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Evaluating peer-influence processes in a prison-based therapeutic community: a dynamic network approach

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ABSTRACT

Background: The Therapeutic Community (TC) is a common treatment modality for incarcerated individuals with substance use disorders. TCs rely on peer group processes to promote lasting behavioral and identity change, yet prior research has not adequately tested the peer influence mechanisms underlying the theoretical model. This study applied dynamic network analysis to estimate peer influence processes central to TC philosophy.

Methods: A stochastic actor-oriented model (SAOM) was applied to ten months of social network data collected from prisoner surveys within a TC unit (N = 62) in a medium-security Pennsylvania prison. Respondents (N = 177, 84% of unit) completed at least one prison survey and provided network and community role model nominations.

Results: Although residents' levels of treatment engagement were significantly correlated with their nominated peers, estimates of peer influence for treatment engagement were non-significant in longitudinal network models. Nor were estimates of peer influence significantly greater for peers perceived as community role models. Rather, inmates connected with peers who were of similar treatment engagement as themselves (i.e., a peer selection process), and the latter primarily resulted from racial homophily in the TC social network.

Conclusions: Inconsistent with the desired treatment model, treatment engagement diffusion was not evident in the sampled TC. Results suggested that highly-engaged residents clustered together at the center of the TC's social structure but had little impact on less-engaged and peripheral inmates. The relatively short (i.e., four-month) program length and moderate-to-low treatment fidelity likely contributed to the lack of peer influence processes.

1. Introduction

Within prisons, the therapeutic community (TC) is a treatment modality that has received considerable research support for addressing the strong correlation between substance use and offending (Jensen and Kane, 2012; Sacks et al., 2012; Vanderplasschen et al., 2013; Welsh and Zajac, 2013; Zhang et al., 2011). In contrast to individual outpatient psycho-educational or medication-assisted treatment (e.g., Methadone or Naltrexone Maintenance) therapies, TCs are long-term residential treatment programs focused on *peer group processes* to promote lasting identity transformation and behavioral change (Campbell et al., 2018; De Leon, 2000; Stevens, 2012). Consistent with the axiom of "community-as-method" and social learning principles (Akers, 2017; De Leon, 1997), TCs target interpersonal interactions as primary treatment mechanisms. Accordingly, senior TC residents are expected to model, monitor, and reinforce community behaviors that are consistent with long-term drug abstinence and "right living." An intensive, inpatient community-as-method model is expected to heighten positive peer interactions and supervision necessary to alter antisocial attitudes, behaviors, and values. Meta-analyses of incarceration-based treatment programs have found that TCs consistently reduce both post-release offending and drug use (Magor-Blatch et al., 2014; Mitchell et al., 2007, 2012). The perceived effectiveness of TCs has resulted in their extensive implementation in state correctional systems (Taxman et al., 2007).

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Although outcome evaluations abound, few researchers have rigorously investigated the group mechanisms underlying the TC model (but see Campbell et al., 2018; Doogan and Warren, 2017a, 2017b). In this study, we apply dynamic network methods to evaluate peer processes within a Pennsylvania prison TC. If a TC is effective and operating with high fidelity, then highly engaged peers, particularly those peers perceived as community role models (Hodge et al., 2014), should positively influence the treatment engagement of other community residents. Alternatively, highly-engaged residents may connect with one another and be central to unit functioning yet fail to influence less-engaged peers. The latter pattern, suggestive of strong peer selection and clustering processes, could prevent positive peer influence from diffusing to all parts of a community and lower the overall TC effectiveness. We test these competing peer processes with ten monthly waves of social network data collected in a prison TC unit and stochastic actor-oriented models for network dynamics (i.e., SAOM: Snijders et al., 2010).

1.1. Group-based treatment programs

Therapeutic communities (TCs) belong to a class of substance abuse interventions that rely on group delivery formats to achieve positive results. For group-based approaches, "the nature and quality of participant interactions—*group processes*—are believed to influence whether and how much participants benefit from a program" (Elreda et al., 2016: 925). Such approaches differ from individual curriculum or drug-replacement therapies in that they inherently target intra-group mechanisms for behavioral change.

Within a TC, residents show "responsible concern" for their TC peers, making progress in their own recovery by assisting in the recovery of others (De Leon, 2000). Throughout their time in the program, individuals are expected to become increasingly embedded in the community, taking on leadership roles and providing guidance to new TC residents. In this "community-as-method" model, peers are intended to be principal agents of change (De Leon, 2000).

The TC model has been modified for implementation within prison settings. Specifically, curriculum has been adapted to address criminal thinking alongside substance abuse and TC participation is either mandated or driven by perceived extrinsic rewards (e.g. positive parole consideration or a more peaceful housing environment). Prison mandates and incentives, in turn, may "lower intrinsic motivation for change" (De Leon, 2000: 388) and increase the likelihood that prison TC residents "coast" through treatment. Given this unique obstacle, prison-based TCs often focus on increasing personal commitment and strengthening individual-level motivations for recovery.

Empirically testing TC peer processes is not straightforward. One challenge is that perceived community role models may not adhere to the standards put forward in the TC model. If TC leaders are not "walking the walk," then they would not act as strong community role models and the diffusion of their attitudes and behaviors may not benefit other community residents (Kreager et al., 2018). Another challenge is that a positive correlation between the treatment engagement of two TC residents does not necessarily imply that one resident has influenced the engagement of the other. Such between-person correlations can occur either because individuals *change* their behaviors to be consistent with their peers (consistent with peer influence) or because individuals *select* peers who already have similar attitudes and behaviors to themselves. For example, within a TC context, a new resident may enter treatment with low engagement, connect with highly engaged peers, and subsequently increase his or her own engagement. This process aligns with peer influence. By contrast, a new resident entering treatment with high engagement may connect with peers similarly high in engagement and then maintain his or her engagement level. This process aligns with peer selection. In the extreme, such selection processes would divide a unit into groups of engaged and disengaged residents, with little-to-no treatment effects among the already disengaged residents. Absent means of disentangling the dynamic peer influence and selection processes, typical correlational and cross-sectional statistical approaches will *overestimate* peer influence and arrive at conclusions whereby a TC appears successful when, in fact, it is not. Distinguishing peer influence from selection necessarily requires longitudinal data for both within-treatment behaviors and peer relationships.

Another challenge to understanding TC peer processes is that such processes do not occur at the level of isolated dyads. Rather, peer processes occur within a dynamic system where individuals (1) enter and exit the system, (2) form and dissolve social ties with unit peers, and (3) become more or less engaged with the treatment over time. The complexity and interdependence of these dynamic processes complicate their evaluation and necessitate a more sophisticated methodology.

1.2. Dynamic network analysis

The peer-driven mechanisms associated with prison TC effectiveness are inherently relational yet remain largely untested (De Leon, 2000; Kreager et al., 2018; Mitchell et al., 2012). Measuring peer influence mechanisms within a prison TC requires an analytical approach explicitly focused on the structure and dynamics of interpersonal relationships. Social network analysis accomplishes these tasks by focusing on the relational patterns among individuals and, in the case of the prison TC, how inmate relationships co-evolve with treatment outcomes (e.g., program engagement) over time (Campbell et al., 2018; Kreager et al., 2016, 2017,2018; Schaefer et al., 2017). Although residents regularly interact with staff, TCs are designed such that key mechanisms of change operate through residents' informal relationships with one another. These ties constitute the "peer network" that is our primary focus.

We investigate three questions about the association between treatment engagement and the structure of relations among TC residents. First, we investigate whether residents who are more socially integrated in the unit report higher treatment engagement. Second, we test whether residents who are socially connected to more highly engaged residents are themselves more highly engaged, such as would occur through peer influence. Third, we test whether recognized role models on the unit exert stronger peer influence on engagement than other unit residents.

2. Material and methods

2.1. Participants

Participants were 177 male inmates admitted to a 62-bed, 4-month modified therapeutic community (TC) drug treatment program at a medium security Pennsylvania men's prison over a 10-month period in 2016-17. The specific TC unit was identified by the PA Department of Corrections Central Treatment Bureau as representative of, or even a "model" for, those within the state prison system. Additionally, the unit was one of several TCs in a facility focused on substance abuse treatment services. All inmates within the sampled TC were given the choice to complete a Computer Assisted Personal Interview (CAPI) every month during their 4-month treatment period. Response rates per month ranged from 73% to 82% of the unit, combining to a sample response rate of 84% of eligible respondents completing at least one CAPI during their time on the unit over the observed period. Participating inmates provided informed consent and completed CAPIs in a confidential setting with an interviewer who read all questions and response options, provided clarification when necessary, and recorded responses on the computer.

TC treatment is determined based on inmates' scores on the Texas Christian University (TCU) Drug Screen II (TCU Institute of Behavioral Research, 2014) administered at prison intake. Those who decline TC treatment are likely to be denied parole at their minimum sentence date due to incompletion of stipulated programming. Within the prison, the TC are stand-alone residential units where prisoners live on the unit with their TC peers, participate in a daily schedule of TC treatment groups, and have limited interactions with non-TC inmates.

2.2. Measures

2.2.1. Dependent measures

2.2.1.1. Peer relationship nominations. During the CAPI surveys, respondents were asked to nominate other unit residents that they "get along with most." These positive relational ties were unlimited and respondents nominated peers from an alphabetized roster of all unit residents listed on the computer screen. When aggregated across all respondents, the nominations formed a peer relationship network. Overall, researchers found that residents easily engaged with the nomination procedure.

2.2.1.2. Treatment engagement. Treatment engagement was self-reported using the Client Assessment Summary, a validated scale developed by TC experts (CAS; Kressel et al., 2000), that was administered at each survey wave. Responses at each wave were averaged to create a treatment engagement score with a minimum score of 1.0 to maximum score of 5.0 (α = 0.86) (see Appendix A). Across all waves and observations, the mean treatment engagement score is 3.85 (stddev = 0.51) and measured scores range from 2.64 to 4.93. For purposes of the network model, which requires dependent variables be integers, we rescaled this measure by multiplying it by 2 and rounding.

2.2.2. Independent measures

2.2.2.1. Role model nominations. During the resident CAPI surveys, respondents were asked to nominate up to three residents who "people see as the role models in the community." As with the "get along with most" nominations, "community role models" were chosen from an alphabetized roster of all unit inmates listed on the computer screen. To understand which residents are nominated as role models, we summed nominations received by each respondent in a wave. Residents who received at least 3 nominations were coded as a role model in that wave.

2.2.2.2. Controls. Our models control for demographic characteristics and administrative variables provided by the Pennsylvania Department of Corrections (PADOC). Mean respondent age was 35.6 (stddev = 10.4) and our sample was 59% white, 33% black, and 8% Hispanic. The Offense Gravity Score (OGS) was taken from the Pennsylvania sentencing code and ranged from 1 (misdemeanor) to 18 (1st degree murder). The OGS mean in our sample was 6.54 (stddev = 3.12), which is approximately equivalent to motorized vehicle theft, aggravated assault, or possession with the intent to sell small amounts of an illicit substance. The TCU drug screening score ranged from 0 to 9, where a score of 3 or above corresponds to substance dependence. Within the PADOC, a score of six or above typically results in assignment to the prison-based TC. The mean TCU score for respondents was 6.74 (standard deviation 1.21). The Tests of Adult Basic Education (TABE) grade equivalent scores in our sample ranged from 30 to 130, indicating math, language, and reading proficiency. Mean respondent TABE score was 93.92 (stddev = 31.11), roughly equating to a 9th grade level of academic achievement. Time on unit, or the number of days the respondent was on the TC unit at the time of the survey-wave, had a mean of 59.2 days for all surveys across all waves (stddev = 35).

2.3. Analyses

Our first step was to examine how well the bivariate associations between treatment engagement and residents' patterns of connections to one another aligned with TC philosophy. If peer influence is present, then we would expect a positive correlation between respondents' treatment engagement scores and the average engagement scores of the peers they nominated in their "get along with most" network. We would also expect residents with higher levels of engagement to be more embedded in the unit network. We thus examined correlations between treatment engagement and the count of (1) received get along with nominations and (2) received TC role model nominations. Positive correlations would suggest that, consistent with TC philosophy, more socially embedded residents and perceived unit role models, respectively, are more highly engaged with the treatment program than other TC residents.

Observing homophily on treatment engagement is evidence that influence *could* be occurring and observing positive correlations between engagement and number of nominations would suggest unit group dynamics that foster engagement. However, these bivariate patterns do not rule out selection as an alternative explanation. Thus, our second step was to investigate the causal forces responsible for patterns observed in step one. Here, we used a stochastic actor-oriented model (SAOM), which is a longitudinal network model capable of discerning network influences on behavior from selection mechanisms. The SAOM jointly models change in network structure and individual behaviors (i.e., treatment engagement) over time. Although mathematically complex and requiring multiple waves of network data (see Snijders et al., 2010, for more information), SAOMs are one of very few methods that can identify if a peer influence (treatment) process is operating as expected.[1]

Our SAOM was specified using two functions. The *engagement function* predicted change in treatment engagement across waves. The key predictor testing for peer influence was a measure of the treatment engagement of those nominated in the respondent's get along with network. We calculated this using the average of nominees' engagement, weighted by the number of nominees (i.e., the *total alter* effect; Ripley et al., 2019).[2] This function also tested for whether being embedded in the get along with network increased engagement across time. We specified this mechanism using effects representing the number of get along with most nominations a resident (1) received from other residents and (2) sent to other residents (i.e., *indegree* and *outdegree* effects respectively; Ripley et al., 2019). In predicting engagement, we controlled for the resident's race, age, TABE, TCU score, OGS, and time on the unit.

The SAOM also contained a *network function* that estimated change in the network across time. This function treated each dyad as the unit of analysis and asked whether a get along with most tie formed or persisted across time. This function controlled for selection into relationships based on treatment engagement and several additional controls.[3] Specifically, we controlled for whether residents with similar

[1] Another approach to measuring peer influence is the random assignment of peers to specific individuals. For example, several authors have examined if (randomly assigned) roommates or cellmates influence behavior (e.g., Harris et al., 2018). Such approaches are statistically appropriate for identifying peer influence processes, but less applicable for a unit-level peer-influence process such as in the TC.

[2] To check the robustness of our results to alternative specifications, we tested for the following variations of peer influence, none of which produced substantively different results: (1) Treatment engagement moves toward the average of one's network (*avSim*). (2) Treatment engagement moves toward the average of one's network, with influence stronger for residents with larger networks (*totSim*). (3) Treatment engagement moves up or down depending on, respectively, whether one's network has higher or lower engagement compared to the overall unit (*avAlt*).

[3] We control for how race, age TABE, TCU score, offense severity, and time on the unit affect network selection processes. These covariates were included using *ego*, *alter*, and *similarity* effects (Ripley et al., 2019) In addition, we control for common endogenous network processes. For instance, in networks like

engagement levels were more likely to have a network tie (i.e., the *similarity* effect; Ripley et al., 2019). We also controlled for whether residents with greater treatment engagement were more likely to nominate peers or receive nominations from peers (i.e., *ego* and *alter* effects; Ripley et al., 2019). In combination with effects in the engagement function, these effects parsed whether any bivariate associations observed between the network and engagement were due to selection or influence processes. Additional SAOMs also tested whether the strength of peer influence differed based on whether the peer was a role model (defined as receiving at least 3 nominations of being a community role model).[4]

Finally, we conducted a fidelity assessment of the unit following data collection due to concerns raised by residents during survey administration. This assessment was conducted by three of study's coauthors. The assessment reviewed both the adherence of the program to accepted standards of TC operation (e.g. a resident hierarchy, peer interactions such as verbal corrections) and the fidelity of the implementation of this model – what the TC was actually doing in practice relative to what it claimed to be doing. The assessment included a survey of the elements of the TC using the SEEQ (Scale of Essential Elements Questionnaire) administered to four key program staff, direct observation of regular program activities throughout a day, and interviews with TC staff, participants and peer assistants to discuss the activities that we observed and how and why they are done in relation to TC theory. We return to a discussion of this fidelity assessment and its implications after presenting the findings.

3. Results

To address our research questions, we begin by first estimating bivariate associations between individual treatment engagement and that of nominated peers in the TC social network.[5] The correlation between respondent's engagement and the average engagement of their nominated peers in the "get along with most" network was positive and statistically significant. Across the 10 waves, the average resident-peer treatment engagement correlation was $r = .19$, $p < .001$. Residents of similar treatment engagement values thus tended to cluster together in the TC unit (i.e., we observed a pattern of homophily on treatment engagement). Next, we examined if those residents who were highly engaged with the treatment were also highly embedded in the unit's social structure. The correlation between resident treatment engagement and the number of received "get along with most" nominations was non-significant (r = .06, *n.s.*) while the correlation with outgoing nominations was positive and significant ($r = .20$, $p < .001$). The correlation with number of incoming role model nominations was also positive and significant ($r = .28$, $p < .001$). Overall, and as expected within a well-operating TC, we found patterns that were consistent with unit integration being associated with treatment engagement, leaders being more engaged, and a significant correlation between individual and peer treatment engagement necessary for peer influence. Our next step used SAOMs to discern the causal direction responsible for these patterns, and whether they persisted net of controls for confounding factors.

Looking at the SAOM *engagement function*, which tests how the TC network affects engagement across time, we found a non-significant effect of unit embeddedness (indegree and outdegree) on engagement (bottom of Table 1). We also found a non-significant effect for peer influence, and for the moderation of peer influence by connections to unit role models. This pattern was similar when the network function contained only engagement or the full set of controls. These results suggest that, inconsistent with a peer influence process, the TC unit network did not affect residents' treatment engagement over time.

Turning to the *network selection function*, we first evaluated whether engagement affected network structure (top of Table 1). Model 1 is a base model that reports change over time in the network due to engagement without other selection controls. It shows that residents with higher levels of engagement named more peers when asked who they get along with most (b = .148, $p < .001$), but were not named more often (b = -.014, n.s.). We also see evidence that residents tended to select peers whose treatment engagement was more similar to their own level of engagement (b = .464, $p < .001$). In combination with the results for the engagement function above, this suggests that selection processes were responsible for observed associations between engagement and the network. The next set of models serve to more finely determine the basis of this selection process.

Models 2–4 test whether the effects of engagement on network selection persist net of controls for selection on other individual attributes or through common network processes. Across models, we find that the effect of engagement on naming more peers persists across specifications and with the full set of controls in Model 4 (b = .162, $p < .001$). Specifically, a one-unit increase in treatment engagement increased a resident's odds of nominating a peer by 18% (exp [.162]). This result indicates that more engaged residents were more integrated into the TC network.

By contrast, the effect of selection based on engagement similarity decreases in magnitude when introducing controls, becoming indistinguishable from zero by Model 4 (b = .070, n.s.). Introducing the network terms in Model 2 attenuates the Treatment Engagement Similarity coefficient by 31%, suggesting that peers who are similar in their levels of treatment engagement are also more likely to reciprocate nominations or create transitive triads (the latter being evidence of clustering or grouping). This decrease is most pronounced in comparing Model 1 to Model 3, which introduced controls for other individual attributes. These models show that residents tended to select peers similar in race, age, TABE score, and tenure in the TC. In addition, there were differences in the tendency to nominate peers (*ego* effects) and be nominated (*alter* effects) for several of these attributes. Follow-up models (not shown) testing attributes independently indicated that introducing the Same Race parameter produced the greatest decrease in the Treatment Engagement Similarity coefficient, reducing it to statistical non-significance. This implies that when residents befriended peers of the same race they created ties to peers with a similar level of engagement. Thus, homophilous selection on engagement was a spurious outcome.

Results from the fidelity assessment suggested that while the program staff and participants were knowledgeable about at least some core TC principles and were enthusiastic about the TC approach, and while program manuals and polices included elements that are essential to a classical TC model, the program *as implemented* was best characterized as *TC oriented* rather than as a full or even a modified TC. The TC missed the mark on several key TC elements, such as a peer stratified hierarchy trained in community management, peers trained in verbal interaction (corrections and affirmations), therapeutic group processes typically found in TCs, and the absence of robust aftercare services.

4. Discussion

This study presented a novel longitudinal network analysis of peer processes within a prison-based therapeutic community. In a well-

(*footnote continued*)
friendship person i is more likely to nominate person j ($i \rightarrow j$) if j has nominated i ($j \rightarrow i$), referred to as *reciprocity*, or if they have a mutual connection to k ($i \rightarrow k$ and $k \rightarrow j$), known as *transitivity* (Snijders et al., 2010). These two processes are typically strong enough that they substitute for one another, thus we include their interaction (Block, 2015).

[4] Tests using cutoffs of at least 2 or at least 10 role model nominations produced equivalent results.

[5] These bivariate associations treat each respondent in each wave as the unit of analysis and hence do not account for non-independent observations. Their purpose is to illustrate the associations of interest. By contrast, the SAOMs explicitly control for non-independence.

Table 1
Stochastic Actor-Oriented Models of Social Ties in a Prison Therapeutic Community.

	M1			M2			M3			M4		
Network Selection Function	b		(se)	b		(se)	b		(se)	b		(se)
Rate (period 1)	16.95	***	(1.38)	16.06	***	(1.28)	17.26	***	(1.19)	14.49	***	(1.07)
Rate (period 2)	10.46	***	(0.76)	10.26	***	(0.86)	10.58	***	(0.77)	9.63	***	(0.74)
Rate (period 3)	9.28	***	(0.81)	9.34	***	(0.91)	9.38	***	(0.82)	8.56	***	(0.74)
Rate (period 4)	13.02	***	(1.12)	13.59	***	(1.41)	14.37	***	(1.18)	12.99	***	(1.13)
Rate (period 5)	15.60	***	(1.15)	15.89	***	(1.37)	16.65	***	(1.18)	14.64	***	(1.04)
Rate (period 6)	12.79	***	(0.96)	12.73	***	(1.01)	14.45	***	(1.07)	13.07	***	(1.06)
Rate (period 7)	12.88	***	(0.90)	13.18	***	(1.16)	14.11	***	(1.12)	13.12	***	(1.03)
Rate (period 8)	14.89	***	(1.09)	15.38	***	(1.24)	16.65	***	(1.30)	15.12	***	(1.17)
Rate (period 9)	12.66	***	(1.14)	12.59	***	(1.09)	13.70	***	(1.10)	12.66	***	(1.07)
Outdegree (density)	−.80	***	(0.03)	−1.43	***	(0.03)	−1.15	***	(0.05)	−1.67	***	(0.05)
Reciprocity				1.67	***	(0.09)				1.58	***	(0.09)
Transitive Triplets				.25	***	(0.02)				.29	***	(0.02)
Transitive Reciprocal Triplets				−.31	***	(0.05)				−.31	***	(0.05)
Same Race							.67	***	(0.05)	.53	***	(0.05)
Alter Age							−.009	***	(0.002)	−.007	***	(0.002)
Ego Age							.009	**	(0.004)	.009	***	(0.003)
Age Similarity							.87	***	(0.12)	.75	***	(0.11)
Alter Offense Gravity Score							.01		(0.01)	.01	†	(0.01)
Ego Offense Gravity Score							.03	*	(0.01)	.02	*	(0.01)
Offense Gravity Score Similarity							.14		(0.16)	.06		(0.15)
Alter TABE Score							.002	*	(0.001)	.001		(0.001)
Ego TABE Score							−.001		(0.001)	−.001		(0.001)
TABE Similarity							.24	***	(0.09)	.22	***	(0.09)
Alter TCU Score							.03		(0.02)	.01		(0.02)
Ego TCU Score							.08	*	(0.03)	.04		(0.03)
TCU Score similarity							.25	†	(0.14)	.16		(0.13)
Alter Time on Unit							−.001		(0.001)	−.005	***	(0.001)
Ego Time on Unit							−.008	***	(0.001)	−.010	***	(0.001)
Time on Unit Similarity							1.83	***	(0.11)	1.19	***	(0.12)
Alter Treatment Engagement	−.01		(0.03)	−.07	**	(0.03)	.07	*	(0.03)	−.001		(0.03)
Ego Treatment Engagement	.15	***	(0.03)	.09	***	(0.03)	.24	***	(0.04)	.16	***	(0.03)
Trtmt. Engagement Similarity	.46	***	(0.16)	.32	*	(0.14)	.22		(0.16)	.07		(0.16)
Engagement Function												
Rate (period 1)	.70	*	(0.34)	.68	**	(0.28)	.71	***	(0.25)	.71	***	(0.24)
Rate (period 2)	.74	**	(0.29)	.76	***	(0.29)	.76	**	(0.32)	.77	**	(0.30)
Rate (period 3)	.96	†	(0.51)	.97	**	(0.38)	.98	*	(0.44)	.98	**	(0.39)
Rate (period 4)	.63	*	(0.31)	.64	**	(0.26)	.65	***	(0.24)	.65	**	(0.25)
Rate (period 5)	1.14	**	(0.48)	1.14	**	(0.48)	1.15	*	(0.54)	1.16	***	(0.42)
Rate (period 6)	.52	**	(0.21)	.50	***	(0.19)	.52	**	(0.22)	.51	***	(0.20)
Rate (period 7)	.68	***	(0.26)	.69	***	(0.25)	.69	***	(0.27)	.69	***	(0.23)
Rate (period 8)	.50	**	(0.19)	.50	**	(0.21)	.50	**	(0.20)	.50	**	(0.21)
Rate (period 9)	.50	**	(0.21)	.49	***	(0.19)	.51	**	(0.21)	.51	*	(0.23)
Linear Shape	−.41		(0.88)	−.41		(0.67)	−.42		(0.85)	−.33		(0.64)
Quadratic Shape	−.31		(0.38)	−.31		(0.27)	−.30		(0.27)	−.29		(0.23)
Indegree	−.03		(0.09)	−.03		(0.08)	−.02		(0.07)	−.02		(0.07)
Outdegree	.02		(0.07)	.03		(0.07)	.03		(0.07)	.02		(0.07)
Total Alter (Peer Influence)	−.08		(0.29)	−.10		(0.23)	−.07		(0.18)	−.07		(0.20)
Total Alter X Alter Role Model	1.17		(2.52)	1.18		(1.78)	1.03		(1.55)	1.00		(1.49)
Black Race	.52		(0.75)	.55		(0.63)	.51		(0.58)	.49		(0.54)
Hispanic Race	1.19		(1.55)	1.16		(1.05)	1.16		(1.14)	1.10		(0.99)
Age	.04		(0.05)	.04		(0.04)	.03		(0.03)	.03		(0.03)
Offense Gravity Score	.02		(0.06)	.02		(0.06)	.01		(0.06)	.01		(0.06)
TABE Score	.004		(0.008)	.004		(0.007)	.004		(0.007)	.004		(0.006)
TCU Score	−.08		(0.16)	−.08		(0.15)	−.08		(0.14)	−.08		(0.14)
Time on Unit	.005		(0.009)	.005		(0.009)	.005		(0.008)	.006		(0.007)

Note: Standard errors in parentheses. †p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests).

functioning TC, highly engaged residents should be at the core of the social structure and increase engagement among their peers over time. We found that residents of the TC clustered together according to their treatment engagement, but there was no evidence that treatment engagement diffused in the network through peer influence processes. Moreover, although perceived unit role models had higher treatment engagement levels than other TC residents, these individuals were not influential for increasing the engagement of their peers. Overall, our analyses suggested a unit where those residents who fully participated in the program connected with others of similar persuasion, while disengaged residents clustered together in their own community-within-a-community. This is consistent with recent findings that TC graduation is clustered within networks (Campbell et al., 2018) but suggests a dark side. Although community segregation based on treatment engagement may increase cooperation and synergies among the highly engaged (Fu et al., 2012), it fails to positively affect those less-engaged residents most in need of rehabilitation.

That we did not find evidence for a peer influence process was particularly concerning given the intended program model. TC philosophy presents the community of peers as the principle mechanism for behavioral and identity change (De Leon, 2000). Our results, however, suggested that peer selection processes swamped peer influence for treatment engagement in this particular TC. We believe that there are three likely causes for the lack of peer influence in our sampled unit. First, the TC program in Pennsylvania prisons has been shortened from the recommended range of six to twelve or more months (De Leon, 2000) to just four months. While many correctional institutions have shortened their TCs, this modification to the program has not been adequately evaluated (Taxman et al., 2007) and prior TC evaluations finding significant treatment effects have been based upon much longer program lengths (Mitchell et al., 2012). Second, the shortened TC length combined with mandated TC completion for prisoners with substance use disorders to reach parole eligibility inflates selection issues and pressures TC staff to maintain high graduation rates. The result is more TC residents seeking to "check the box" without fully engaging with the treatment. Finally, a fidelity assessment of the sampled unit found it to be of low-medium fidelity compared to a conventional TC model. Importantly, it had largely removed peer corrections (i.e., "pull-ups") as a therapeutic tool, which past TC research has emphasized as a key mechanism of peer influence (Doogan and Warren, 2017a, 2017b). Overall, the TC may have been of insufficient length and intensity to allow for the emergence of a robust peer community.

Although we suspect that our results generalize to other TCs in Pennsylvania state prisons at the time of the study, the short program length and marginal fidelity reduce generalizability to prison TCs in other states or at other times. We are clearly unable to determine if significant peer influence processes would be found in TCs of longer length and higher treatment fidelity. Future research using a similar network methodology should estimate peer influence effects in prison-based TCs of varying lengths and treatment fidelity levels.

It is also the case that we do not present outcome analyses for post-treatment relapse, recidivism, and reincarceration. The focus here was on dynamic treatment processes and testing the peer influence mechanisms underlying TC philosophy. Future analyses will follow our sample outside of prison and examine how between-person differences in treatment engagement and network position predict post-release outcomes.

Although limitations exist, our study provides a valuable benchmark for future TC process evaluations. In their simplest form, peer network surveys can be implemented by treatment staff to examine the social structures within their programs. Descriptive analyses of these data can identify subgroups or peripheral unit residents who require targeted intervention. Longitudinal analyses such as those presented here can then identify best-practices for implementation across TCs to increase positive peer processes and increase desirable long-term recovery outcomes.

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Contributors

DAK and GZ coordinated activities with PA Department of Corrections. KD led prison data collection. DRS conducted all network analyses. GDL conducted TC fidelity assessment. All authors contributed to written manuscript, interpretation of results, revisions, and final manuscript approval.

Declaration of Competing Interest

No conflict declared.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.drugalcdep.2019.05.018.

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