effectiveness from a recovery-oriented perspective. ScientificWorldJournal. 2013, 1–22. 10.1155/2013/427817

Warren K Campbell B, and Cranmer S, In review. Tightly bound: The relationship of network clustering coefficients and reincarceration at three therapeutic communities. J. Subst. Abuse

Warren KL, Doogan N, De Leon G, Phillips GS, Moody J & Hodge A, 2013 Short-run prosocial behavior in response to receiving corrections and affirmations in three therapeutic communities. J. Offender Rehabil, 52, 270–286. 10.1080/10509674.2013.782776 [PubMed: 23935258]

Wasserman S, Faust K, 1994 Social network analysis: methods and applications. Cambridge University Press, Cambridge.

Wellman B, Frank K, 2001 Network capital in a multi-level world: Getting support from personal communities. Social capital: Theory and research, 233–273.

Yates R, Burns J, McCabe L, 2017 Integration: too much of a bad thing? J. Groups Addict. Recover 12, 196–206. 10.1080/1556035X.2017.1320487

Highlights

- Network formation in three therapeutic communities over eight years.
- Residents show a tendency to close triads.
- When residents are not previously connected they tend to affirm different peers.
- Residents who graduate are more likely to affirm peers who also graduate.
- Residents are more likely to affirm peers who were admitted about the same time.

Table 1:

Descriptive statistics for all facilities.

Facility	Percentage Graduating	Percentage European American	Mean Age	Standard Deviation Age
Facility 1 men	84%	58%	28.48	9.06
Facility 1 women	84%	77%	30.06	7.89
Facility 2 men	77%	80%	26.39	8.44
Facility 3 men	75%	82%	27.00	8.09
Facility 3 women	81%	91%	31.11	6.85

Table 2:

Results of the TERGM model in a weekly time frame.

Variable	Facility 1, Men	Facility 1, Women	Facility 2, Men	Facility 3, Men	Facility 3, Women
Edges	−3.62 * [−3.68; −3.55]	−2.42 * [−2.49; −2.36]	−3.14 * [−3.25; −3.09]	−3.45 * [−3.50; −3.39]	−0.85 * [−1.09; −0.62]
GWDSP	−0.10 * [−0.11; −0.09]	−0.09 * [−0.10; −0.09]	−0.03 * [−0.04; −0.03]	−0.04 * [−0.04; −0.04]	−0.29 * [−0.32; −0.26]
GWESP	1.03 * [1.00; 1.06]	0.68 * [0.66; 0.70]	0.72 * [0.70; 0.75]	0.71 * [0.69; 0.72]	0.66 * [0.58; 0.77]
Homophily by Age	−0.02 * [−0.02; −0.01]	−0.01 * [−0.01; −0.00]	________	________	−0.01 * [−0.02; −0.01]
Homophily by Race	0.45 * [0.41; 0.49]	0.10 * [0.07; 0.13]	0.09 * [0.06; 0.12]	0.17 * [0.14; 0.20]	0.07 [−0.02; 0.14]
Preferential Affirmation for Nongraduates	−0.14* [−0.32; −0.01]	−0.12* [−0.20; −0.04]	−0.10 [−0.18; 0.03]	−0.05 [−0.12; 0.01]	−0.33 [−0.61; 0.04]
Preferential Affirmation for Graduates	−0.00 [−0.00; 0.00]	0.02 [−0.01; 0.06]	−0.00 [−0.00; 0.14]	0.06 * [0.04; 0.09]	0.00 [−0.00; 0.22]
Homophily by Cohort	−0.00 * [−0.01; −0.00]	−0.00 * [−0.00; −0.00]	−0.00 * [−0.00; −0.00]	−0.00 * [−0.00; −0.00]	−0.00 * [−0.00; −0.00]

Table 3:

Results of the TERGM model within a monthly time frame.

Variable	Facility 1, Men	Facility 1, Women	Facility 2, Men	Facility 3, Men	Facility 3, Women
Edges	−2.98 * [−3.19; −2.80]	−1.50* [−1.63; −1.37]	−3.22 * [−3.28; −3.15]	−2.62 * [−2.75; −2.47]	0.53 [−0.39; 1.29]
GWDSP	−0.15* [−0.17; −0.13]	−0.21* [−.23; −.20]	−0.04 * [−0.04; −0.03]	−0.12 * [−0.13; −0.11]	−0.55* [−0.71; −0.47]
GWESP	1.09* [0.30; 1.13]	0.80* [0.74; 0.86]	0.72 * [0.70; 0.75]	0.85 * [0.82; 0.88]	0.65* [0.30; 1.13]
Homophily by Age	−0.01* [−0.02; −0.01]	−0.01* [−0.01; −0.00]	___________	___________	−0.00 [−0.01; 0.01]
Homophily by Race	0.36* [0.31; 0.42]	0.10* [0.04; 0.17]	0.09 * [0.06; 0.12]	0.12 * [0.08; 0.16]	0.06 [−0.24; 0.35]
Preferential Affirmation for Nongraduates	−0.30* [−0.51; −0.12]	−0.21* [−0.32; −0.10]	Preferential Affirmation by Graduation Status:	−0.12 * [−0.20; −0.05]	−0.77* [−1.44; −0.27]
Preferential Affirmation for Graduates	0.08* [0.01; 0.14]	0.09* [0.03; 0.14]	0.10 * [0.06; 0.13]	0.13 * [0.09; 0.17]	0.32* [0.07; 0.57]
Homophily by Cohort	−0.01* [−0.01; −0.01]	−0.01* [−0.01; −0.01]	−0.00 * [−0.00; −0.00]	−0.00 * [−0.00; −0.00]	−0.01* [0.07; 0.57]