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ORIGINAL ARTICLE

Dynamic Social Networks in Recovery Homes

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Abstract Acute treatment aftercare in the form of sober living environments—i.e., recovery houses—provide an inexpensive and effective medium-term treatment alternative for many with substance use disorders. Limited evidence suggests that house-situated social relationships and associated social support are critical determinants of how successful these residential experiences are for their members, but little is known about the mechanisms underlying these relationships. This study explored the feasibility of using dynamic social network modeling to understand house-situated longitudinal associations among individual Alcoholics Anonymous related recovery behaviors, length of residence, dyadic interpersonal trust, and dyadic confidant relationship formation processes. Trust and confidant relationships were measured 3 months apart in U.S. urban-area recovery houses, all of which were part of a network of substance use recovery homes. A stochastic actor-based model was successfully estimated from this data set. Results suggest that confidant relationships are predicted by trust, while trust is affected by recovery behaviors and length of residence. Conceptualizing recovery houses as a set of independent, evolving social networks that can be modeled jointly appears to be a promising direction for research.

Keywords Dynamic social networks · Oxford Houses · Recovery homes · Substance use disorders

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Introduction

Ecologically based behavioral theory describes a dynamic *transactional* interchange between the individual and his or her social environment (e.g., Bronfenbrenner 1979; Kelly 2006; Magnusson 1987). Individual behavior is constrained by social environments, yet such behaviors, in the aggregate, also *form* the social environment. Although this two-way flow idea underlies and informs the field of community psychology (Jason and Glenwick 2012), theoretical formulations need to be concrete enough to be empirically evaluated with quantitative methods. Moreover, methods for studying social systems from a transactional perspective are still quite limited: even advanced statistical techniques like multilevel modeling are primarily useful for studying the effect of context on behavior, but not the reverse (e.g., Todd et al. 2012). In contrast, a dynamic network approach provides a framework for thinking about and describing two-way transactional dynamics, as well as a methodological approach for studying such systems empirically.

The social network paradigm is distinguished from other behavioral science research by its focus on relationships, rather than on individual characteristics. In seeing behavior as fundamentally contextual, social network research shares the transactional tenet with community psychology (Bogat et al. 2012). Moreover, recent advances in dynamic modeling of social networks using well-grounded principles of statistical inference have provided the capability to estimate fully transactional models from network and behavioral data.

One of these approaches is the stochastic actor-based model (for details, see Snijders 2001 and Snijders et al. 2010). Briefly put, the stochastic actor-based model conceptualizes social networks as a set of individuals whose relationships evolve over time according to an underlying probability structure. This process can depend on a linear combination of predictors (*effects*), which are interpretable as hypothesized mechanisms that jointly predict network evolution. Dependence on predictors ("effects") is formulated as a linear log-odds model, similar to a logistic regression, although the underlying model structure is different.

Model effects include both fixed (e.g., gender, ethnicity) and time-varying (attitudes, behaviors, etc.) measured characteristics of individuals, but also characteristics of pairs of individuals, or *dyads* (e.g., physical distance between them). Such predictors are familiar from ordinary regression modeling. A major contribution of the network perspective to the study of social relationships is the idea that structural constraints also matter. Relationship dynamics, in other words, normally depend not only on individual characteristics, needs, and preferences, but also on *the state of the network*. Two important structural effects are reciprocity (the tendency for reciprocated relationships to be developed, i.e. where each member of a dyad chooses the other) and transitivity (the tendency for all members of triads to share the same relationship).

Network approaches in community psychology have been limited largely to studies of "personal" networks, that is, the personal friendships or other significant relationships reported by study participants. For example, personal network studies of substance use recovery have established the relevance of participant-reported associates as facilitators of treatment entry (Davey et al. 2007; Kelly et al. 2010) and mediators of ongoing sobriety (Humphreys and Noke 1997; Humphreys et al. 1999; Kaskutas et al. 2002; Longabaugh et al. 1995; Polcin et al. 2010). Personal networks tend to focus only on the relationships of a focal actor (ego) and his/her alters rather than on all of the relationships in a system (i.e., whole network data). In contrast, a whole network provides a structural map of the entire social ecosystem, and allows models that include the sorts of network-state effects described earlier.

In recent years, whole network studies have opened a new level of insight into the social dynamics of substance use, especially among youth (e.g. Veenstra et al. 2103), but also in adult populations (Cruz et al. 2012). The whole network approach has been less commonly applied to treatment and recovery issues, however, in part because recovering individuals typically are not members of the same whole network. Residential recovery houses are an important exception. Recovering individuals may reside in such houses for periods ranging from a few weeks to many months, and is natural to suspect that the social dynamics within these houses may play an important role in residents' willingness to remain in these supportive environments, and the level of abstinence-maintaining personal change they are thus able to achieve.

Substance Use Disorders and Networks

People in recovery from substance use disorders face many obstacles to maintaining abstinence (Montgomery et al. 1993). For example, many people who finish substance use treatment relapse over time (Richman and Neumann 1984; Vaillant 2003), and this might be due to the lack of longer-term community-based housing and employment support (Jason et al. 2008). A number of self-help organizations provide support to individuals following treatment, including Alcoholics Anonymous (AA), but such programs do not provide needed safe and affordable housing, or access to employment. For these needs, a variety of professionally run and resident-run residential programs is available in the US (Polcin et al. 2010). Although such recovery programs are important sources of housing and employment support, they do not work for everyone (Longabaugh et al. 1995; Moos and Moos 2006; Zywiak et al. 2002). For instance, early dropout from recovery homes often occurs due to a new resident's failure to become integrated into the house social ecology (Moos 1994; Vaillant 1983). The dynamics of social integration in recovery houses may be studied by conceptualzing them as social networks that evolve based on both structural tendencies and network members' characteristics.

Research on sobriety-focused social support suggests two mechanisms whereby participation in self-help groups such as AA may promote more recovery-supportive personal friendship networks: as a source for recovery-supportive friends, and also a source of behavioral modeling, advice, and encouragement for staying sober (Kaskutas et al. 2002). Positive effects of personal network composition have also been associated with recovery house stays, though the mechanisms underlying this relationship are unknown (Polcin et al. 2010). Nevertheless, it is plausible that a recovery house stay benefits residents in the same way as AA involvement, in being a source for alternative friendships, modeling, advice, and support. Thus, predictors of strong within-house relationships would be important to investigate. Relevant relationships would be those that promote discussion of recovery-threatening topics like negative feelings such as stress, anxiety, and loneliness. Such relationships, which could be called "confidants," are also important as a source of interactive problem-solving that are less likely in 12-step meetings.

Regarding formation of confidant relationships, studies have found that *trust* is a critical precursor of close relationships (Bonaventura et al. 2006; Horst and Coffé 2012). Trust tends to develop in groups in part as a function of time and interindividual exposure (Patulny 2011), especially when the individuals in the group are dependent on each other for desired outcomes (Schachter 1951). Recovery homes might promote interdependence through the house self-governance structure, as well as norms of mutual support for recovery. Thus, we hypothesize that if a house member trusts a fellow member, he or she is more likely to confide in that individual. Moreover, we hypothesize that once a confidant relationship forms, trust is more likely to be maintained; that is, trust and confidant relationships should mutually reinforce each other in a positive feedback loop.

If trust is typically a precondition for a confidant relationship to form, then we would expect trust to mediate the effects of other predictors of confidant relationships. For instance, 12-step activities–attending self-help group meetings, reading literature, etc.–are behaviors readily observable by other house members. Since the recoveries of all members are threatened by anyone who does not engage in 12-step activities, because such an individual may appear to not support the norms of recovery (Malloy 1988), we hypothesize that residents who exemplify active, behavioral participation in the shared goal of recovery will be more trusted by others. We also hypothesize that longer-time residents are more likely to be trusted, due to their experience and demonstrated commitment to recovery.

Summarizing, our objective is to test a simple model of "social integration" dynamics—formation of trust and confidant relationships—in a sample of recovery houses, as a function of individuals' range of 12-step activities and time in residence. Understanding this process may be a key to explaining the apparent therapeutic value of recovery house residence for some individuals, and extending it to a broader population.

Method

We collected baseline and 3-month follow-up data on five Oxford House recovery houses with 31 participants. House size averaged 6.2 residents, somewhat fewer than the national average (Jason et al. 2007). There were four men's and one women's Oxford House that participated in this study, a total of 5 women (16 %) and 26 men (84 %). We were able to successfully recruit nearly all house members (only 2 out of 33 did not participate) and we could follow all but four at a 3 months follow-up. The present study excluded 3 individuals who were not present in their house for both waves, bringing the analysis sample to 28. Each interview was conducted by phone. Any individuals living at a recruited house at the time the study commenced or entering the participating Oxford House prior to the second and final assessment were enrolled in the study if they provided informed consent. Consent was obtained verbally over the phone on an individual basis. No monetary incentives were used to secure participants' involvement in the study. Although Oxford House programs are self-governed, all Oxford Houses operate with similar rules, and these standardized procedures help limit extraneous variance that might otherwise be present (Jason et al. 2008).

Measures

The baseline assessment obtained participant's sex, age, race, length of residency, length of current sobriety, and referral method to Oxford House.

The Alcoholics Anonymous Affiliation instrument (Humphreys et al. 1998) was used to measure 12-step behaviors. It consists of 9 items and operates as a strength index of an individual's affiliation with a mutual, self-help group, designed originally for use with AA members. Items include, for instance, "Do you now have an AA sponsor?" and "Have you ever called an AA member for help?" The scale is unidimensional and reliable (current sample alpha $= 0.82$).

Confidant and trust relationships were obtained from what was intended to be a multi-item measure of "relationship closeness" developed by our research team. The original instrument (alpha $= 0.81$) asked house residents to rate their relationships with fellow residents on several dimensions including trust and "type of relationship" on 5-point scales. Trust was measured in terms of willingness to loan "alter" different amounts of money. For nearly all house residents, money is scarce, and "pulling one's own weight" is a major norm of Oxford House residence. Willingness to loan money is thus a plausible indicator of trust in this context. Amounts that could be selected were \$0, \$10, \$20, \$50, and \$100. Given the goal of the present analysis to examine temporal dynamics of trust, we dichotomized trust into willingness to lend \$100 to alter (scored as 1) versus willingness to lend less than that (scored as 0). In other words, willingness to loan money served as the indicator of trust in the house context. For "type of relationship", the categories were confidant, friend, acquaintance, stranger, or adversary (from most to least close). Relationship types were classified into dichotomous ratings of "confidant" (scored as 1) versus any less-close relationship than confidant (which would include friend, acquaintance, stranger, or adversary) (scored as 0). We interpreted a rating of confidant as signifying a very close friendship. About a quarter of potential confidant and trust dyads were scored as 1's at each wave, and these relationships are shown by house in Figs. 1 and 2.

These single-item-based relationship designations are typical in social network research, in part because ego's perception of relationships with alters is considered important, and also in part to reduce what could be a sizeable response burden if multiple-item ratings had to be applied to all potential alters (Marsden 2011). Social network relationships that use ordinal ratings, as in the current study, have been found to be reliable (Hlebec and Ferligoj 2002).

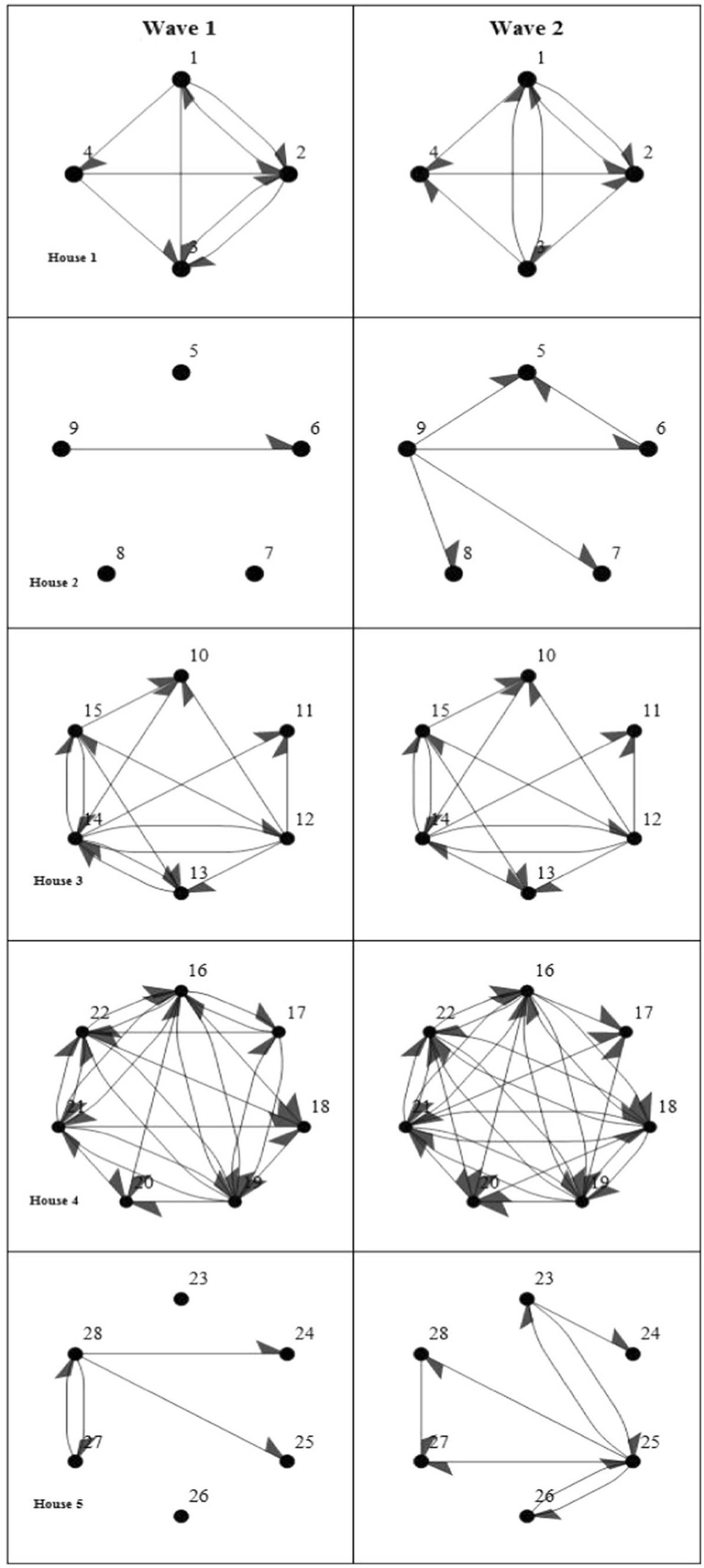

Fig. 1 Trust ($100) relationships. *Note*: Includes 28 residents who participated in both waves

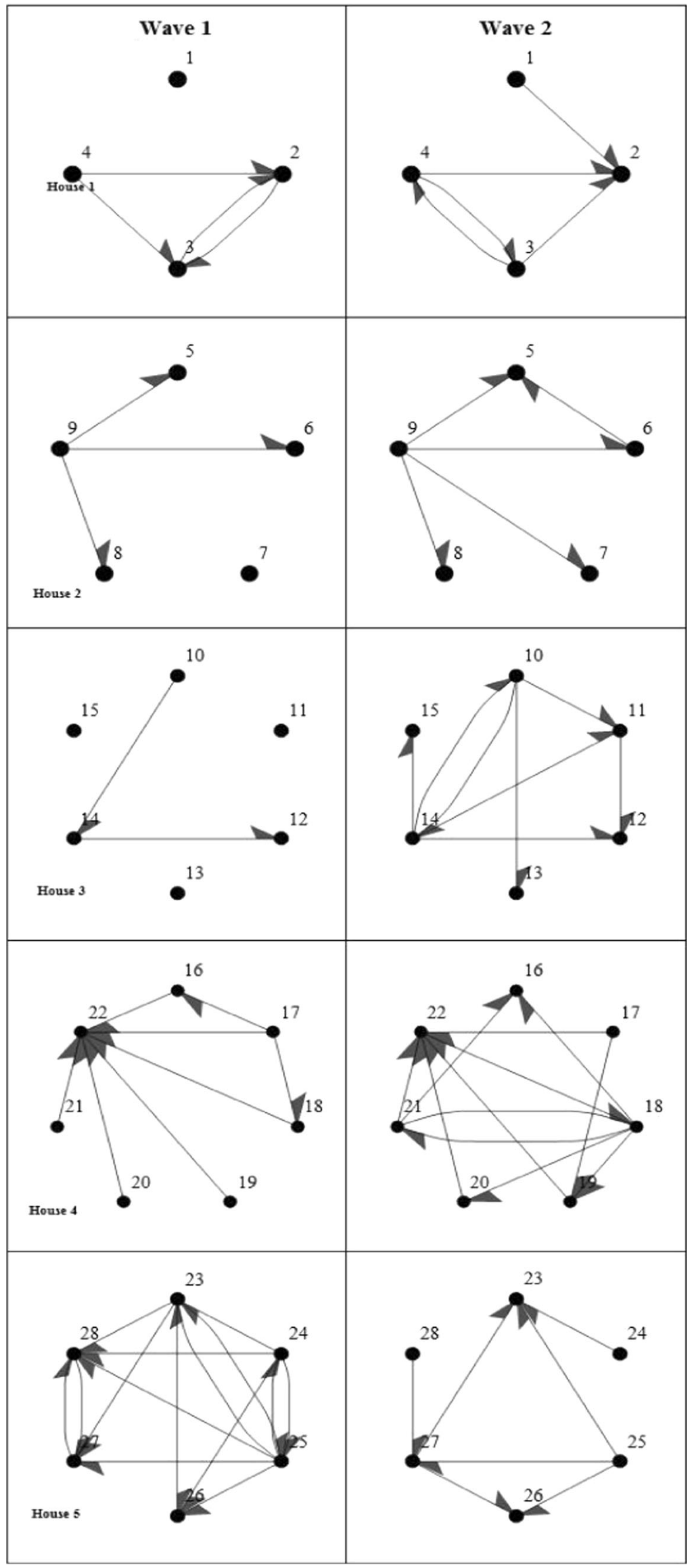

Fig. 2 Confidant relationships. *Note*: Includes 28 residents who participated in both waves

Statistical Analyses

A changing house relationship structure may be described at the micro-level in terms of a set of interdependent network tie changes, that is, dyadic and directed (not necessarily symmetrical) relationships represented by a changing "multiplex network", defined as network linkages of several types among the same individuals. Individual house networks may be pooled into a single longitudinal network where linkages are constrained to occur only within houses, provided that the basic dynamics—possibly conditional on measured covariates—are similar (Ripley et al. 2013). Thus, the individuals in all houses in the study are thought of as the same population, and as subject to the same social dynamics, conditional on covariates and initial relationship structures. These assumptions can be represented with the stochastic actor-based model and estimated using the R package RSiena (Ripley et al. 2013).

Estimation was carried out using maximum likelihood with a multiplication factor (affecting the number of simulations) of 50. The model we developed was a multiplex network model, involving two networks: trust and confidant relationships. Each of these relationships served as a predictor for the other, to test for a reciprocal relationship. Additionally it is important to control for so-called "endogenous" network effects (i.e. structural tendency effects) in these models, as they may otherwise be confounded with substantive predictor effects (Steglich et al. 2012). We specifically included outdegree, reciprocity, transitivity.[1]

As for most models iteratively estimated from a small data set, including all these effects simultaneously led to convergence issues. The recommended strategy in this cases (Ripley et al. 2013) is to start with basic endogenous network effects and build up the model, retaining significant effects and, to the extent possible, insignificant effects as well, provided model convergence statistics (described later) are still acceptable. Some non-significant effects could not be retained in our final model for these reasons; they are listed at the bottom of Table 2.

Results

Figures 1 and 2 show the network linkages for trust and confidant relationships, respectively, at baseline (Wave 1) and 3-month follow-up (Wave 2). Relationship designations are directed, with arrows showing direction of choice. Figure 2 shows that a confidant relationship is usually asymmetrical, confirming its low reciprocity. Of the 28 Wave 1 dyadic confidant links among participants, only four (14 %) are symmetrical, shown by looped pairs of arrows; at Wave 2, three out of 34 are symmetrical (9 %). This structure suggests that a confidant relationship has an element of role specialization to it, where one confides, the other listens, and not vice versa. Note that confidant relationships could still have asymmetrical reciprocity (the strength of the relationship is not equally rated by both members of the dyad), which would not be captured in this dichotomized measure, but this level of detail could not be investigated in a small study. On the other hand, trust relationships were more often symmetric, with 14 of 37 (38 %) dyadic linkages mutual at wave 1, and 16 of 46 (35 %) mutual at wave 2. Reciprocity rates for both confidant and trust relationships varied both over time and across houses, indicating both longitudinal and cross-sectional variation.

Descriptive statistics by house are shown in Table 1. Network statistics varied somewhat across houses, but also between waves, indicating a significant amount of change in relationships over just a 3-month period. Reciprocity was low for confidant relationships, actually zero for half the observed wave-house combinations. These descriptive results suggested patterns that might be modeled, so we proceeded to estimate a stochastic actor-based model with RSiena. Results of the final model are shown in Table 2. Convergence is measured by *t*-ratios of simulated compared to observed statistics for each predictor. A value of .10 or less is preferred for each effect, and it is evident that this criterion was met. Also, the maximum autocorrelation of successive simulation effect statistics, measuring the independence of successive simulations, was .22, within the recommended upper limit of 0.30 (Ripley et al. 2013). Thus, even with a small data set, we found we could estimate a simple, reasonable-quality stochastic actor-based model in RSiena.

[1] Outdegree captures the probability of ego adding one more tie given how many he/she has already, and it is usually negative for friendships, meaning that new friendships become less likely the more ego has. According to exchange theory (e.g. Blau 1964), reciprocity is predicted in non-hierarchical relationships like close friendships, which we assumed characterized confidant and trust relationships. Transitivity, meanwhile, often serves as a stand-in for either physical or social proximity effects, which affect the opportunity to form ties with others. Recovery houses probably provide very similar physical interaction opportunities for all possible dyads, but social proximity may nevertheless be affected by residents' preferences for similar recovery-related or leisure activities, similar schedules (e.g. "night owls" vs. early risers), and so on.

Also ego, alter, and similarity effects of 12-step activities and time in residence were examined as potential predictors of both trust and confidant ties. An ego effect captures the effect of an individual characteristic X on the number of ties ego tries to create; for example, newer residents may initially attempt to form more ties than longer-time residents. An alter effect is the reverse: it captures the effect of and alter being chosen, depending on X. Similarity, as the name suggests, indicates whether the choosing individual is more likely to direct a relationship to another if he or she is more similar on X, whereas "higher X" captures tendencies to select alters for whom ego has a higher value on X.

Table 1 Descriptive statistics of recovery house networks by wave

House	1		2		3		4		5	
Wave	1	2	1	2	1	2	1	2	1	2
Number of residents[a]	4		5		6		7		5	
Percent female	100 %		0 %		0 %		0 %		0 %	
Mean age	46.5		53.0		47.8		46.4		47.8	
Percent non-white	100 %		100 %		0 %		0 %		0 %	
Percent HS grad/GED	75 %		80 %		67 %		86 %		100 %	
Confidant outdegree[d]	1.00	1.25	0.60	1.00	0.33	1.33	1.14	1.71	2.50	1.67
Confidant reciprocity	0.33	0.25	0.00	0.00	0.00	0.14	0.00	0.09	0.25	0.00
Confidant transitivity[c]	1.00	1.00	0.00	1.00	0.00	0.43	1.00	0.78	0.83	0.50
Trust $100 outdegree[d]	2.00	2.00	0.20	1.00	2.33	2.17	3.43	4.00	0.67	1.33
Trust $100 reciprocity	0.33	0.33	0.00	0.00	0.27	0.18	0.50	0.56	0.33	0.33
Trust $100 transitivity[c]	0.70	0.70	0.00	0.00	0.74	0.88	0.78	0.93	0.00	0.13

[a] Includes residents present for both waves

[b] Data are provided for residents who completed both waves of the study ($n = 27$)

[c] Proportion of "weakly transitive" triads, i.e. triads {i, j, k} such that if i → j and j → k, then i → k. Defined to be zero when there are no triads {i,j,k} such that i → j and j → k

[d] Average outdegrees (out-choices) per participant

[e] Outdegree, reciprocity, and transitivity were calculated using the R package 'sna' (Butts 2010), v. 2.2–0

Table 2 Stochastic actor-based model results

	Parameter Estimate	SE	p Value	95 % confidence interval	Convergence t-ratio[a]
Final model					
Trust $100: rate	1.71	0.35	**<.01**	(1.0,2.4)	0.01
Trust $100: outdegree	1.49	1.14	.19	(−0.7,3.7)	0.02
Trust $100: reciprocity	−0.40	0.86	.64	(−2.1,1.3)	0.00
Trust $100: transitivity	−0.10	0.30	.74	(−0.7,0.5)	0.04
Trust $100: higher house time versus alter	−3.21	1.65	**.05**	(−6.4,0.0)	0.01
Trust $100: 12-step ego	4.48	1.49	**<.01**	(1.6,7.4)	0.06
Confidant: rate	2.32	0.61	**<.01**	(1.1,3.5)	0.02
Confidant: outdegree	−1.49	0.64	**.02**	(−2.7,−0.2)	0.01
Confidant: reciprocity	−0.92	0.69	.18	(−2.3, 0.4)	0.07
Confidant: transitivity	0.18	0.44	.68	(−0.7,1.0)	0.05
Confidant: 12-step ego	−0.27	0.18	.13	(−0.6,0.1)	0.03
Confidant: trust $100	2.52	0.87	**<.01**	(0.8,4.2)	0.07
Other non-significant effects[b]					
Trust $100:12-Step alter, Trust $100:12-step similarity, Trust $100:12-step similarity x reciprocity					
Trust $100:house time alter, Trust$100:house time ego, Trust $100:house time similarity					
Confidant:12-Step alter, Confidant:12-Step similarity, Confidant:house time alter, Confidant:house time ego					
Confidant:house time similarity					

Bold values are statistically significant p less than or equal to .05

[a] Ratio of deviations of simulated versus observed statistics for each effect, calculated in Phase 3 of the RSiena model estimation procedure. Conventionally, a value of less than 0.10 indicates good convergence (Ripley et al. 2013)

[b] Non-significant effects that could not be included in the final model without affecting model quality (t-ratios, autocorrelations, standard error estimates)

We hypothesized that if one individual trusts another, there is a greater probability the other will be named as a confidant, and vice versa. The parameter showing the effect of trust on confidant is 2.52 ($p < .01$), but the converse effect of confidant on trust was not found (not shown). Trust was not predicted by alter's 12-step activity, but we did find a significant positive “12-step ego” effect (4.48, $p < .01$), implying that individuals who engaged in more 12-step activity were generally more likely to form trust relationships.

We also found weak evidence that length of house residence made an individual more likely to be trusted (“house time alter”), but when we substituted an effect of relative house time for ego compared to alter (“higher house time ego vs. alter”), the effect was substantial and significant (-3.21, $p = .05$), corresponding to a 25-fold increase in the odds of ego trusting alter per month of additional alter house time, compared to ego.

In addition, because of the relative novelty of this type of analysis, we examined variations of hypothesized effects, on an exploratory basis. These are listed at the bottom of Table 2. None was statistically significant, but including any in the final model led to convergence issues. Given the limited sample, we express no certainty that any of these effects are null; a larger study will be needed to draw such conclusions.

Discussion

Moos (Moos 2008) has described the hypothesized “active ingredients” present in successful recovery house programs—the presumed *causal* mechanisms—based upon the well-established theoretical traditions of social control, social learning (Bandura 1971), behavioral economics (Bickel and Vuchinich 2000), and stress/coping theory (Kaplan 1996). Although perhaps the clearest attempt to link recovery house social processes with outcomes, Moos’ framework says very little about the group processes thought to generate successful outcomes. Our study’s general approach and findings thus bring a social dynamics perspective to Moos’ framework.

Two of our hypothesized dynamic mechanisms were confirmed. First, trust predicts formation of confidant relationships: the odds of ego establishing a confidant relationship with alter are over 11 times larger (exp (2.52)) when ego trusts alter. However, confidant relationships do not predict greater trust, suggesting that trust *precedes* formation of confidant relationships. If having a confidant should turn out to be supportive of recovery–not investigated here but consistent with other studies, e.g. Kelly and Urbanoski (2012), Rynes and Tonigan (2012)—such a finding would focus attention on the importance trust-formation processes in recovery house settings. In that regard, we found a pattern of newer residents coming to trust longer-time residents. This finding suggests that one feature of a successful recovery house may be a mix of residents in which new arrivals are balanced by longer-tenured veterans.

Our thinking about confidants had originally conceived this relationship from the perspective of the social support literature, as something like a very close friendship, which would in most cases be a source of mutual support (Carley and Krackhardt 1996). We did indeed find that confidant relationships, like friendships, tended to be relatively exclusive, in that the more alters nominated by ego, the increasingly less likely they were to nominate another alter. Combined with the substantial (though not significant at a .05 level) anti-reciprocity effect, it follows that a single non-reciprocated confidant is typical, since the odds of a second confidant are only 10 % the size of the first, and a third is just 1 % of the first ($\exp(-2.2) \approx 0.10$). This was further reflected in the low incidence of reciprocated confidant relationships. Such evidence is consistent not so much with friendship as it is with hierarchy. It appears that longer-time residents (or those possessing other residence tenure-related attributes, e.g. length of abstinence, perceived stability, experience, and knowledge) hold the higher-status positions, possibly supplying mentoring and support for recovery in exchange for respect and gratitude. According to social exchange theory (e.g. Blau 1964), the asymmetric exchange of dissimilar goods or services is characteristic of hierarchical social relationships.

The question of the role of true and symmetrical friendships versus the apparently hierarchical confidant-like relationships in supporting substance abuse recovery remains. It is doubtful that our sample was large and diverse enough to tease apart separate dynamics of these relationships, but probably both exist; e.g. some of the confidant relationships *were* mutual, but not enough to establish a clear picture of what predicts their formation. This distinction could be investigated in a larger study. Moreover, although use of multi-item instruments is not typical in social network studies (Marsden 2011), future studies will be more clearly interpretable if such instruments can be developed and fielded.

The model also suggested several trust-related dynamic mechanisms. The positive ego effect of 12-Step activity means that individuals with higher levels of 12-Step activity are more likely to form trust relationships. However, level of 12-Step activity had no effect on the trustworthiness of alters, nor was there any tendency for ego-alter similarity on level of 12-Step activity as a basis for trust (not shown). Furthermore, the negative higher house time effect indicates that newer residents are more likely to trust longer-time residents. Taken together, these results suggest that newer members are most likely to trust other residents based on their tenure, rather than their behavioral investment in 12-step activities.

Further insight into the nature of trust relationships in a recovery house context is gained from endogenous network effects. First, the marginally positive out degree effect for trust indicates that trust relationships are definitely not exclusive, and there may even be a tendency for trusting others to "cascade", in that doing so becomes easier the more others the individual already trusts. Confidants (and, as we know from other studies, friendship) carry with them an obligation to commit scarce resources (time and energy) to maintain them. Trust does not, although a willingness to trust seems to grow as a result of initial experiences. Interestingly and a bit surprisingly, trust is not typically reciprocal, however, which could indicate that trust develops from ego's experiences with alter, rather than as a reaction to alter's opinion of (willingness to trust) ego.

The major weakness of this study is its small size and short duration. Indeed, our data collection was intended as more a proof of concept from which we might also glean a few useful descriptive facts, for example, whether social dynamics in recovery houses actually vary over time in a way that suggests they could be modeled. Results are suggestive and promising, but should be interpreted cautiously. The very simple model presented here could not control for many alternatives. For instance, our inability to separately estimate relationship change rates and number of out-choices by house, despite evident heterogeneity in these statistics, suggests that some of the effects we are interpreting as within-house change mechanisms could actually be more about between-house differences. This ecological correlation problem (cf. Snijders and Bosker 2012) could be overcome simply with more data.

Another side effect of study design was our inability to determine the key predictors of the outcomes of ultimate interest: likelihood of relapse, re-establishment of work and family relationships, and improved mental health, etc. Had they been measured, the 3-month time window and small sample would have limited the likelihood of any significant findings. Nevertheless, components of the house dynamic social network system may predict important proximal and distal recovery-related outcomes. This theoretical expectation rests on studies that have linked social support, self-help group attitudes (e.g., spirituality, personal responsibility), behaviors (e.g., having a sponsor, being a sponsor, reading literature) with successful abstinence. For example, Jason et al. (2012) found that early friendships in an Oxford House reduce the likelihood of future relapse. Additionally, there is reason to expect that these recovery house constructs will positively affect mediators of abstinence, such as a minimal 6-month stay, a more supportive personal network outside the house, and recovery-specific self-efficacy. Stevens et al. (2011) found a significant relationship between in-house sense of community and likelihood of leaving, and a minimum 6-month Oxford House stay is related to increased self-efficacy and continued abstinence. DiClemente et al. (1995) also found that efficacy expectations stabilize after six months of abstinence. In this study, we primarily found evidence of individuals selecting others for support, but many questions remain. Does success at establishing these apparently asymmetrical relationships suffice to improve recovery prospects? Is there a value-added effect of being chosen as a source of support, instead or in addition? And what about symmetrical *friendship* relationships—are they important? More generally, as suggested above, there is much yet to be learned about which dynamics lead to positive, supportive, and protective house social environments, and who fits in well, and who has difficulty, and why.

Inspired by Moos (2008) and Vaillant (2003), our perspective in this investigation was trans-theoretical. We suggest that recovery from addiction can be advantageously viewed as a transactional process of interaction between the individual and his or her social environment. More specifically, the effectiveness of a recovery house stay in promoting recovery can be viewed in a similarly transactional framework. This type of process is clearly a complex system, involving a variety of mutually interacting variables. Moos and Vaillant proposed a variety of individually simple subprocesses that are likely to explain the beneficial effects of self-help group involvement, most of which would extend to recovery house residence, that is, social bonding, monitoring, goal direction, modeling, positive reinforcement, rewarding alternatives to using, and advice and outlets for dealing with negative emotions and stress. Such complex, transactional systems are difficult to model, and all too often, simplified representations adopted for the sake of tractability end up omitting the very mechanisms of interest; thus, for example, a regression model that shows a correlation between two variables over time ignores the fact that such a correlation could come about through many different mechanisms. All models are simplifications, of course, but the dynamic network approach modeled by stochastic actor- based model represents a clear advance, in our view, in regards both to accurately representing the transactional system of interest, as well as providing a tractable link to data.

In summary, our study takes a unique approach to understanding recovery house social dynamics that may support abstinence and mediators of abstinence. The social network design and accompanying stochastic actor-based model analysis enabled us to measure house-specific multiplex networks, and pool data across houses to model relationship dynamics as longitudinal network development These relationships could ultimately be predictors of key recovery outcomes. Though this is a preliminary study with a relatively small sample, it suggests that a dynamic network framework is a promising approach. In larger studies, it could help answer long-standing questions of how and why community-based recovery houses support sobriety, perhaps moving them more into the mainstream of substance use disorders treatment protocols.

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References

Bandura, A. (1971). *Social learning theory*. New York, NY: General Learning Press.

Bickel, W. K., & Vuchinich, R. E. (Eds.). (2000). *Reframing health behavior change with behavior economics*. Mahwah, NJ: Erlbaum.

Blau, P. M. (1964). *Exchange and power in social life*. New York: Wiley.

Bogat, G. A., Zarrett, N., Peck, S. C., & von Eye, A. (2012). The person-oriented approach and community research. In L. A. Jason & D. S. Glenwick (Eds.), *Methodological approaches to community-based research* (pp. 89–110). Washington, DC: American Psychological Association.

Bonaventura, M., Ames, K., Brumpton, R., Garratt, R., Hall, K., & Wilson, N. (2006). Human friendship favours cooperation in the Iterated Prisoner's Dilemma. *Behaviour, 143*, 1383–1395.

Bronfenbrenner, U. (1979). *The ecology of human development*. Cambridge, MA: Harvard University Press.

Butts, C. T. (2010). *sna: Tools for social network analysis. R package version 2.2-0*. Retrieved from http://CRAN.R-project.org/package=sna.

Carley, K. M., & Krackhardt, D. (1996). Cognitive inconsistencies and non-symmetric friendship. *Social Networks, 18*, 1–27. doi:10.1016/0378-8733(95)00252-9.

Cruz, J. E., Emery, R. E., & Turkheimer, E. (2012). Peer network drinking predicts increased alcohol use from adolescence to early adulthood after controlling for genetic and shared environmental selection. *Developmental Psychology, 48*(5), 1390–1402.

Davey, M. A., Latkin, C. A., Hua, W., Tobin, K. E., & Strathdee, S. (2007). Individual and social network factors that predict entry to drug treatment. *American Journal on Addictions, 16*(1), 38–45. doi:10.1080/10601330601080057.

DiClemente, C. C., Fairhurst, S., & Piotrowski, N. (1995). The role of self-efficacy in the addictive behaviors. In J. Maddux (Ed.), *Self-efficacy, adaption and adjustment: Theory, research and application* (pp. 109–141). New York, NY: Plenum Press.

Hlebec, V., & Ferligoj, A. (2002). Reliability of social network measurement instruments. *Field Methods, 14*(3), 288–306.

Horst, M., & Coffé, H. (2012). How friendship network characteristics influence subjective well-being. *Social Indicators Research, 107*, 509–529.

Humphreys, K., Kaskutas, L. A., & Weisner, C. (1998). The Alcoholics Anonymous Affiliation Scale: Development, reliability, and norms for diverse treated and untreated populations. *Alcoholism, Clinical and Experimental Research, 22*, 974–978. doi:10.1111/j.1530-0277.1998.tb03691.x.

Humphreys, K., Mankowski, E. S., Moos, R. H., & Finney, J. W. (1999). Do enhanced friendship networks and active coping mediate the effect of self-help groups on substance abuse? *Annals of Behavioral Medicine, 21*, 54–60. doi:10.1007/BF02895034.

Humphreys, K., & Noke, J. (1997). The influence of post-treatment mutual help group participation on the friendship networks of substance abuse patients. *American Journal of Community Psychology, 25*(1), 1–16.

Jason, L. A., Davis, M. I., Ferrari, J. R., & Anderson, E. (2007a). The need for substance abuse after-care: Longitudinal analysis of Oxford House. *Addictive Behaviors, 32*, 803–818. doi:10.1016/j.addbeh.2006.06.014.

Jason, L. A., & Glenwick, D. S. (2012). Introduction: An overview of methodological innovations in community research. In L. A. Jason & D. S. Glenwick (Eds.), *Methodological approaches to community-based research* (pp. 3–10). Washington, DC: American Psychological Association.

Jason, L. A., Olson, B. D., & Foli, K. (2008). *Rescued lives: The Oxford House approach to substance abuse*. New York, NY: Routledge.

Jason, L. A., Stevens, E., Ferrari, J. R., Thompson, E., & Legler, R. (2012). Social networks among residents in recovery homes. *Advances in Psychology Study, 1*, 4–12.

Kaplan, H. B. (1996). Psychosocial stress from the perspective of self theory. In H. B. Kaplan (Ed.), *Psychosocial stress: Perspectives on structure, theory, life-course and methods* (pp. 175–244). San Diego, CA: Academic Press.

Kaskutas, L. A., Bond, J., & Humphreys, K. (2002). Social networks as mediators of the effect of Alcoholics Anonymous. *Addiction, 97*, 891–900. doi:10.1046/j.1360-0443.2002.00118.x.

Kelly, J. G. (2006). *Becoming ecological: An expedition into community psychology*. New York, NY: Oxford University Press.

Kelly, J. F., Stout, R. L., Magill, M., Tonigan, J. S., & Pagano, M. E. (2010). Mechanisms of behavior change in Alcoholics Anonymous: Does AA lead to better alcohol use outcomes by reducing depression symptoms? *Addiction, 105*, 626–636. doi:10.1111/j.1360-0443.2009.02820.x.

Kelly, J. F., & Urbanoski, K. (2012). Youth recovery contexts: The incremental effects of 12-step attendance and involvement on adolescent outpatient outcomes. *Alcoholism, Clinical and Experimental Research, 36*(7), 1219–1229.

Longabaugh, R., Wirtz, P. W., Beattie, M. C., Noel, N., & Stout, R. (1995). Matching treatment focus to patient social investment and support: 18-month follow-up results. *Journal of Consulting and Clinical Psychology, 63*, 296–307. doi:10.1037/0022-006X.63.2.296.

Magnusson, D. (1987). *Individual development from an interactional perspective*. Hillsdale, NJ: Lawrence Erlbaum.

Malloy, J. P. (1988). *Oxford house manual 2*. Silver Spring, MD: Oxford House Inc.

Marsden, P. V. (2011). Survey methods for network data. In J. Scott & P. J. Carrington (Eds.), *The SAGE handbook of social network analysis* (pp. 370–388). Thousand Oaks, CA: Sage.

Montgomery, H. A., Miller, W. R., & Tonigan, J. S. (1993). Differences among AA groups: Implications for research. *Journal of Studies on Alcohol, 54*, 502–504.

Moos, R. H. (1994). *The Social Climate Scales: A user's guide* (3rd ed.). Palo Alto, CA: Mind Garden Inc.

Moos, R. H. (2008). Active ingredients of substance use-focused self-help groups. *Addiction, 103*, 387–396. doi:10.1111/j.1360-0443.2007.02111.x.

Moos, R. H., & Moos, B. S. (2006). Rates and predictors of relapse after natural and treated remission from alcohol use disorders. *Addiction, 101*, 212–222. doi:10.1111/j.1360-0443.2006.01310.x.

Patulny, R. (2011). Social trust, social partner time and television time. *Social Indicators Research, 101*, 289–293.

Polcin, D. L., Korcha, R., Bond, J., Galloway, G., & Lapp, W. (2010). Recovery from addiction in two types of sober living houses: 12-month outcomes. *Addiction Research and Theory, 18*, 442–455. doi:10.3109/16066350903398460.

Richman, A., & Neumann, B. (1984). Breaking the 'detox loop' for alcoholics with social detoxification. *Drug and Alcohol Dependence, 13*, 65–73. doi:10.1016/0376-8716(84)90033-4.

Ripley, R. M., Snijders, T. A. B., & Preciado, P. (2013). *Manual for RSiena*. Oxford, UK: Department of Statistics, Nuffield College.

Rynes, K. N., & Tonigan, J. S. (2012). Do social networks explain 12-step sponsorship effects? A prospective lagged mediation analysis. *Psychology of Addictive Behaviors, 26*(3), 432–439.

Schachter, S. (1951). Deviation, rejection, and communication. *Journal of Abnormal and Social Psychology, 46*, 190–207. doi:10.1037/h0062326.

Snijders, T. A. B. (2001). The statistical evaluation of social network dynamics. *Sociological Methodology, 31*, 361–395. doi:10.1111/0081-1750.00099.

Snijders, T. A. B., & Bosker, R. J. (2012). *Multilevel analysis: An introduction to basic and advanced multilevel modeling* (2nd ed.). Thousand Oaks, CA: Sage.

Snijders, T. A. B., van de Bunt, G. G., & Steglich, C. E. G. (2010). Introduction to stochastic actor-based models for network dynamics. *Social Networks, 32*, 44–60. doi:10.1016/j.socnet.2009.02.004.

Steglich, C., Sinclair, P., Holliday, J., & Moore, L. (2012). Actor-based analysis of peer influence in a stop smoking in schools trial (ASSIST). *Social Networks, 34*, 359–369.

Stevens, E. B., Jason, L. A., & Ferrari, J. R. (2011). Measurement performance of the Sense of Community Index in substance abuse recovery communal housing. *Australian Community Psychologist, 23*, 135–147.

Todd, N. R., Allen, N. E., & Javdani, S. (2012). Multilevel modeling: Method and application for community-based research. In L. A. Jason & D. S. Glenwick (Eds.), *Methodological approaches to community-based research* (pp. 167–186). Washington, DC: American Psychological Association.

Vaillant, G. E. (1983). *The natural history of alcoholism*. Cambridge, MA: Harvard University Press.

Vaillant, G. E. (2003). A 60-year follow-up of alcoholic men. *Addiction, 98*, 1043–1051. doi:10.1046/j.1360-0443.2003.00422.x.

Veenstra, R., Dijkstra, J. K., Steglich, C., & Van Zalk, M. H. W. (2103). Network–behavior dynamics. *Journal of Research on Adolescence, 23*(3), 399–412.

Zywiak, W. H., Longabaugh, R., & Wirtz, P. W. (2002). Decomposing the relationships between pretreatment social network characteristics and alcohol treatment outcome. *Journal of Studies on Alcohol, 63*(1), 114–121.