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## Running head: COMPLEX CONTEXTS

## Complex Contexts within Oxford Houses: Psychiatrically Comorbid Social Networks

A Dissertation Proposal Defense

Presented in

Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

By

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May 11, 2022

Department of Psychology

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## **Biography**

The author was born in Chicago, IL. on March 5<sup>th</sup>, 1979. He graduated from Richard J. Daley Community College as an Associate of Arts with high honors in 2014; in 2016, he earned a Bachelor of Arts degree in Psychology from Governors State University, a Master of Arts (2020), and a Ph.D. (2022) in Community Psychology from DePaul University.

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#### Abstract

The benefits of social network activity within a recovery home are demonstrative through friendships that are manifested by abstinent individuals through their day-to-day interactions. The social network bonds that these residents build serve as motivating factors that prompt the engagement of pro-social behaviors while also discouraging destructive behaviors such as relapse. Recovery home residents with psychiatric comorbidities experience unique challenges, regarding long-term recovery outcomes. The aim of the current research is to explore the microcosms of comorbid recovery home (Oxford House) residents on loaning, friendship, and advice-seeking ties, and to understand their overall recovery factor scores. We found that psychiatrically comorbid Oxford House residents had lower recovery factor scores (overall), created and maintained friendships at the same rate as their non-comorbid counterparts, were more likely to seek advice from other psychiatrically comorbid residents, and were more likely to receive a loan – a measure of trust.

*Keywords*: psychiatric comorbidity, recovery home, Oxford House, substance use disorder, long-term recovery

#### Complex Contexts within Oxford Houses: Psychiatrically Comorbid Social Networks

#### **Introduction: Literature Review and Project Overview**

#### **Oxford House Systems and Networks**

Recovery homes are the most utilized form of substance use disorder (SUD) post-treatment aftercare in the United States (Polcin et al., 2010). It is estimated that there are over 17,000 recovery homes in the United States that serve about 270,000 individuals over the course of a calendar year (Jason, Wiedbusch, Bobak, & Taullahu, 2020). Recovery homes provide transitional, cost effective, recovery supportive housing (Jason & Ferrari, 2010), and serve to bridge the gap between inpatient treatment, or an institutional setting, and the full reentry into mainstream society. The National Association of Recovery Residences (NARR) categorize recovery homes into four (4) levels: 1) Peer-Run, 2) Monitored, 3) Supervised, and 4) Service Provider. These criteria are a classification system for recovery homes located within the United States. Levels 2, 3, and 4 each have at least one compensated employee (e.g., counselor, recovery coach, registered nurse), with level 1 relying solely on its residents to democratically oversee and enforce the day-to-day responsibilities. Recovery homes are construed as safe residences that provide a community reinforcement approach, attempting to reverse the reinforcing properties of SUD by creating immersive environments that emphasize the rewards of living an abstinence-based lifestyle (Meyers & Miller, 2001).

Oxford Houses are classified as NARR level-one recovery homes, because they are democratically run, single sex (exceptions are made for minor children), non-professional, self-governing recovery homes. Prior to Oxford House residency, current house members interview prospective applicants who must receive an 80% majority vote to be accepted into the home. Oxford Houses are widespread throughout the United States and the spectrum of their locations is diverse (Kassanits et al., 2019). Currently, there are nearly 3,000 Oxford Houses located throughout the United States and several other countries (Oxford House, 2020). Oxford Houses are an attractive setting for individuals seeking post-treatment aftercare because they are a low-cost, socially

supportive, and effective transitional environments that assist individuals with abstinence-based integration into mainstream society (Jason & Ferrari, 2010).

Oxford House Inc. was listed on the Substance Abuse and Mental Health Services Administration's National Registry of Evidence-based Programs and Practices in 2011 (SAMHSA, 2018). The average number of residents who co-inhabit an Oxford House ranges anywhere between six and twelve individuals. Each house is responsible for conducting weekly business meetings, which are facilitated by the democratically elected house president. Current residents are expected to attend these business meetings, contribute an equal portion toward house expenses (i.e., rent, fines), refrain from disruptive behaviors, maintain house cleanliness through assigned chores, and abstain from alcohol and illicit substance use (Jason & Ferrari, 2010). Per Oxford House Inc. policy, the Oxford House organization does not own any of the residential properties; it simply encourages groups of individuals who are seeking abstinence-based recovery to rent a house from the property owner and then seek affiliation with the Oxford House organization (Oxford House, 2020). The Oxford House Annual Report (2020) states that new Oxford Houses are established when/if there are none in an area where they are needed, or when the demand for an Oxford House exceeds the availability of existing ones in that area (e.g., if the existing Oxford Houses in the area are full). Unlike typical recovery homes, Oxford Houses have no length of stay restrictions; residents can stay indefinitely, if they choose.

The Oxford House recovery home model is a total abstinence approach to recovery where residents typically attend 12-step groups (e.g., Alcoholics Anonymous, Narcotics Anonymous). A randomized clinical trial (Majer, Jason, Aase, Droege, & Ferrari, 2013) demonstrated that individuals who were randomly assigned to an Oxford House, upon completing inpatient treatment, were 5.7 times more likely to maintain complete abstinence at 2-years, independent of 12-step involvement, compared to those who were randomly assigned to a usual care condition (Majer, Jason, Aase, Droege, & Ferrari, 2013). Residential post-treatment/aftercare settings have shown to

reduce relapse rates (Laudet & White, 2009) and psychiatric severity, when compared to nonresidential aftercare settings, in a randomized clinical trial among residents with psychiatric comorbidity (Majer, Jason, & Chapman, 2016). Schaefer, Cronkite, and Hu (2011) found that for each additional month spent in aftercare (e.g., recovery home), the odds of continued abstinence increased by 20%. In another randomized clinical trial by Jason, et al. (2007), participants assigned to an Oxford House, compared to those assigned to the usual aftercare condition reported less substance abuse at the six-month follow-up. Additionally, an Oxford Houses have been found to be effective resources that facilitate community reintegration among residents with SUD/psychiatric comorbidity (Majer et al., 2002a; Majer et al., 2008), and for persons with high levels of psychiatric severity who are living in recovery residences (Bobak, Majer, & Jason, 2021; Laudet et al., 2000).

#### Psychiatric Comorbidity and Severity

Psychiatric disorders consist of behavioral and psychological symptomologies that are atypical, maladaptive, impair function, are contextually inappropriate, and/or cause personal distress according to the current Diagnostic Manual of Mental Disorders (American Psychiatric Association; APA, 2022). The term "comorbidity" refers to the simultaneous presence of two or more independent mental disorders (e.g., SUD and post-traumatic stress disorder) with symptoms that exist alongside one another and typically do not overlap (Morisano et al., 2014), whereas "severity" refers to the number of diagnostic criteria of disorder endorsed by the patient and referring to the degree of impairment or distress (APA, 2022). Daigre et al. (2017) found that greater SUD severity is associated with higher levels of psychiatric severity, resulting in greater levels of impaired functioning; further challenging intervention efforts aimed at reducing psychiatric symptoms. Furthermore, those affected by high levels of psychiatric severity - the extent to which psychiatric symptoms cause impairment - are exposed to higher levels of risk that are related to negative health, emotional, psychological, and social outcomes (Morisano et al., 2014; Drake, Mueser, Burnette, & McHugo, 2004). In the present study, the terms "psychiatric comorbidity" and "psychiatric severity"

are used to indicate the presence of a SUD and a co-occurring mental disorder (comorbidity) and to address the degree of symptomatological impairment (severity). This language will be used to avoid confusion and misunderstanding by creating a precise framework for communication.

Research has shown that roughly half of those who report a mental illness throughout their lifetime also report similar lifetime prevalence rates for a SUD (Morisano, Babor, & Robaina, 2014; Kelly & Daley, 2013), suggesting that psychiatric symptoms are associated with SUDs. The prevalence of comorbidity is proportionally greater among persons with a SUD than those who do not have a SUD (Torrens et al., 2012), while nearly half of adults with a SUD psychiatric comorbidity fail to receive treatment for either the SUD or the mental disorder (SAMHSA, 2016). For example, studies have found that individuals with SUD and co-occurring psychiatric disorders were less likely to have either disorder in remission at a 2-year follow-up (Ritsher et al., 2002; Ouimette, Finney & Moos, 1999), with lower retention rates in SUD treatment being related to deficits in recovery outcomes and social adjustment (Kelly & Daley, 2013; Moos, 2006).

The prognoses for those who are experiencing psychiatric comorbidity are poor, due to the presence of complexity in overlapping symptomology. For example, individuals with a psychiatric comorbidity had poorer post-treatment outcomes compared to those had a SUD and no co-occurring mental disorder (Aase, Jason, Ferrari, Li, & Scott, 2014); moreover, individuals with psychiatric comorbidity were found to have lower quality of life scores when compared to the general population and individuals with minor health problems (Fei, Yee, & Habil, 2016). Additionally, substance misuse has shown to be a risk factor (among others) for the onset of psychiatric disorders (Enez-Darcin, Nurmedov, Noyan, Yilmaz, & Dilbaz, 2015). Individuals with SUDs experience various impairments that include cognitive, behavioral, and physiological symptoms which may contribute to psychiatric comorbidity patterns and prevalence rates for co-occurring psychiatric disorders (American Psychiatric Association, 2022). Psychiatric comorbidity prevalence rates were

highest for anxiety disorders, affective disorders, and antisocial personality disorder among Oxford House recovery home residents (Majer et al., 2002a).

#### Juxtaposing Social Exchange, Social Network, and Dynamic Systems Theories

Social exchange theory is based on the premise that relationships are created and maintained through a cost/benefit analysis. Social exchange theory does not measure social relationships based on emotional metrics but relies on logic to determine the strength or directionality of a relationship. These measurements may produce data that can determine if a participant is putting more, equal, or less effort into a relationship. Social network theory takes it a step further, by providing a framework that allows researchers to understand how relationships form between people, groups, or organizations with similar interests/dislikes; explaining how networks influence behavior. Social network theory examines the formation (creation), development (strength) and the dissolution (dissolvement) of a social network. Dynamic systems theory incorporates similar principles to social network theory, but without limitations; addressing principles of change and development over time, without constraints on any specific endpoint (Thelen & Ulrich, 1991). What separates dynamic systems theory from social network theory is that dynamic systems theory examines the processes of change, over time, instead of the outcomes. Dynamic systems theory allows researchers to examine cycles of change, from one timepoint to the next, of stabilization and destabilization (Thelen & Ulrich, 1991), providing the groundwork for measuring the dimensions of a dynamic system. Applying dynamic systems theory can help us understand the ways that components, or actors of a network are interconnected and how individuals interact and behave (Houchin and MacLean 2005; Stoebenau and Valente 2003).

**Social Exchange Theory and Friendship Ties.** Sociologist George Homans (1958) proposes that social relationships are the result of an exchange process. Throughout this process, participants seek to minimize costs and maximize benefits. Social exchange theory focuses on the creation of social relationships through repeated exchanges, assessing the costs and benefits to determine whether to

continue or terminate the association, and the ways that these relationships both constrict and promote actors to exercise their influence and power (Cook et al., 2013). For example, if the risks outweigh the rewards, it is likely that the relationship will be abandoned. Typically, issues like social support have been addressed by assuming the social environment is fixed over the period of a study; this has even been true in network-based conceptualizations (Walker, Wasserman & Wellman, 1993).

Friendship provides access to social support, consisting of information sharing, emotional support, positive feedback, and a myriad of recovery resources (e.g., monetary loaning; Cohen & McKay, 1984), which predict long-term abstinence (Longabaugh, Wirtz, Zywiak, & O'malley, 2010). In a study by Jason, Davis, Ferrari, and Anderson (2007), recovery home residents who endorsed one other housemate as a friend were likely to be abstinent at the one-year follow-up. Additionally, individuals who remained in a recovery home for a minimum of six months showed significant improvements in their recovery outcomes (Jason, Stevens, Ferrari, Thompson, & Legler, 2012). Individuals who are interested in recovering from a SUD have been shown to benefit from social support (Kelly, Hoeppner, Stout, & Pagano, 2012), and one recent investigation (Majer, Jason, & Bobak, 2021) demonstrated abstinence social support, compared to general social support, to be a more robust stress buffer among recovery home residents with psychiatric comorbidity. However, identifying social dynamics in terms of recovery home friendships among abstinent individuals in their day-to-day interactions would help explain how abstinent social support produces recovery home benefits. Therefore, the friendship bonds that recovery home residents build tend to serve as motivating factors that prompt the engagement of pro-social behaviors while also discouraging destructive behaviors such as relapse (Polcin, 2009).

**Social Network Theory and Willingness to Loan.** Social network theory supposes that relationship attributes (e.g., willingness to loan) are more important than any insular actor. A social network is a map that links individuals in a social relationship, and these relationships are discussed

in terms of nodes and ties. The term 'social network' has evolved to mean anything from an exclusive club to a social media website, which can therefore lead to confusion (Borgatti & Halgin, 2011). For this study, any relationships among a dyad of actors will be referred to as a social network (Hahm et al., 2012). These dyads connect along shared points (edges) that link the nodes or actors (vertices), sometimes indirectly, of a social network. Dissimilar to groups, social networks do not have natural boundaries, and they do not need to be connected. These disconnected parts of the social network hold the potential to become connected over time, meaning that networks are dynamic and ever changing.

Trust is an important element within a recovery-based social network, leading to greater social support and cooperation among individuals (Yeng, Tseng, & Wang, 2015). Obligations and expectations are dependent on trustworthiness, contributing to the ability of the social network to facilitate information-flow and move towards cultivating social norms, and sanctions when those norms are breached (Coleman, 1988). A willingness to loan money (\$100 or \$500) is a quantifiable measure of trust, which is required for an individual to feel confident that someone within his or her social network can return the favor (Rost, 2010). Lastly, wages provide an individual with stability and allow for the pursuit of recovery related activities (Cloud & Granfield, 2008).

**Dynamic Systems Theory and Advice Seeking.** Dynamic systems theory is commonly used to explain a system in which a large network of factors, absent of a central control, with simple rules of operation that give rise to complex collective behavior patterns, sophisticated advice processes, and adaptation via information sharing and learning (De Bot, Lowie, & Verspoor, 2007). Dynamic systems theory can be used to describe the complex changing behaviors of a social network that emerge from the collective actions of many interacting components (Mitchell et al., 2009). Dynamic systems theory can be used to explain a set of variables that interact over time, and advice seeking falls within the realm of a dynamic process. There are several characteristics of dynamic systems theory, such as the longitudinal interaction of factors and systems, initial condition dependency,

non-linear, resource dependence, and iterative development (De Bot et al., 2007). Unpredictability and nonlinearity are characteristics of a dynamic system (Winder 2007; Scoones 1999).

Complex systems (e.g., recovery home residents sharing a living space) can be broken down into sets of interacting factors. Dynamic systems models tend to be characterized by a complete interconnectedness, where every variable is interrelated (De Bot, Lowie, & Verspoor, 2007). Therefore, changes in one variable result in changes to all other variables that are part of the same network. In the complex systems framework, the outcome of development over time cannot be accurately calculated because the interacting variables are fluid and continuously change (De Bot et al., 2007). To analyze a dynamic system trajectory, the system must be simulated through iterations. Dynamic systems theory may help to explain the fluid nature of advice seeking behaviors. Through a dynamic systems theory perspective, this study will include an analysis of the network goal of advice seeking, to better understand complex systems that will provide insight by examining the fluidity of goal-oriented nodes within a social network.

#### **Recovery Factor**

The Substance Abuse and Mental Health Services Administration (SAMHSA, 2011) revised its framework of recovery to reflect a more inclusive and holistic approach for the individual and to include contextual components of well-being (i.e., hope, self-efficacy, purpose, self-esteem, personal wellbeing, social support, having a stable and safe home, financial stability). A single factor that could represent recovery at both the environmental and individual levels was constructed in the present investigation across four markers that coincide with a recovering individual's wellbeing: the amount of money they make, levels of stress that they are experiencing, the stability of their social support network, and their self-esteem. The recovery factor scores were derived from a confirmatory factor analysis across the following recovery capital indicators: wages, self-efficacy, stress, self-esteem, social support, Alcoholics Anonymous (AA) affiliation, quality of life, and length of stay in a recovery residence. A factor analysis supports the single latent recovery factor

(Jason et al., 2021). The latent recovery factor is meant to be a global representation comprised of the elements that have been shown to encompass recovery from SUD (Jason et al., 2021). Therefore, it is a useful tool for studying the interrelations of network measures (i.e., centrality, density, reciprocity, transitivity) in identifying how these network measures relate to psychiatric comorbidity among Oxford House recovery home residents.

#### Rationale

The current study seeks to build on previous social network literature from Bobak, Majer, and Jason (2021) that demonstrated homophily with respect to psychiatric severity among Oxford House residents by conducting a longitudinal analysis that will explore the formation, maintenance, and disillusion of network ties. The present research uses social exchange, social network, and dynamic systems theories as a foundation, coupled with a stochastic actor-oriented modelling framework (described below), to explore if friendship, loaning, and advice seeking ties, along with recovery factor scores, are predictive dimensions for persons with psychiatric comorbidity who are living in an Oxford House.

Psychiatric symptoms are contributory factors for substance misuse, usually resulting in selfmedicating behaviors (Laudet et al., 2000) making individuals with psychiatric comorbid substance use disorders a high-risk population. Although individuals with SUDs and psychiatric comorbidity are responsive to initial treatment interventions (Burns, Teesson, & O'Neill, 2005), their posttreatment outcomes tend to be worse compared to individuals with SUDs who do not have a cooccurring psychiatric disorder (Kushner, Abrams, Thuras, Hanson, Brekke, & Sletten, 2005). However, Majer et al. (2008) found Oxford House residents who exhibited psychiatric comorbidity demonstrated significant improvements in mental health outcomes at a one-year follow-up and reported statistically comparable length of stay rates compared to residents who did not report psychiatric comorbidity. Although research evidence suggest Oxford Houses are effective in helping residents with psychiatric comorbidity, there is a need to understand how social dynamics create

therapeutic outcomes for this vulnerable population. The proposed analyses, which include an examination of the latent recovery factor, will provide deeper insights into social support by critically examining aspects of social dynamics related to recovery outcomes for this vulnerable population.

An Oxford House resident's selection and endorsement of friendship, monetary loaning (trust), and advice-seeking behaviors describe elements of social capital within the home (Jason, Guerrero, Lynch, Stevens, Salomon-Amend, & Light, 2020). Although the body of research that examines SUD, recovery homes, and comorbid psychiatric severity is robust (Abou-Saleh & Janca, 2004; Grant et al., 2004; Majer, Payne, & Jason, 2014; Regier et al., 1990), the literature lacks a clear description of the linkages between psychiatric severity and social network composition, recovery capital, and the dynamic processes that exist at the individual and house levels.

It is important for an Oxford House resident to have at least one friend in the house, during their stay. This has shown to increase their odds of maintaining abstinence (Jason, Davis, Ferrari, & Anderson, 2007). Friendships are created, maintained, and dissolve through a cost/benefit analysis of the relationship (Cook, 2013), as stated in social exchange theory (Homans, 1958), and provide social support resources that are contributory factors towards sustaining long-term recovery. However, it is unclear whether high PSI scoring Oxford House residents with psychiatric comorbidity can create and maintain friendships at the same rate as residents without a psychiatric comorbidity.

After the formation of a friendship tie, it would be beneficial to explore the role that trust contributes towards maintaining a friendship. Through a social network theory lens of exploration, this research will examine psychiatric comorbid Oxford House residents' interactions with others inside of their house-specific social network, in terms of their willingness to loan money (a catalyst for trust) to other residents. These behavior processes are not static, as they tend to change over time. Dynamic systems theory is an ideal framework for explaining these changes. The need to form

and maintain friendships, cultivate trust, and seek or give advice and guidance from members in their immediate social network are determinant recovery factors that predict long-term abstinence. Little is known about the underlying mechanisms behind seeking advice from trusted friends, over time, and how they affect individual and house level recovery factor scores. Therefore, we hypothesize that these processes will look different for Oxford House residents who have psychiatric comorbidity than other residents.

The current study proposes to contribute in several ways. Firstly, an exploration into possible differences between high and no PSI scoring groups is necessary to parse out the significant vs. non-significant relationships among recovery factors. Secondly, an analysis of social network ties among Oxford House residents will be used to understand cohesion, influence, and selection differences between these two groups. Lastly, the purpose of this research will be to explore the microcosms of PSI scoring Oxford House residents at the loaning, friendship, and advice-seeking levels to understand how these domains contribute to their overall recovery factor scores.

#### **Aims: Statement of Hypotheses**

*Hypothesis I.* At the resident's initial survey wave, Oxford House residents with psychiatric comorbidity will significantly have fewer loaning, friendship, and advice seeking ties, as well as lower recovery factor scores.

*Hypothesis II.* Over time (longitudinally), Oxford House residents with psychiatric comorbidity will form fewer friendship ties, have a lower willingness to loan, seek less advice, and have lower recovery factor scores, in contrast to Oxford House residents without psychiatric comorbidity.

#### DESIGN

*Participants and Procedures*. Self-report survey data were collected every four months, over a two-year period, from Oxford House residents in Texas, Oregon, and North Carolina for a total of seven (7) waves – including baseline; the three geographical sites were selected to amplify the

generalizability of our results. There were 714 Oxford House residents throughout the 2-year study period; 93% (n = 666) agreed to participate in the study. Of those, 74% (n = 497) left the Oxford House at some time during the 6-wave study period. The present sample had a PSI mean of 0.146 and a SD of 0.185. Participants (n = 82) with PSI scores  $\ge 0.331$  (0.146 + 0.185) comprised the high PSI group, whereas other participants (n = 472) represented the low/zero PSI group. The survey included questions regarding sociodemographic information: age, race/ethnicity, sex/gender, marital status, drug of choice, length of substance misuse and abstinence, length of stay in an Oxford House, level of education, and employment status. The sample percentages, broken down by race/ethnicity: White (78.8%), Latinx (10.1%), Black (8.6%), and Other (2.5%). The small number of cases within ethnicity categories in the present study limited a full analysis of ethnicity groups. However, a recent investigation found unique effects among African American recovery home residents (Jason, L.A., Guerrero, M., Bobak, T., Light, J.M., & Stoolmiller, M., 2021; Jason et al., 2020), so to extend these findings in relation to social dynamics among residents with psychiatric comorbidity, race/ethnicity was categorized into a dichotomous variable for analyses by comparing participants who reported their ethnicity as African American (n = 62) to a collapsed group of all other reported ethnicities ("other," n = 565). Participants were relatively equal with respect to their gender/sex (51.7% male & 48.3% female). Oxford Houses are single sexed, which allows researchers to dichotomize sex into a house level predictor. Participants were evenly split on education level (high school or less = 43.9%vs. some college = 43.7%), with 12.4% reporting college degree or higher, and the majority were employed full-time (59%). In addition, participants reported an average length of stay in an Oxford House of 6.13 months with a SD of 9.36.

Participants were recruited with the assistance of individual Oxford House presidents, who provided a synopsis of the research project from a script that the research team constructed, recruited the study participants, during their monthly house meeting. Trained recruiters, through individual face-to-face interactions, conducted the survey interviews. They began with a brief overview of the project; acceptance criteria included that the house president and all, or all minus one resident agreed to participate in the study. The survey questionnaires were de-identified to ensure participant confidentiality, and the DePaul University Institutional Review Board granted permission to conduct the study. Each participant was compensated \$20 for completing the survey, at every data collection wave. A social network analysis of the 42 Oxford Houses in this study will be implemented through a stochastic actor-oriented modeling (SAOM) framework using the RSIENA package in R (Ripley et al., 2020).

#### Measures

*Addiction Severity Index-Lite.* The Addiction Severity Index-Lite (ASI-Lite; McLellan et al., 1997) is used to assess problematic drug and alcohol use over the past 30 days. The ASI-Lite is shown to have good validity and reliability (Cacciola, et al., 2007).

The *Psychiatric Severity Index* (PSI) – a subscale of the ASI – is used for assessing psychiatric problem severity. The composite scores are calculated using a weighted formula that generates scores ranging from .00 to 1.00, with higher scores indicating greater psychiatric severity (McLellan et al., 1992). The PSI has excellent test-retest reliability ( $\geq$ .83) and has been used in substance abuse research for over nearly four decades (McLellan, Luborsky, Woody, O'Brien, & Druley, 1983). The PSI is a measure of overall psychiatric severity that was used as a proxy to indicate psychiatric comorbidity, by dichotomizing PSI scores into two groups (i.e., high vs low/zero) where the high PSI group indicates psychiatric comorbidity, an approach consistent with assessing psychiatric comorbidity in previous studies (Ball et al., 2004; Cridland et al., 2012; Majer et al., 2008, 2016). The high PSI group is defined by PSI scores that are  $\geq$  +1 *SD* above the mean (McLellan et al., 1983).

*Social Network Instrument.* The Social Network Instrument (SNI; Jason & Stevens, 2017) will be utilized to capture the social dynamics within each Oxford House. This instrument has been

used in several investigations on the social networks of recovery home residents (Jason & Stevens, 2017; Jason et al., 2018). This type of network measure is a reliable instrument (Hlebec & Ferligoj, 2002). The SNI has a Cronbach's alpha of .81 and all items contribute positively. The SNI is used to measure multiple relationship characteristics, where Oxford House residents rated each member of their house on the network relationships of *money loaning*, *friendship*, and *advice-seeking*; data were also collected on frequency and strength of these network ties. Each social network relationship type was measured with a 5-point Likert scale. Participant ratings were represented by an adjacency matrix with each row representing the ratings provided by an individual and each column representing the ratings received by an individual. The SAOM framework requires that all rating values be dichotomized (0 = no relationship present; 1 = relationship present) and entered as a corresponding element of the matrix. An *advice-seeking* relationship was present if the respondent reported seeking advice from another resident "very often" or "quite often", but not present otherwise (e.g., regularly, rarely, never). A money loaning relationship (i.e., a willingness to lend resources) was present if the respondent endorsed a willingness to loan either \$500 or \$100 to another house resident but was not considered present if the respondent reported lesser amounts (i.e., \$0, \$10, \$50). Friendship was present if the respondent reported that the other house resident was either a "close friend" or a "friend" but was not considered to be present if they endorsed "acquaintance", "stranger", or "adversary".

*Latent Recovery Factor.* The latent recovery factor – where higher scores indicate more positive recovery outcomes - was calculated from a confirmatory factor analysis across several recovery capital indicators (Jason et al., 2020). This measure was constructed from the following instruments:

*Wages*. Self-report data for wages, up to 30 days before survey completion, were square root transformed to reduce right skew and treated as a continuous variable.

*Quality of Life*. The World Health Organization Quality of Life Assessment-Brief (WHOQOL Group, 1998) is a 24-item questionnaire that assesses participant quality of life across social, environmental, physical, and psychosocial dimensions. This scale has been validated in substance-misusing populations (Garcia-Rea & LePage, 2010). The subscales varied in their reliability ( $\alpha$  = .89 for social relationships, .84 for environment, .83 for physical, and .83 for psychological). The alpha for the entire measure, in our sample, was .89.

Abstinence Coping Self-efficacy. The brief Drug Taking Confidence Questionnaire (DTCQ-8, Sklar, Annis, & Turner., 1999) is an 8-item survey, derived from the 50-item Drug Taking Confidence Questionnaire (DTCQ-50), that measures abstinence self-efficacy (Stevens, Jason, Ferrari, & Hunter, 2010). The DTCQ-8 accounts for 95% of the total variance from the DTCQ-50 and correlated with 0.97 of the total DTCQ-50 scores (Skylar, Annis, & Turner, 1999). The survey includes questions that prompt participants to consider themselves in eight, theoretically high-risk situations and indicates how confident they are in their abilities to resist the temptation to use alcohol, or illicit substance given the hypothetical circumstances. This measure, for our sample, has good reliability ( $\alpha$  =.95).

Self-esteem. The Rosenberg's Self-Esteem Scale (Rosenberg, 1965) measures participants' positive and negative perspectives about themselves. The Self-Esteem Scale (SES) is a 10-item measure that utilizes a 4-point Likert Scale that ranges from "strongly agree" to "strongly disagree". Items from this measure include but are not limited to: "I think I have a number of good qualities", "I take a positive attitude towards myself", and "I feel I do not have much to be proud of". The internal reliability ( $\alpha$  =.92) of the SES is good, for our sample.

*Stress*. The Perceived Stress Scale (PSS, Cohen et al., 1983) measures the degree in which participants perceive situations in their lives to be stressful, in the last 30 days. The

PSS consists of 4-items measured on a 5-point Likert scale ranging from "never" to "very often". The four items are: 1) "how often have you felt that you were unable to control the important things in your life", 2) "how often have you felt confident about your ability to handle your personal problems", 3) "how often have you felt that things were going your way", and 4) "how often have you felt difficulties were piling up so high that you could not overcome them". The internal reliability of the PSS, for our sample, was .73.

*Social support*. The Interpersonal Support Evaluation List (ISEL, Cohen & Wills, 1985; Cohen, Mermelstein et al., 1985) measures three (3) types of perceived social support (tangible, appraisal, and belonging). Tangible support refers to instrumental aid and monetary assistance; appraisal support refers to having someone to talk to about one's problems; and belonging support refers to the availability of people with whom one might engage in activities. The ISEL consists of 12-items measured on a 4-point Likert scale ranging from definitely false to definitely true. The internal reliability of the support scale, for our sample, was .88.

Sense of Community. The Psychological Sense of Community (SOC) is a 9-item scale utilized to measure participant's sense of community (Jason et al., 2015). Examples of items include "This Oxford House is important to me" and "For me, this Oxford House is a good fit". The three subscales are Entity, Membership, and Self, and for our sample, they have Cronbach alphas of .67, .92, and .91, respectively. The SOC scale was used as a whole measure ( $\alpha = .91$ ) (Stevens, Jason, Ferrari, & Hunter, 2010; Graham, Jason, & Ferrari, 2009).

*Hope*. The State Hope Scale (Snyder et al., 1996) consists of 6 items that measure participants' current state of *hope*. The Hope measure contains two sub-scales Agency ( $\alpha = .94$ ) and Pathways ( $\alpha = .81$ ). We included a 3-item subscale of hope that measures Environmental Context (Stevens et al., 2014) ( $\alpha = .97$ ). This 9-item scale was analyzed as a whole measure, and for our sample the  $\alpha = .90$ .

#### Procedure

A social network analysis was conducted of 42 Oxford Houses using R (R Core Team, 2022) - a free, open-source statistical software environment and programming language that can be used to wrangle, analyze, and graph data. The "data.table" (Dowle, M., & Srinivasan, A., 2021), "keyring" (Csárdi, 2021), "blastula" (Iannone & Cheng, 2020), "dtplyr" (Wickham, Girlich, Fairbanks & Dickerson, 2022), "naniar" (Tierney, Cook, McBain & Fay, 2021), "network" (Butts, 2015), "sna" (Butts, 2020), "Matrix" (Bates, Maechler & Jagan, 2022), "haven" (Wickham, Miller & Smith, 2022), and "xtable" (Dahl, Scott, Roosen, Magnusson & Swinton, 2019) statistical packages were utilized to calculate network metrics. Additionally, the "RSIENA" (Ripley et al., 2020) - that is generally used to analyze the dynamics in a social network - was utilized to implement a stochastic actor-oriented model (SAOM) that will examine the endogenous co-evolution of behavior and social relationships (e.g., selection and influence). A thorough review of the construction and estimation of the SAOM framework can be found at Snijders, van de Bunt, and Steglich (2010). These statistical methodologies move beyond the individual-level focus; instead, they seek to explore the transactions between recovery home residents and their environments by illuminating the mechanisms that coalesce individual factors with their environment (Jason & Glenwick, 2016; Parkin, 2015).

#### **Analytic Approach**

*Hypothesis I*: A Multivariate Analysis of Covariance (MANCOVA) was employed to compare high (n = 85) vs. low/zero (n = 456) PSI groups. Length of stay in an Oxford House was entered as a covariate (coded 0, less than six months; coded 1, six or more months) to control for possible duration effects of recovery home living for six or more months found to influence outcomes in previous research (Jason et al., 2007), along with ethnicity (White, Asian, Native American, LatinX, and other categories coded as 0, African American category coded as 1), in relation to four dependent variables: willingness to loan money to housemates, friendship ties,

advice seeking, and recovery factor scores. This analysis was conducted to examine baseline mean differences in outcomes in relation to psychiatric comorbidity.

*Hypothesis II*: Social network analysis in RSIENA (Ripley et al., 2020) will examine bidirectional relationship patterns (i.e., reciprocity, density). Reciprocity measures the symbiosis of a friendship tie. Density is the number of friendship ties, divided by the total possible friendship ties. This statistical method will examine correlations between the latent recovery factor (social capital) and network ties (for friendship, loaning, and advice seeking); visual representations for the aforementioned network effects can be found on Figure 1.

Effect (name in RSIENA)	Representation	Explanation
Out-degree (density)		Basic tendency to have ties/form relationships
Reciprocity (recip)		Tendency toward reciprocation
PSI ego (egoX)		Actors with higher PSI scores <b>give</b> more nominations
PSI alter (altX)		Actors with higher PSI scores <b>receive</b> more nominations
PSI similarity (simX)		Tendency to nominate based on similar PSI scores/characteristics

Figure 1. Effects, Representations, and Explanations



creation of a tie maintenance of a tie termination of a tie maintenance of a 'no-tie'

RSIENA simulates longitudinal data (i.e., decisions by individual actors) based on the cumulating effects of network change mechanisms by deducing from the observed networks (Veenstra & Steglich, 2012). Several indicators of the data were considered, prior to running a SOAM (e.g., test of normality). RSIENA can be used to model network mechanisms of change through a method of moments estimation (Ripley et al., 2020), where a series of steps are utilized to respectfully measure selection, creation, maintenance, and dissolvement phenomena. Each of the 42 Oxford House networks were constrained to only include within house participant endorsements per data collection wave (e.g., wave 2 house 10) using a structural zero approach that allows researchers to combine several smaller networks into a larger one that is required in a SAOM (Snijders, van de Bunt, & Steglich, 2010). Additionally, longitudinal composition changes, accounting for actors who leave or join the network in-between waves/observations, also utilizes the structural zero approach which signifies the introduction (1) or absence (0) of an actor into the network at any data collection wave (Ripley et al., 2020; Snijders et al., 2007, 2010b; Steglich et al., 2010; Veenstra et al., 2013). RSIENA allows for a maximum of 20% missingness in data per wave (Ripley et al., 2020); there is less than 20% of missing data (e.g., network, covariate, behavioral) per wave in the current dataset. The default method for treating missing data in RSIENA were examined by Zandberg et al. (2019) and Huisman et al. (2008) and found to provide the best performance when compared to other methods of handling missing data. RSIENA also executes repeated imputations via the Robbins-Monro stochastic approximation that provide estimation results on structural and actor-level effects for longitudinal network changes. The model estimation reliability is determined via convergence statistics such as *t*-ratios (simulated vs. observed), instead of R<sup>2</sup> statistics, for each predictor. A good model convergence is determined when *t*-ratio values are  $\leq .10$ , where lesser values demonstrate better convergence, with a maximum convergence ratio threshold of 0.25 (Ripley et al., 2020).

The SAOM is structured around four (4) functions: 1) rate, 2) evaluation, 3) creation, and 4) endowment/maintenance (Ripley et al., 2020). The rate function is utilized for modeling the speed at which the dependent variable(s) changes; the evaluation function determines the probability of change; while the creation and endowment/maintenance functions identify old and new network ties and any changes (i.e., increases or decreases) in behavioral scores (Ripley et al., 2020). Currently, a method for selecting model criteria does not exist (Snijders et al., 2010), and the best way to implement stepwise modeling procedures is by adding effects (forward selection) and deleting effects (backwards selection), where significance tests and convergence statistics are used as guiding figures (Ripley et al., 2015; Schweinberger, 2012; Snijders et al., 2010). However, if too many effects are included into the model at once, the model is likely experience convergence issues (Ripley et al., 2020).

The next steps are to specify the model parameters and select effects that are theoretically relevant for this study. The relationship types that were examined in this study, via structural network effects (i.e., density, reciprocity, similarity, indegree and outdegree – see Figure 1), are friendship ties, willingness to loan, and advice-seeking; along with behavioral effects (i.e., latent recovery factor scores), and individual attributes (age, sex, and race/ethnicity); descriptive statistics for density (number of ties) and mutual dyads (reciprocity) across the friendship, loaning, and advice-seeking networks can be found below in Table 1.

	Wave 1	2	3	4	5	6
<u>Friendship Network</u>						
Density	0.76	0.81	0.75	0.75	0.79	0.81
Number of ties	822	547	728	634	778	733
Mutual dyads	327	235	292	260	331	317
Asymmetric dyads	164	77	135	110	113	92
Loaning Network						
Density	0.27	0.30	0.30	0.27	0.29	0.25

Table 1. Descriptive Statistics for Friendship, Loaning, and Advice-Seeking Networks

Number of ties	317	210	321	210	275	234
Mutual dyads	75	50	83	47	63	61
Asymmetric dyads	166	110	154	115	148	109
Advice-Seeking Network						
Density	0.37	0.49	0.41	0.45	0.49	0.54
Number of ties	320	306	407	383	499	496
Mutual dyads	88	104	126	128	158	165
Asymmetric dyads	143	95	151	127	182	165

#### Results

For hypothesis I, a MANCOVA was performed to examine differences between PSI (high vs. low/zero) groups in relation to four (baseline) outcome measures: friendship, loaning, advice-seeking, and latent recovery factor scores, while controlling for ethnicity groups (other = 0, African American = 1) and length of stay in an Oxford House (less than six months = 0, six or more months = 1). Results from the MANCOVA test demonstrated a significant main effect for PSI group, Wilks'  $\lambda$  (4, 534) = .82, p < .001,  $\eta p^2$  = .18. Follow-up ANOVA tests revealed participants with psychiatric comorbidity (high PSI group, n = 85) reported significantly lower latent recovery factor scores [M = 1.88 vs. 2.69; SE = .08, .03; F (1, 540) = 97.10, p < .001,  $\eta p^2 = .15$ ], advice-seeking scores [M = .31 vs. .48; SE = .03, .01; F (1, 540) = 29.10, p < .001,  $\eta p^2 = .05$ ], and friendship scores [M = .70 vs. .78; SE = .02, .01; F (1, 540) = 19.70 p < .001,  $\eta p^2 = .05$ ] compared to participants who did not report having psychiatric comorbidity (low/zero PSI group, n = 456). No significant differences were observed between PSI groups in relation to loaning [F (1, 540) = .125, p < .62].

In addition, although a significant covariate effect was observed for ethnicity, Wilks'  $\lambda$  (4, 534) = .98, p < .04,  $\eta p^2$  = .02, follow-up ANOVA tests and parameter estimates revealed no significant relationships for ethnicity with any dependent variable of the model (recovery factor, advice-seeking, loaning, friendship). However, length of stay in an Oxford House was a significant covariate of the model, Wilks'  $\lambda$  (4, 534) = .89, p < .001,  $\eta p^2$  = .11. Follow-up ANOVA tests revealed a significant relationship for length of stay with advice seeking, F (1, 540) = 17.72, p <

.001,  $\eta p^2 = .03$ , loaning, F(1, 540) = 27.71, p < .001,  $\eta p^2 = .05$ , and latent recovery factor scores, F(1, 540) = 27.30, p < .001,  $\eta p^2 = .05$ , but not for friendship. Parameter estimates of the model revealed length of stay was a significant negative predictor of advice-seeking, B = -.11, t(541) = -4.21, p < .001 [CI = -.155, -.056], a significant predictor of loaning, B = .09, t(541) = 5.26, p < .001 [CI = .058, .127], and a significant predictor of latent recovery factor, B = .35, t(541) = 5.23, p < .001 [CI = .216, .476].

For hypothesis II, a stochastic actor-oriented modeling (SAOM) framework was utilized via the RSIENA (R - Simulation Investigation for Empirical Network Analysis) package (Ripley et al., 2020). Table 1 includes descriptive statistics for network density, number of ties, and the numbers of mutual and asymmetric dyads across the three network types (e.g., friendship, loaning, and advice-seeking), over the six data collection waves; the number of possible ties vary between waves, as participants entered or exited the recovery homes throughout the duration of the study. Table 2 shows parameter estimates, standard errors, *p* values, confidence intervals (*b* = estimate, [95% CI Lower, Upper]), and *t* ratio statistics. The overall maximum convergence ratio (a summary measure across effects) was .1884 (the conventional threshold is 0.25; Ripley et al., 2020), indicating that this model convergence is very good; each individual parameter convergence *t* ratio (an autocorrelation between successive iterative estimates) was  $\leq$  .06 (scores closer to zero are ideal).

# Table 2: Stochastic Actor-Oriented Model Results-maximum likelihood estimationMax Overall Convergence t-ratio = 0.1884

		Parameter Estimate	SE	<i>p</i> -Value	95% Confidence Interval	Convergence <i>t</i> -ratio
Netwo	ork Dynamics					
1.	Friend rate (period 1)	3.80	0.89	<.001	(2.1, 5.5)	-0.03
2.	Friend rate (period 2)	2.61	1.03	.001	(0.6, 4.6)	0.02
3.	Friend rate (period 3)	3.32	0.79	<.001	(1.8, 4.9)	0.01

4.	Friend rate (period 4)	2.69	0.75	<.001	(1.2, 4.2)	-0.01
5.	Friend rate (period 5)	3.84	1.425	.006	(1.1, 6.6)	-0.02
6.	Friend: outdegree (density)	0.74	0.185	<.001	(0.4, 1.1)	0.05
7.	Friend: reciprocity	1.05	0.215	<.001	(0.6, 1.5)	0.04
8.	Advice rate (period 1)	1.99	0.27	<.001	(1.5, 2.5)	-0.02
9.	Advice rate (period 2)	2.21	0.44	<.001	(1.4, 3.1)	-0.03
10.	Advice rate (period 3)	2.03	0.38	<.001	(1.3, 2.8)	0.05
11.	Advice rate (period 4)	1.86	0.35	<.001	(1.2, 2.5)	0.03
12.	Advice rate (period 5)	5.62	1.20	<.001	(3.3, 7.9)	0.05
13.	Advice: outdegree (density)	-0.26	0.09	.003	(-0.4, -0.1)	-0.01
14.	Advice: reciprocity	0.88	0.14	<.001	(0.6, 1.2)	0.01
15.	Advice: PSI similarity	0.33	0.15	.002	(0.0, 0.6)	0.01
16.	Loan rate (period 1)	3.08	0.61	<.001	(1.9, 4.3)	0.03
17.	Loan rate (period 2)	2.81	0.72	<.001	(1.4, 4.2)	-0.04
18.	Loan rate (period 3)	2.46	0.42	<.001	(1.6, 3.3)	0.02
19.	Loan rate (period 4)	2.54	0.52	<.001	(1.5, 3.6)	0.02
20.	Loan rate (period 5)	3.47	0.68	<.001	(2.1, 4.8)	0.01
21.	Loan: outdegree (density)	-0.50	0.08	<.001	(-0.7, -0.3)	-0.04
22.	Loan: reciprocity	0.81	0.13	<.001	(0.6, 1.1)	-0.01
23.	Loan: PSI alter	0.38	0.18	<.001	(0.1, 0.7)	-0.04
Behav	ior Dynamics					
24.	Rate RF (period 1)	1.46	0.30	<.001	(0.9, 2.0)	0.04
25.	Rate RF (period 2)	1.22	0.29	<.001	(0.6, 1.8)	-0.01
26.	Rate RF (period 3)	1.56	0.39	<.001	(0.8, 2.3)	0.01
27.	Rate RF (period 4)	1.41	0.29	<.001	(0.8, 2.0)	0.01
28.	Rate RF (period 5)	1.83	0.48	<.001	(0.9, 2.8)	-0.05
29.	RF linear shape	0.53	0.11	<.001	(0.3, 0.8)	0.02
30.	RF quadratic shape	-0.49	0.09	<.001	(-0.7, -0.3)	-0.01
31.	RF: effect from Sex	-0.47	0.15	.002	(-0.8, -0.2)	0.01
32.	RF: effect from Race	0.57	0.25	.020	(0.1, 1.1)	0.01
33.	RF: effect from PSI	-0.66	0.25	<.001	(-1.1, -0.2)	0.06

## **Network Dynamics**

Rate parameters for friendship, advice, and loaning are classified as inter-wave-specific estimates that show the amount of change in each endogenous variable – changed or determined by its relationship with other variables within the model – and sufficiently confirms variation for the model to explain (Jason, Lynch, Bobak, Light, and Doogan, 2021). Network closure parameters (e.g., outdegree [density] & reciprocity) are used to index structural tendencies that predict network ties and provide descriptive information (see Tables 1 & 2). The outdegree (density) parameters for friendship (b = 0.74, [0.4, 1.1]), advice (b = -0.26, [-0.4, -0.1]), and loaning (b = -0.50, [-0.7, -0.3]) were all significant. The negative outdegree effects for density show that the loan networks are relatively sparse and that the more such ties one has, the less likely they are to add more. Reciprocity for friendship (b = 1.05, [0.6, 1.5]), advice (b =0.88, [0.6, 1.2]) and loaning (b = 0.81, [0.6, 1.1]) were also significant and positive for all networks, suggesting a tendency for these relationships to be bidirectional. For advice networks, the more similar the PSI level between ego and alter, the more likely they are to seek advice from one another (b = 0.33, [0.0, 0.6], p = .002). For loan networks, the alter reported being willing to loan to those who high PSI scores and this effect was significant (b = 0.31, [0.1, 0.7]).

#### **Behavior Dynamics**

The model also examined predictors of latent recovery factor (RF) scores, specifically sex, race, and PSI. The RF quadratic and linear shape effects, that are included in the model, represent the shape and location of the RF distribution for the three predictors (i.e., sex, race, PSI), when the other model terms are set to zero; beyond this function, the quadratic and linear shape effects are primarily irrelevant (Jason, Lynch, Bobak, Light, & Doogan, 2021). For the RF, a negative significant parameter for sex effects show that male residents were less likely to improve their RF than females (b = -0.39, [-0.8, -0.2]). Additionally, a positive significant parameter for African American ethnicity (race) shows that African Americans had better RF scores than the other ethnicities in the sample (b = 0.63, [0.1, 1.1]). Lastly, the model included effects of PSI on the RF; a negative significant effect of high PSI as a risk factor for lower RF scores (b = -0.34, [-1.1, -0.2]) was found.

#### Discussion

This study aimed to answer three questions: 1) are there differences between Oxford House residents with psychiatric comorbidity in their ability to form, maintain, and dissolve friendship ties, loan money, and seek advice when compared to Oxford House residents without comorbidity (Hypothesis I), 2) if differences do exist, are those ties mono- or bi-directional (Hypothesis II), and 3) are the existing ties based on selection or similarity (Hypothesis II)?

Findings from the MANCOVA analysis demonstrated significant baseline deficits among residents with psychiatric comorbidity in terms of advice-seeking, friendships, and latent recovery factor scores, consistent with clinical research that demonstrated low levels of social support upon admission to inpatient treatment for persons with psychiatric comorbidity (Haverfield et al., 2019). Taken together, these findings are characteristic of functional deficits among those with psychiatric comorbidity (APA, 2022), indicating a degree of criterion-related validity for how psychiatric comorbidity was assessed in the present investigation. In addition, length of stay in an Oxford House was a significant covariate of the model. The significant positive relationship between length of stay and the latent recovery factor suggests that increased recovery home living produces crucial recovery resources for those needing a recovery home. In addition, increased length of stay was related to a greater degree of loaning, and it is possible that residents who live longer in a recover home are more financially stable to lend to others. Furthermore, the negative significant relationship between length of stay and advice-seeking suggests that newer recovery home members are more inclined to seek advice whereas more senior members are probably more experienced in their recovery and thus in less need for seeking advice. Although these claims can only be substantiated by further research, findings from Hypothesis 1 testing provide a baseline for understanding changes in social dynamics and interdependencies.

In terms of the second hypothesis, three unique interdependencies were identified among individuals with psychiatric comorbidity: advice seeking, loaning, and RF scores, but no significant interdependencies regarding friendship. These results are based on a system of stochastic difference equations, and a SOAM framework (Snijders et al., 2010), which allows researchers to treat behaviors/attitudes and relationships as mutually interacting endogenous system that longitudinally co-evolves (Jason, Lynch, Bobak, Light, & Doogan, 2021). A deeper understanding of the interplay among these dynamics is essential toward understanding how Oxford House recovery homes promote long-recovery in a shared community setting.

The results of this investigation are consistent with the social exchange, social network, and dynamic system conceptions of community-based recovery. Recovery homes provide access to social

capital, via the residents' social network, by facilitating recovery-oriented social exchanges, which can lead to changes to the recovery home social dynamics. Upon interpreting the results of this study, components from both social exchange and social network theories emerged via the dynamic systems theory (e.g., explaining the processes that preserve or undermine the development, maintenance, and dissolution of a network) (De Bot, Lowie, & Verspoor, 2007; Michelle et al., 2009); therefore, the dynamic systems theory was used as a foundational framework for interpreting the friendship, loaning, advice-seeking, and the latent recovery factor networks and their relationship with psychiatric comorbidity.

#### **Implications for Theory**

The first major finding comes from residents with psychiatric comorbidity seeking advice from those who also have psychiatric comorbidity. The dynamic systems theory can be used to explain the behavioral changes of a social network that emerge from the collective actions of many interacting components (Mitchell et al., 2009). In this case, the collective actions refer to the tendency of residents with psychiatric comorbidity to seek advice from those who also have psychiatric comorbidity. This phenomenon is often referred to as a homophily - the tendency of those who are socially connected to display preferences towards others who have similarities across demographics (i.e., values, beliefs, experienced stigma) (Bobak, Majer, & Jason, 2021). Although advice seeking was related to higher stress and lower positive recovery outcomes (Jason et al., 2020) seeking advice from individuals who are more "recovered" (i.e., who have higher RF scores) was related to beneficial outcomes (Jason, Lynch, Bobak, Light, & Doogan, 2021). Thus, findings in the present investigation draw attention to the importance of examining homophily effects when examining social dynamics, extending our understanding of social networks in terms of homophily with respect to abstinence social support (Majer et al., 2002).

The second major finding occurred on the loaning network via the PSI *alter* effect. The significant "alter" effect - a sum of the loaning scores from all the alters that the ego can utilize for a loan at any given time – suggests that alters are more likely to loan money to a housemate with psychiatric comorbidity, giving rise to complex collective behavior patterns (loaning). When a

person fails to repay a loan, the loaner may lose interest in loaning to that person in the future. However, the willingness to loan money can be seen as a measure of trust, which promotes confidence in the loan receiver's ability to pay back the loan (Rost 2010). In this instance, the alter may perceive the housemate with psychiatric comorbidity (ego) as being a low-risk candidate for receiving a loan. In addition, wages provide an individual with stability and allow for the pursuit of recovery related activities (Cloud & Granfield, 2008). A question on the Addiction Severity Index; Psychiatric Status measure reads: "Do you receive a pension for a psychiatric disability?" and alters might be more confident to loan money to those with psychiatric comorbidity because the alter believes this ego is receiving a monthly pension due to a psychiatric disability, and therefore assume that the ego is very likely to pay back the loan upon receiving their monthly entitlement. Although such a conclusion can only be corroborated in future studies, fostering trust and confidence in the (psychiatric comorbid) ego's loan repayment abilities seems to be a realistic expectation given the data in the present study. It is also possible that those with comorbid conditions are seen as needing more support or resources, and the fact that other residents are willing to share funds with the residents with comorbid status might reflect just wanting to reach out to those who are vulnerable, which is what the ethos of Oxford House recovery homes embodies.

Another major finding in this study is involves psychiatric comorbidity groups and RF scores. This negative relationship (see Table 2) indicates that as PSI scores trend higher, RF scores tend to go lower. These results are consistent with other research that demonstrated inverted relationships between increases in PSI scores and decreases in quality-of-life scores (Bobak, Majer, & Jason, 2020), along with lower levels of drug taking confidence, hope, abstinence self-efficacy, and self-esteem (Abbinanti, Bobak, & Jason, 2022). In addition, they are consistent with findings from the preliminary analysis (MANCOVA) of the present investigation that demonstrated differences in recovery factor scores in relation to psychiatric comorbidity, representing functional differences related to psychiatric comorbidity and provides empirical support for dichotomizing PSI scores as a proxy measure of psychiatric comorbidity. Perhaps more
importantly, the preliminary analysis of the SAOM found no significant effect of *ego*, *alter*, *or similarity* on the friendship network via PSI scores - thus, these effects were excluded from the final SAOM; via the dynamic systems theory, high PSI scoring OH residents, who are early in their recovery from substance use disorder, tend to fluctuate as they learn to discern what works for them and what does not. This finding suggests that high scoring PSI residents are creating, maintaining, and dissolving friendships at the same rate as their low/zero PSI scoring counterparts.

Lastly, findings of interest that are replicated from previous studies include significant RF score differences with respect to race (African American/Black) and sex (men vs. women). Jason et al. (2021) found that African American residents showed greater improvements on their RF scores when compared to the other races (Caucasian, Asian, American Indian, LatinX, Other). These findings are consistent with Harvey (2014), who found that African Americans, who were living in a recovery home at the time of data collection, had lower relapse rates than Non-Hispanic Caucasian counterparts. Additionally, men showed improved RF score outcomes that were significantly greater than their female counterparts. However, Davis and Jason (2005) found that social support characteristics are different for women than for men; where women tend to have higher levels of social support from unrelated friends, while men were more likely to endorse family members as their primary source of social support (Robles et al., 1998). In addition, Porcaro et al. (2020) found a significant negative relationship between PSI scores and coping resources among male OH residents, but this relationship was positive among the female OHs. This could be explained by the previously mentioned tendencies of men to seek social support from their family members, which could make it more difficult for them to seek that support from their recovery home roommates.

### **Implication for Practice**

In this section, I will articulate the implications for practice involving both residents and recovery homes, as well as state and federal bodies. Our work helps to understand the stigma surrounding psychiatrically comorbid Oxford House residents, which continues to be a barrier in how these individuals are provided treatment and opportunities to be re-integrated into community

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settings. Based on the literature reviewed in the introduction, those with SUDs and comorbid conditions are often not provided the types of community re-entry experiences that they need. Yet, what is often lacking is inexpensive but widely available support to help these at-risk individuals to have an ecologically positive setting to maintain their current abstinence. What we have learned is that even those with psychiatric comorbid conditions seem to make friends, and provided advice and resources, while living in these recovery homes. Although their recovery scores have a lower trajectory than others, their trajectories are still positive over time. What this means is that at the house level when current residents are voting on whether to admit a new house member, it is worth giving psychiatrically comorbid residents a chance to be successful in these settings, as they do tend to have good outcomes overall. In addition, based on prior work, there are implications as we know psychiatrically comorbid Oxford House residents are more likely to go to other psychiatrically comorbid housemates when seeking advice.

We know that an increased length of stay is a predictor for positive long-term recovery outcomes (Jason et al., 1999) and that having at least one friend in the house increases both residents' length of stay (Jason et al., 2007), which mitigates the likelihood of relapse (Bishop et al., 1998). Those with comorbid conditions that enter an Oxford House recovery home are exposed to these facilitating conditions. In fact, what we have found is that these higher risk residents are actually provided more loans from their roommates, an unexpected outcome. Federal officials, state administrators, and local jurisdictions can be assured that when these at-risk individuals are provided an Oxford House environment following SUD detox, treatment, or after existing the criminal justice system, there is a very good chance that they will be greeted positively by other residents in these recovery settings. Thus, Oxford Houses appear to be a safe and inexpensive setting in which referrals can be made, even to those with comorbid conditions.

### Limitations

One limitation of this study concerns longitudinal network analyses on small networks

where all the members are not involved in each wave. For example, our sample included 627 residents across six waves; an unrestricted network with 627 participants could hypothetically have (627 x 627) 393,129 ties per wave. However, the restricted Oxford House networks that comprise 627 participants across 42 houses – grouped together and contained within each respective recovery home - resulted in a total of 5,389 ties per wave; much fewer ties than a single, whole-network that is comprised of an equal number of participants. Therefore, increasing the total number of Oxford House specific networks in future studies would offer insight into a broader range of recovery trajectories.

Secondly, recovery homes are the largest residential, community-based post-inpatient treatment modality for individuals who are seeking recovery from SUD in the United States (Jason, Wiedbusch, Bobak, & Taullahu, 2020). Findings from this study of Oxford House recovery homes may not generalize to other types of recovery homes that are run by (or have parttime professional) staff. Oxford Houses are democratically peer-run (i.e., a Level 1 recovery home), where residents are solely responsible for managing the day-to-day house operations, financial obligations, maintenance, and rule enforcement. These characteristics make them unique, with respect to their peer-run model, in that it may influence how relationship ties form within the homes.

Lastly, regarding psychiatric comorbidity, there exists a need to measure it more accurately with specialized diagnostic instruments. The current study used the psychiatric subscale of the Addiction Severity Index (McLellan et al., 1992). This instrument only measures whether a person might have a psychiatric comorbidity but fails to capture the specific mental disorder associated with the comorbidity. In other words, our score on the PSI does not indicate which mental disorder is comorbid with the SUD.

### **Future Directions**

Future research should include whole network data from recovery homes where professional staff are present to better understand their influence on residents' long-term recovery outcomes, as

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there is a considerable research evidence (Jason et al., 2014; Light et al., 2016; Doogan et al., 2019, Jason et al., 2021) showing that social relationship dynamics affect individual recovery outcomes and vice versa. Understanding this complex process is, therefore, key to elucidating how recovery is promoted in these settings through social support, why the residential experience seems to work for some but fails for others, and how this experience might be improved or broadened to other types of settings. Overall, this investigation presents a comprehensive dynamic model of recovery home social networks that include interrelationships with friendship, advice, and loaning networks, latent recovery factor and psychiatric severity. This study demonstrates that social embeddedness (i.e., an ego's position in the relationship network) influences recovery related outcomes and has important implications for future studies to focus on the mechanisms that predict the formation of such ties.

### Conclusion

Although there are numerous studies that have examined OH recovery home residents (Jason et al., 1994), those with psychiatric comorbidity (Majer et al., 2008), and social support for residents with psychiatric comorbidity (Majer et al., 2021; Majer et al., 2002a), this study contributes to the existing literature by providing basis for using a more comprehensive, dynamic model for understanding recovery home social dynamics; particularly among psychiatric comorbid residents. Specifically, this study demonstrates how social embeddedness (i.e., one's position in a relationship network) affects recovery outcomes, loaning tendencies, and advice seeking behaviors for this population. Future studies should focus on examining mechanisms that more precisely predict the formation, maintenance, and disillusion of these types of network ties. Examining these complex processes would be instrumental in understanding how long-term recovery is facilitated within these residential, community-based settings, how social dynamics might be improved and generalized to other types of settings (i.e., recovery homes with a professional staff presence), and offer insight into why these residential experiences work for some but not for others.

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### References

- Aase, D. M., Jason, L. A., Ferrari, J. R., Li, Y., & Scott, G. (2014). Comorbid mental health and substance abuse issues among individuals in recovery homes: Prospective environmental mediators. *Mental health and substance use: dual diagnosis*, 7(2), 170-183.
- Abou-Saleh, M.T. and Janca, A. (2004), The epidemiology of substance misuse and comorbid psychiatric disorders. Acta Neuropsychiatrica, 16: 3-8. <u>https://doi.org/10.1111/j.1601-5215.2004.0075.x</u>
- American Psychiatric Association. (2022). Diagnostic and statistical manual of mental disorders (5th ed. text revision). Arlington, VA: American Psychiatric Association.
- Bates, D., & Maechler, M. (2021). Matrix: Sparse and Dense Matrix Classes and Methods. R package version 1.3-4. https://CRAN.R-project.org/package=Matrix
- Bobak, T.J., Majer, J.M., & Jason, L.A. (2021). An examination of psychiatric severity and social cohesion outcomes within Oxford Houses. *Community Mental Health Journal*, DOI: <u>https://doi.org/10.1007/s10597-021-00825-6</u>
- Borgatti, S., & Halgin, D. (2011). On Network Theory. DOI: http://dx.doi.org/10.2139/ssrn.2260993
- Burns, L., Teesson, M. and O'Neill, K. (2005), The impact of comorbid anxiety and depression on alcohol treatment outcomes. Addiction, 100: 787-796. <u>https://doi.org/10.1111/j.1360-0443.2005.001069.x</u>
- Butts, C., T. (2020). sna: Tools for Social Network Analysis. R package version 2.6. https://CRAN.R-project.org/package=sna
- Butts, C. (2015). \_network: Classes for Relational Data\_. The Statnet Project (<URL: http://www.statnet.org>). R package version 1.13.0.1, <URL: https://CRAN.R-project.org/package=network>.
- Butts, C. (2008). "network: a Package for Managing Relational Data in R." \_Journal

of Statistical Software\_, \*24\*(2). <URL: https://www.jstatsoft.org/v24/i02/paper>.

- Cacciola JS, Alterman AI, McLellan AT, Lin Y-T, & Lynch KG. (2007). Initial evidence for the reliability and validity of a "Lite" version of the Addiction Severity Index. *Drug and Alcohol Dependence*, 87:297–302.
- Cloud W, & Granfield R. (2008). Conceptualizing recovery capital: expansion of a theoretical construct. *Subst Use Misuse*, 43(12-13):1971-86. doi: 10.1080/10826080802289762.
  PMID: 19016174.
- Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A global measure of perceived stress. *Journal of Health and Social Behavior*, 24, 385–396.
- Cohen, S., & McKay, G. (1984). Social support, stress and the buffering hypothesis: A theoretical analysis. In A. Baum, S. E. Taylor, & J. E. Singer (Eds.), Handbook of psychology and health (pp. 253-267). Hillsdale, NJ: Erlbaum.
- Cohen, S., & Wills, T. A. (1985). Stress, social support, and the buffering hypothesis. *Psychological Bulletin*, 98, 310–357.
- Coleman, J. S. (1988). Social Capital in the Creation of Human Capital American Journal of Sociology, 94:, S95-S120
- Cook K.S., Cheshire C., Rice E.R.W., Nakagawa S. (2013) Social Exchange Theory. In: DeLamater J., Ward A. (eds) Handbook of Social Psychology. Handbooks of Sociology and Social Research. Springer, Dordrecht. https://doi.org/10.1007/978-94-007-6772-0\_3
- Cook S.H., Bauermeister J.A., Gordon-Messer, D., Zimmerman M.A. (2013). Online network influences on emerging adults' alcohol and drug use. *Journal of Youth and Adolescence*, 42(11):1674–1686
- Csárdi, G. (2021). keyring: Access the System Credential Store from R. R package version 1.2.0. https://CRAN.R-project.org/package=keyring
- Daigre, C., Grau-López, L., Rodríguez-Cintas, L., Ros-Cucurull, E., Sorribes-Puertas, M.,

Esculies, O., Bones-Rocha, K., & Roncero, C. (2017). The role of dual diagnosis in health-related quality of life among treatment-seeking patients in Spain. *Quality of Life Research: An International Journal of Quality of Life Aspects of Treatment, Care & Rehabilitation*, 26(12), 3201–3209. https://doi-org.ezproxy.depaul.edu/10.1007/s11136-017-1668-4

- De Bot, K., Lowie, W., & Verspoor, M. (2007). A Dynamic Systems Theory
  approach to second language acquisition. *Bilingualism: Language and Cognition*, 10(1), 7-21.
  doi:10.1017/S1366728906002732
- Drake, R. E., Mueser, K. T., Brunette, M. F., & McHugo, G. J. (2004). A review of treatments for people with severe mental illnesses and co-occurring substance use disorders. *Psychiatric Rehabilitation Journal*, 27(4), 360–

374. https://doi.org/10.2975/27.2004.360.374

- Dowle, M., & Srinivasan, A. (2021). data.table: Extension of `data.frame`. R package version 1.14.0. https://CRAN.R-project.org/package=data.table
- DSM-5. (2013). *Diagnostic and statistical manual of mental disorders*. American Psychiatric Association; Washington, D.C.

Enez Darcin, A., Nurmedov, S., Noyan, C. O., Yilmaz, O., & Dilbaz, N. (2015).
 Psychiatric comorbidity among inpatients in an addiction clinic and its association with the process of addiction. *Düşünen Adam: Journal of Psychiatry and Neurological Sciences*, 28(3), 196–203.

- Fei, Teoh Bing., J., Yee, A., & Habil M, H. (2016). Psychiatric comorbidity among patients on methadone maintenance therapy and its influence on quality of life. *American Journal on Addiction*, 25(1):49–55.
- Garcia-Rea, E. A., & LePage, J. P. (2010). Reliability and validity of the World Health
   Organization Quality of Life: Brief version (WHOQOL-BREF) in a homeless substance dependent
   veteran population. *Social Indicators Research*, *99*(2), 333–340. <u>https://doi.org/10.1007/s11205-</u>
   <u>010-9583-x</u>

- Graham, B. C., Jason, L. A., & Ferrari, J. F. (2009). Sense of community within recovery housing: Impact of resident age and income. In L.A. Jason, & J.R. Ferrari (Eds.). Recovery from addiction in communal living settings: The Oxford House model [Special Issue]. Journal of Groups in Addiction & Recovery, 4, 62-70. PMCID: PMC2909140 https://doi.org/10.1080/15560350802712405
- Grant BF, Stinson FS, Dawson DA, et al. (2004). Prevalence and co-occurrence of substance use disorders and independent mood and anxiety disorders: Results from the National Epidemiologic Survey on Alcohol and Related Conditions. *Arch Gen Psychiatry*, 61(8):807–816. doi:10.1001/archpsyc.61.8.807
- Hahm, H. C., Kolaczyk, E., Jang, J., Swenson, T., & Bhindarwala, A. M. (2012). Binge drinking trajectories from adolescence to young adulthood: The effects of peer social network. Substance Use &Amp; Misuse, 47(6), 745–756.
- Harris, P. A., Taylor, R., Thielke, R., Payne, J., Gonzalez, N., Conde, J. G. (2009). Research electronic data capture (REDCap) – A metadata-driven methodology and workflow process for providing translational research informatics support, *J Biomed Inform*;42(2):377-81.
- Haverfield, M.C., Ilgen, M., Schmidt, E., Shelley, A., Timko, C. (2019). Social support networks and symptom severity among patients with co-occurring mental health and substance use disorders.
  Community Ment. Health J., 55 (2019), pp. 768-776, <u>10.1007/s10597-019-00396-7</u>
- Hlebec V, Ferligoj A. Reliability of Social Network Measurement Instruments. *Field Methods*. 2002;14(3):288-306. doi:10.1177/15222X014003003
- Homans, G. C. (1958). Social behavior as exchange. *American Journal of Sociology*, *63*, 597–606. <u>https://doi.org/10.1086/222355</u>
- Houchin, K. and MacLean, D. (2005), Complexity Theory and strategic change: An empirically informed critique\*. *British Journal of Management*, 16: 149-166. <u>https://doi.org/10.1111/j.1467-8551.2005.00427.x</u>
- Iannone, R., & Cheng, J. (2020). blastula: Easily Send HTML Email Messages. R

package version 0.3.2. https://CRAN.R-project.org/package=blastula

- Jason, L.A., Wiedbusch, E., Bobak, T., & Taullahu, D. (2020). Estimating the number of substance use disorder recovery homes in the United States. *Alcoholism Treatment Quarterly*, *38*(4), 506 514. DOI: <u>https://doi.org/10.1080/07347324.2020.1760756</u>
- Jason, L. A., Davis, M. I., Ferrari, J. R., & Anderson, E. (2007). Longitudinal analysis of Oxford House. Addictive Behaviors, 32(4), 803-818.
- Jason, L. A., & Ferrari, J. R. (2010). Oxford House recovery homes: Characteristics and effectiveness. *Psychological Services*, 7, 92-102. DOI: <u>https://doi.org/10.1037/a0017932</u>
- 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. <u>PMCID:</u> <u>PMC3744109</u>
- Jason, L.A., Guerrero, M., Lynch, G., Stevens, E., Salomon-Amend, M., & Light, J.N. (2020). Recovery home networks as social capital. *Journal of Community Psychology*, 48, 645–657. <u>https://doi.org/10.1002/jcop.22277</u>
- Jason, L.A., Guerrero, M., Bobak, T., Light, J.M., & Stoolmiller, M. (2021). Reducing health disparities among Black individuals in the post-treatment environment. *Journal of Ethnicity in Substance Abuse*. <u>http://dx.doi.org/10.1080/15332640.2020.1861497</u>
- Jason, L.A., Guerrero, M., Salomon-Amend, M., Stevens, E., Light, J.N. & Stoolmiller, M. (2021). Context matters: Home-level but not individual-level recovery social capital predict residents' relapse. American Journal of Community Psychology, 67(3-4), 392-404. https://doi.org/10.1002/ajcp.12481
- Jason, L.A., Guerrero, M., Salomon-Amend, M., Lynch, G., Stevens, E. B., Light, J.N., Stoolmiller, M., & Doogan, N.J. (2021). Network measures of advice-seeking and resource sharing are related to well-being in recovery homes. *International Journal of Drug Policy*,
  - 92, <u>https://doi.org/10.1016/j.drugpo.2020.102970</u>
- Jason, L.A., & Stevens, E. (2017). The reliability and reciprocity of a social network

measure. Alcoholism Treatment Quarterly, 35, 317–327.

DOI: https://doi.org/10.1080/07347324.2017.1355220

- Jason, L. A., Stevens, E. & Ram, D. (2015) Development of a three-factor psychological sense of community scale. *Journal of Community Psychology*, 43 973–985.
- Kassanits, J., Bobak, T., Stevens, E., Guerrero, M., Light, J., & Jason, L.A. (2020). The relationship of Oxford Houses across heterogeneous house and setting characteristics. *American Journal of Orthopsychiatry* 90(3), 324-327. DOI: <u>https://doi.org/10.1037/ort0000437</u>
- Kelly JF, Hoeppner B, Stout RL, Pagano M. (2012). Determining the relative importance of the mechanisms of behavior change within Alcoholics Anonymous: a multiple mediator analysis. *Addiction*, 107(2):289-99. doi: 10.1111/j.1360-0443.2011.03593.x. Epub 2011 Sep 19. PMID: 21917054; PMCID: PMC3242865.
- Kelly, T.M., & Daley, D.C., (2013). Integrated treatment of substance use and psychiatric disorders, *Social Work in Public Health*, 28:3-4, 388-406, DOI: <u>10.1080/19371918.2013.774673</u>
- Kushner, M.G., Abrams, K., Thuras, P., Hanson, K.L., Brekke, M. and Sletten, S. (2005).
  Follow-up Study of Anxiety Disorder and Alcohol Dependence in Comorbid Alcoholism Treatment
  Patients. Alcoholism: *Clinical and Experimental Research*, 29: 1432-1443. https://doi.org/10.1097/01.alc.0000175072.17623.f8
- Laudet, A. B., Magura, S., Vogel, H. S., & Knight, E. (2000). Recovery challenges among dually diagnosed individuals. *Journal of Substance Abuse Treatment*, 18(4), 321-329. <u>http://dx.doi.org/10.1016/S0740-5472(99)00077-X</u>
- Laudet, A. B., & White W., L. (2008). Recovery capital as prospective predictor of sustained recovery, life satisfaction, and stress among former polysubstance users. *Substance Use Misuse*, 43:27–54.
- Light, J., & Doogan, N. (NA). RHNetTools: Data Management Tools for RH-Systems Project. R package version 2.1.3.

- Longabaugh R, Wirtz PW, Zywiak WH, O'Malley SS. (2010). Network support as a prognostic indicator of drinking outcomes: the COMBINE Study. *J Stud Alcohol Drugs*, 71(6):837-46. doi: 10.15288/jsad.2010.71.837. PMID: 20946740; PMCID: PMC2965482.
- Majer, J. M., Jason, L. A., & Bobak, T. J. (2021). An examination of abstinence social support among recovery home residents with psychiatric comorbidity. *Drug and Alcohol Dependence*. https://doi.org/10.1016/j.drugalcdep.2021.108971
- Majer, J. M., Chapman, H. M., & Jason, L. A. (2016). Comparative analysis of treatment conditions upon psychiatric severity levels at two years among justice involved persons. *Advances in Dual Diagnosis*, 9(1), 38-47. DOI: <u>https://doi.org/10.1108/ADD-07-2015-0015</u>
- Majer, J. M., Jason, L. A., Aase, D. M., Droege, J. R., & Ferrari, J. R. (2013). Categorical
  12-step involvement and continuous abstinence at two-years. *Journal of Substance Abuse Treatment*, 44, 46–51. DOI: <u>https://doi.org/10.1016/j.jsat.2012.03.001</u>
- Majer, J. M., Jason, L. A., Ferrari, J. R., & North, C. S. (2002a). Comorbidity among
   Oxford House residents: A preliminary outcome study. *Addictive Behaviors*, 27(5), 837–845.
   <a href="https://doi-org.ezproxy.depaul.edu/10.1016/S0306-4603(01)00214-3">https://doi-org.ezproxy.depaul.edu/10.1016/S0306-4603(01)00214-3</a>
- Majer, J. M., Jason, L. A., Ferrari, J. R., Venable, L. B. & Olson, B. D. (2002b). Social support and selfefficacy for abstinence: Is peer identification an issue? *Journal of Substance Abuse Treatment*, 23, 209-215.
- McLellan A., T, Cacciola J., S, & Zanis D. (1997). The Addiction Severity Index-Lite. *Center for the Studies on Addiction.* University of Pennsylvania/Philadelphia, VA Medical Center.
- McLellan AT, Luborsky L, Woody GE, O'Brien CP, & Druley KA.(1983). Predicting response to alcohol and drug abuse treatments. *Archives of General Psychiatry*, 40:620–625.
- Meyers, R. J., & Miller, W. R. (2001). A community reinforcement approach to addiction treatment. *Cambridge University Press*. <u>https://doi.org/10.1017/CBO9780511570117</u>
- Mitchell, A., Romano, G., Groisman, B. et al. Adaptive prediction of environmental

changes by microorganisms. *Nature* 460, 220–224 (2009). <u>https://doi.org/10.1038/nature08112</u>

- Moos, R. H., & Moos, B. S. (2006). Rates and predictors of relapse after natural and treated remission from alcohol use disorders. *Addiction*, *101*(2), 212-222.
- Morisano, D., Babor, T. F., & Robaina, K. A. (2014). Co-occurrence of substance use disorders with other psychiatric disorders: Implications for treatment services. *Nordic Studies on Alcohol and Drugs*, 31(1), 5-25.
- Ouimette, P.C., Finney, J.W., and Moos, R. H. (1999) Two-year posttreatment functioning and coping of substance abuse patients with posttraumatic stress disorder. *Psychology of Addictive Behaviors*, 13(2):105–114.

Oxford House, (2020). Annual Report, Fiscal Year 2019. Silver Spring, Md.

- Polcin DL. (2009). A model for sober housing during outpatient treatment. *Journal of Psychoactive Drugs*, 41(2):153–61.
- R Core Team (2021). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.
- Regier DA, Farmer ME, Rae DS, et al. (1990). Comorbidity of mental disorders with alcohol and other drug abuse: Results from the epidemiologic catchment area (ECA) Study. *JAMA*, 264(19):2511–2518. doi:10.1001/jama.1990.03450190043026
- Ripley, R., M., Snijders, T., A., B., Boda, Z., Voros, A., & Preciado, P. (2020). Manual for SIENA version 4.0. Oxford: University of Oxford, Department of Statistics; Nuffield College.
- Ritsher, J. B., McKellar, J. D., Finney, J. W., Otilingam, P. G., & Moos, R. H. (2002).
  Psychiatric comorbidity, continuing care and mutual help as predictors of five-year remission from substance use disorders. Journal of Studies on Alcohol, 63, 709–715.
- Rosenberg, M. (1965). Society and the adolescent self-image. Princeton, NJ: Princeton University Press.
- SAMHSA (2011). SAMHSA announces a working definition of "recovery" from mental disorders and

substance use disorders. Available at: <u>https://www.samhsa.gov/newsroom/press-</u> announcements/201112220800

- SAMHSA (2018). Recovery housing: Best practices and suggested guidelines. Available at: <a href="https://www.samhsa.gov/sites/default/files/housing-best-practices-100819.pdf">https://www.samhsa.gov/sites/default/files/housing-best-practices-100819.pdf</a>
- Schaefer, J. A., Cronkite, R. C., & Hu, K. U. (2011). Differential relationships between continuity of care practices, engagement in continuing care, and abstinence among subgroups of patients with substance use and psychiatric disorders. *Journal of Studies on Alcohol and Drugs*, 72, 611-621.
- Scoones, L. (1999). New ecology and the social sciences: What prospects for a fruitful engagement? *Annual Review of Anthropology*, 28:1, 479-507
- 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(1), 44–60. <u>https://doi.org/10.1016/j.socnet.2009.02.004</u>
- Snyder, C. R., Sympson, S. C., Ybasco, F. C., Borders, T. F., Babyak, M. A. & Higgins,
  R. L. (1996) Development and validation of the State Hope Scale. *Journal of Personality and Social Psychology*, 70 321–335.
- Sklar SM, Annis HM, Turner NE. (1999). Group comparisons of coping self-efficacy between alcohol and cocaine abusers seeking treatment. *Psychology of Addictive Behaviors*, 13:123– 133.
- Stevens, E. B., Jason, L. A., Ferrari, J.R., & Hunter, B. (2010). Self-efficacy and sense of community among adults recovering from substance abuse. North American Journal of Psychology, 12, 255-264. PMCID: PMC3596175
- Stoebenau K, Valente TW. (2003). Using network analysis to understand communitybased programs: a case study from highland Madagascar. *Int Fam Plan Perspect*, 29(4):167-73. doi: 10.1363/ifpp.29.167.03. PMID: 14665425.

- Thelen, E., Ulrich, B., & Wolff, P. (1991). Hidden Skills: A Dynamic Systems Analysis of Treadmill Stepping during the First Year. *Monographs of the Society for Research in Child Development*, 56(1), I-103. doi:10.2307/1166099
- The WHOQOL Group. (1996). The World Health Organization quality of life assessment (WHOQOL): Development and general psychometric properties.

Tierney, N., Cook, D., McBain, M., & Fay, C. (2021). naniar: Data Structures, Summaries, and Visualisations for Missing Data. R package version 0.6.1. https://CRAN.R-project.org/package=naniar

- Torrens, M., Rossi C. P., Martinez-Riera, R., Martinez-Sanvisens, D., Bulbena, A. (2012). Psychiatric co-morbidity and substance use disorders: Treatment in parallel systems or in one integrated system? *Substance Use and Misuse*, 47 (8-9):1005–1014.
- Walker, M, Wasserman, S, & Wellman, B. (1993). Statistical models for social support networks. *Sociological Methods & Research*, 22(1):71-98. doi:10.1177/0049124193022001004
- Wickham, H., & Miller, E. (2021). haven: Import and Export 'SPSS', 'Stata' and 'SAS' Files. R package version 2.4.1. https://CRAN.R-project.org/package=haven
- Wickham, H. (2021). dtplyr: Data Table Back-End for 'dplyr'. R package version 1.1.0. https://CRAN.R-project.org/package=dtplyr
- Wickham et al. (2019). Welcome to the tidyverse. *Journal of Open Source Software*, 4(43), 1686, https://doi.org/10.21105/joss.01686
- Winder, N. 2007. Innovation and metastability: a systems model. *Ecology and Society* 12(2): 28. DOI: http://www.ecologyandsociety.org/vol12/iss2/art28/

# APPENDIX A Tables & Figures

Figure 1. Representation and Interpretation of Model Effects

Effect (name in RSIENA)	Representation	Explanation
Out-degree (density)		Basic tendency to have ties/form relationships
Reciprocity (recip)		Tendency toward reciprocation
ego (egoX)		Actors with higher PSI scores <b>give</b> more nominations
alter (altX)		Actors with higher PSI scores <b>receive</b> more nominations
similarity (simX)		Tendency to nominate based on similar PSI scores/characteristics



creation of a tie maintenance of a tie termination of a tie maintenance of a 'no-tie'

Table 1. Descriptive Statistics for Friendship, Loaning, and Advice-Seeking Networks

	Wave 1	2	3	4	5	6
<u>Friendship Network</u> Density	0.76	0.81	0.75	0.75	0.79	0.81

Number of ties	822	547	728	634	778	733	
Mutual dyads	327	235	292	260	331	317	
Asymmetric dyads	164	77	135	110	113	92	
Loaning Network							
Density	0.27	0.30	0.30	0.27	0.29	0.25	
Number of ties	317	210	321	210	275	234	
Mutual dyads	75	50	83	47	63	61	
Asymmetric dyads	166	110	154	115	148	109	
Advice-Seeking Network							
Density	0.37	0.49	0.41	0.45	0.49	0.54	
Number of ties	320	306	407	383	499	496	
Mutual dyads	88	104	126	128	158	165	
Asymmetric dyads	143	95	151	127	182	165	

Table 2: Stochastic Actor-Oriented Model Results-maximum likelihood estimation

Max Overall Convergence t-ratio = 0.1884

Parameter Estimate	SE	<i>p</i> -Value	95% Confidence Interval	Convergence <i>t</i> -ratio
	52			

Netwo	ork Dynamics					
1.	Friend rate (period 1)	3.80	0.89	<.001	(2.1, 5.5)	-0.03
2.	Friend rate (period 2)	2.61	1.03	.001	(0.6, 4.6)	0.02
3.	Friend rate (period 3)	3.32	0.79	<.001	(1.8, 4.9)	0.01
4.	Friend rate (period 4)	2.69	0.75	<.001	(1.2, 4.2)	-0.01
5.	Friend rate (period 5)	3.84	1.425	.006	(1.1, 6.6)	-0.02
6.	Friend: outdegree (density)	0.74	0.185	<.001	(0.4, 1.1)	0.05
7.	Friend: reciprocity	1.05	0.215	<.001	(0.6, 1.5)	0.04
8.	Advice rate (period 1)	1.99	0.27	<.001	(1.5, 2.5)	-0.02
9.	Advice rate (period 2)	2.21	0.44	<.001	(1.4, 3.1)	-0.03
10.	Advice rate (period 3)	2.03	0.38	<.001	(1.3, 2.8)	0.05
11.	Advice rate (period 4)	1.86	0.35	<.001	(1.2, 2.5)	0.03
12.	Advice rate (period 5)	5.62	1.20	<.001	(3.3, 7.9)	0.05
13.	Advice: outdegree (density)	-0.26	0.09	.003	(-0.4, -0.1)	-0.01
14.	Advice: reciprocity	0.88	0.14	<.001	(0.6, 1.2)	0.01
15.	Advice: PSI similarity	0.33	0.15	.002	(0.0, 0.6)	0.01
16.	Loan rate (period 1)	3.08	0.61	<.001	(1.9, 4.3)	0.03
17.	Loan rate (period 2)	2.81	0.72	<.001	(1.4, 4.2)	-0.04
18.	Loan rate (period 3)	2.46	0.42	<.001	(1.6, 3.3)	0.02
19.	Loan rate (period 4)	2.54	0.52	<.001	(1.5, 3.6)	0.02
20.	Loan rate (period 5)	3.47	0.68	<.001	(2.1, 4.8)	0.01
21.	Loan: outdegree (density)	-0.50	0.08	<.001	(-0.7, -0.3)	-0.04
22.	Loan: reciprocity	0.81	0.13	<.001	(0.6, 1.1)	-0.01
23.	Loan: PSI alter	0.38	0.18	<.001	(0.1, 0.7)	-0.04
Behav	vior Dynamics					
24.	Rate RF (period 1)	1.46	0.30	<.001	(0.9, 2.0)	0.04
25.	Rate RF (period 2)	1.22	0.29	<.001	(0.6, 1.8)	-0.01
26.	Rate RF (period 3)	1.56	0.39	<.001	(0.8, 2.3)	0.01
27.	Rate RF (period 4)	1.41	0.29	<.001	(0.8, 2.0)	0.01
28.	Rate RF (period 5)	1.83	0.48	<.001	(0.9, 2.8)	-0.05
29.	RF linear shape	0.53	0.11	<.001	(0.3, 0.8)	0.02
30.	RF quadratic shape	-0.49	0.09	<.001	(-0.7, -0.3)	-0.01
31.	RF: effect from Sex	-0.47	0.15	.002	(-0.8, -0.2)	0.01
32.	RF: effect from Race	0.57	0.25	.020	(0.1, 1.1)	0.01
33.	RF: effect from PSI	-0.66	0.25	<.001	(-1.1, -0.2)	0.06

## APPENDIX B

### Measures

Record ID
Member First & Last Initial
1. How friendly are you with this person? Close Friend Friend Acquaintance Stranger Adversary
<ul> <li>2. If this person asked to borrow money from you, how much would you be willing to lend them?</li> <li>\$10 \$50 \$100 \$500</li> </ul>
<ol> <li>If this person needed help for a day, how likely would you be to help?</li> <li>Very Likely Maybe Probably Not Wouldn't</li> </ol>
4. How often do you have a personal conversation with this person? Daily Almost Daily Every Few Days Weekly Almost Never
5. How often do you go to this person for advice on your recovery and other important life issues?
Very Often Quite Often Regularly Rarely Never
6. Overall, how strong would you relate your relationship with this person?
Very Strong Strong Weak None Negative
Oxford House Member 2 Record ID Member First & Last Initial
1. How friendly are you with this person? Close Friend Friend Acquaintance Stranger Adversary

2. If this person asked to borrow money from you, how much would you be willing to lend them? \$0 \$10 \$50 \$100 \$500

3. If this person needed help for a day, how likely would you be to help? Very Likely Likely Maybe Probably Not Wouldn't

4. How often do you have a personal conversation with this person? Daily Almost Daily Every Few Days Weekly Almost Never 5. How often do you go to this person for advice on your recovery and other important life issues?Very Often Quite Often Regularly Rarely Never

6. Overall, how strong would you relate your relationship with this person?

Very Strong Strong Weak None Negative

### **Oxford House Member 3**

Record ID \_\_\_\_\_\_ Member First & Last Initial \_\_\_\_\_\_

1. How friendly are you with this person? Close Friend Friend Acquaintance Stranger Adversary

2. If this person asked to borrow money from you, how much would you be willing to lend them?
\$10 \$10 \$50 \$100 \$500

3. If this person needed help for a day, how likely would you be to help? Very Likely Likely Maybe Probably Not Wouldn't

4. How often do you have a personal conversation with this person? Daily Almost Daily Every Few Days Weekly Almost Never

5. How often do you go to this person for advice on your recovery and other important life issues?Very Often Quite Often Regularly Rarely Never

6. Overall, how strong would you relate your relationship with this person?

Very Strong Strong Weak None Negative

Oxford House Member 4
Record ID
Member First & Last Initial

1. How friendly are you with this person?Close FriendFriendAcquaintanceStrangerAdversary

2. If this person asked to borrow money from you, how much would you be willing to lend them?
\$10 \$10 \$50 \$100 \$500

3. If this person needed help for a day, how likely would you be to

help? Very Likely Likely Maybe Probably Not Wouldn't

4. How often do you have a personal conversation with this person? Daily Almost Daily Every Few Days Weekly Almost Never

5. How often do you go to this person for advice on your recovery and other important life issues?Very Often Quite Often Regularly Rarely Never

6. Overall, how strong would you relate your relationship with this person?

Very Strong Strong Weak None Negative

### **Oxford House Member 5**

Record ID \_\_\_\_\_ Member First & Last Initial \_\_\_\_\_

1. How friendly are you with this person? Close Friend Friend Acquaintance Stranger Adversary

2. If this person asked to borrow money from you, how much would you be willing to lend them? \$0 \$10 \$50 \$100 \$500

3. If this person needed help for a day, how likely would you be to help? Very Likely Likely Maybe Probably Not Wouldn't

4. How often do you have a personal conversation with this person?

Daily Almost Daily Every Few Days Weekly Almost Never

5. How often do you go to this person for advice on your recovery and other important life issues?

Very Often Quite Often Regularly Rarely Never

6. Overall, how strong would you relate your relationship with this person?

Very Strong Strong Weak None Negative

Oxford House Member 6	
Record ID	
Member First & Last Initial	

1. How friendly are you with this person? Close Friend Friend Acquaintance Stranger Adversary

2. If this person asked to borrow money from you, how much would you be willing to lend them? \$0 \$10 \$50 \$100 \$500

3. If this person needed help for a day, how likely would you be to help? Very Likely Likely Maybe Probably Not Wouldn't

4. How often do you have a personal conversation with this person? Daily Almost Daily Every Few Days Weekly Almost Never

5. How often do you go to this person for advice on your recovery and other important life issues?Very Often Quite Often Regularly Rarely Never

6. Overall, how strong would you relate your relationship with this person?Very Strong Strong Weak None Negative

### **Oxford House Member 7**

Record ID \_\_\_\_\_\_ Member First & Last Initial \_\_\_\_\_\_

1. How friendly are you with this person? Close Friend Friend Acquaintance Stranger Adversary

2. If this person asked to borrow money from you, how much would you be willing to lend them? 10 10 10 10 10

3. If this person needed help for a day, how likely would you be to help? Very Likely Likely Maybe Probably Not Wouldn't

4. How often do you have a personal conversation with this person? Daily Almost Daily Every Few Days Weekly Almost Never

5. How often do you go to this person for advice on your recovery and other important life issues?
Very Often Quite Often Regularly Rarely Never
6. Overall, how strong would you relate your relationship with this person?

Very Strong Strong Weak None Negative

Oxford House Member 8	
Record ID	
Member First & Last Initial	

1. How friend	ly are you	u with this perso	n?	
Close Friend	Friend	Acquaintance	Stranger	Adversary

2. If this person asked to borrow money from you, how much would you be willing to lend them?
\$10 \$50 \$100 \$500

3. If this person needed help for a day, how likely would you be to help? Very Likely Likely Maybe Probably Not Wouldn't

4. How often do you have a personal conversation with this person? Daily Almost Daily Every Few Days Weekly Almost Never

5. How often do you go to this person for advice on your recovery and other important life issues?Very Often Quite Often Regularly Rarely Never

6. Overall, how strong would you relate your relationship with this person?Very Strong Strong Weak None Negative

#### **Oxford House Member 9**

Record ID \_\_\_\_\_\_ Member First & Last Initial \_\_\_\_\_\_

1. How friendly are you with this person? Close Friend Friend Acquaintance Stranger Adversary

2. If this person asked to borrow money from you, how much would you be willing to lend them?  $0 \ 10 \ 50 \ 100 \ 500$ 

3. If this person needed help for a day, how likely would you be to help? Very Likely Likely Maybe Probably Not Wouldn't

4. How often do you have a personal conversation with this person? Daily Almost Daily Every Few Days Weekly Almost Never

5. How often do you go to this person for advice on your recovery and other important life issues?

Very Often Quite Often Regularly Rarely Never

6. Overall, how strong would you relate your relationship with this person? Very Strong Strong Weak None Negative

### World Health Organization Quality Of Life-BREF

Record ID

The following questions ask how you feel about your quality of life, health, or other areas of your life. I will read out each question to you, along with the response options. Please choose the answer that appears most appropriate. If you are unsure about which response to give to a question, the first response you think of is often the best one.

Please keep in mind your standards, hopes, pleasures and concerns. We ask that you think about your life since your last interview.

1. How would you rate your quality of life?

- 1. Very poor
- 2. Poor
- 3. Neither poor nor good
- 4. Good
- 5. Very good

2. How satisfied are you with your health?

- 1. Very dissatisfied
- 2. Dissatisfied
- 3. Neither satisfied nor dissatisfied
- 4. Satisfied
- 5. Very satisfied

### The following questions ask about how much you have experienced certain things in the last four weeks.

3. To what extent do you feel that physical pain prevents you from doing what you need to do?

- 5. Not at all
- 4. A little
- 3. A moderate amount
- 2. Very much
- 1. An extreme amount

#### 4. How much do you need any medical treatment to function in your daily life?

- 5. Not at all
- 4. A little
- 3. A moderate amount
- 2. Very much
- 1. An extreme amount

5. How much do you enjoy life?

- 1. Not at all
- 2. A little
- 3. A moderate amount
- 4. Very much
- 5. An extreme amount
- 6. To what extent do you feel your life to be meaningful?
  - 1. Not at all
  - 2. A little
  - 3. A moderate amount
  - 4. Very much
  - 5. An extreme amount

7. How well are you able to concentrate?

- 1. Not at all
- 2. A little
- 3. A moderate amount
- 4. Very much
- 5. Extremely

8. How safe do you feel in your daily life?

- 1. Not at all
- 2. A little
- 3. A moderate amount
- 4. Very much
- 5. Extremely
- 9. How healthy is your physical environment?
  - 1. Not at all
  - 2. A little
  - 3. A moderate amount
  - 4. Very much
  - 5. Extremely

# The following questions ask about how completely you experience or were able to do certain things in the last four weeks.

- 10. Do you have enough energy for everyday life?
  - Not at all
  - A little
  - Moderately
  - Mostly
  - Completely
- 11. Are you able to accept your bodily appearance?
  - Not at all
  - A little
  - Moderately
  - Mostly
  - Completely
- 12. Have you enough money to meet your needs?
  - Not at all
  - A little
  - Moderately
  - Mostly
  - Completely
- 13. How available to you is the information that you need in your day-to-day life?
  - Not at all
  - A little
- Moderately
- Mostly
- Completely

14. To what extent do you have the opportunity for leisure activities?

- Not at all
- A little
- Moderately
  - Mostly
- Completely

15. How well are you able to get around?

- Very poor
- Poor
- Neither poor nor good
- Good
- Very good

16. How satisfied are you with your sleep?

- Very dissatisfied
- Dissatisfied
  - Neither satisfied nor dissatisfied
  - Satisfied
  - Very satisfied

17. How satisfied are you with your ability to perform your daily living activities?

- Very dissatisfied
- Dissatisfied
- Neither satisfied nor dissatisfied
- Satisfied
- Very satisfied
- 18. How satisfied are you with your capacity for work?
  - Very dissatisfied
  - Dissatisfied
  - Neither satisfied nor dissatisfied
  - Satisfied
  - Very satisfied

19. How satisfied are you with yourself?

- Very dissatisfied
- Dissatisfied
- Neither satisfied nor dissatisfied
- Satisfied
- Very satisfied
- 20. How satisfied are you with your personal relationships?
  - Very dissatisfied
  - Dissatisfied
  - Neither satisfied nor dissatisfied
  - Satisfied
  - Very satisfied
- 21. How satisfied are you with your sex life?

- Very dissatisfied
- Dissatisfied
- Neither satisfied nor dissatisfied
- Satisfied
- Very satisfied

22. How satisfied are you with the support you get from your friends?

- Very dissatisfied
- Dissatisfied
- Neither satisfied nor dissatisfied
- Satisfied
- Very satisfied
- 23. How satisfied are you with the conditions of your living place?
  - Very dissatisfied
  - Dissatisfied
  - Neither satisfied nor dissatisfied
  - Satisfied
  - Very satisfied
- 24. How satisfied are you with your access to health services?
  - Very dissatisfied
  - Dissatisfied
  - Neither satisfied nor dissatisfied
  - Satisfied
  - Very satisfied

### 25. How satisfied are you with your transport?

- Very dissatisfied
- Dissatisfied
- Neither satisfied nor dissatisfied
- Satisfied
- Very satisfied

# The following question refers to how often you have felt or experienced certain things in the last four weeks.

26. How often do you have negative feeling such as blue mood, despair, anxiety, depression?

- 5. Never
- 4. Seldom
- 3. Quite often
- 2. Very often
- 1. Always

Do you have any comments about the assessment?

## **Perceived Stress Scale (PSS)**

Record ID

The questions in this scale ask you about your feelings and thoughts. In each case, you will be asked to indicate how often you felt or thought a certain way

NeverAlmost neverSometimesFairly oftenVery often12345

1. How often have you felt that you were unable to control the important things in your life?

2. How often have you felt confident about your ability to handle your personal problems?

3. How often have you felt that things were going your way?

4. How often have you felt difficulties were piling up so high that you could not overcome them?

# Drug Taking Confidence Questionaire (DTCQ)

Record ID

Listed below are a number of situations or events in which some people experience a drug use problem. Imagine yourself as you are right now in each of these situations. Indicate on the scale provided how confident you are that you will be able to resist the urge to use your drug of choice in that situation.

Circle 100 if you are 100% confident right now that you could resist the urge to use your drug of choice; 80 if you are 80% confident; 60 if you are 60% confident. If you are more unconfident than confident, circle 40 to indicate that you are only 40% confident that you could resist the urge to use your drug of choice; 20 for 20% confident; or 0 if have no confidence at all about that situation.

I would be able to resist the urge to use...

Not at all confident				Very c	onfident
0	20	40	60	80	100

1. If I were angry at the way things had turned out

- 2. If I had trouble sleeping
- 3. If I remembered something good that had happened
- 4. If I wanted to find out whether I could use occasionally without getting hooked
- 5. If I unexpectedly found my drug of choice or happened to see something that reminded me of my drug of choice
- 6. If other people treated me unfairly or interfered with my plans
- 7. If I were out with friends and they kept suggesting we go somewhere and use my drug of choice
- 8. If I wanted to celebrate with a friend

## **Snyders State Hope Scale**

Record ID

Read each item carefully. Please rank on the 8-point scale what best describes how you think about yourself right now.

Definitely FalseMostly FalseSomewhat False Slightly False Slightly TrueSomewhat TrueMostly True Definitely12345678

1. If I should find myself in a jam, I could think of many ways to get out of it.

2. At the present time, I am energetically pursuing my goals.

3. There are lots of ways around my problems that I am facing now.

4. Right now, I see myself as being pretty successful.

5. I can think of many ways to reach my current goals.

6. At this time, I am meeting the goals that I have set for myself.

7. Right now I don't feel limited by the opportunities that are available.

8. I feel like I have plenty of good choices in planning my future.

9. The obstacles I face are similar to what everybody else faces.

## **Rosenberg Self-Esteem Scale**

Record ID

Instructions: Below is a list of statements dealing with your general feelings about yourself.

### Please indicate how strongly you agree or disagree with each statement.

Strongly agree Agree Disagree Strongly disagree 1 2 3 4

1. I feel that I'm a person of worth, at least on an equal plane with others.

2. I feel that I have a number of good qualities.

3. All in all, I am inclined to feel that I am a failure.

- 4. I am able to do things as well as most other people.
- 5. I feel I do not have much to be proud of.
- 6. I take a positive attitude toward myself.
- 7. On the whole, I am satisfied with myself.
- 8. I wish I could have more respect for myself.

9. I certainly feel useless at times.

10. At times I think I am no good at all.

# Psychological Sense Of Community Scale

Record ID

Respondents answer whether they Strongly Disagree, Disagree, Slightly Disagree, Slightly Agree, Agree, or Strongly Agree with thequestions below.

- 1. I think this Oxford House is a good Oxford House
- 2. I am not planning on leaving this Oxford House
- 3. For me, this Oxford House is a good fit
- 4. Residents can depend on each other in this Oxford House
- 5. Residents can get help from other residents if they need it
- 6. Residents are secure in sharing opinions or asking for advice
- 7. This Oxford House is important to me
- 8. I have friends in this Oxford House
- 9. I feel good helping Oxford House and the residents

### **Interpersonal Support Evaluation List (ISEL)**

Record ID

INSTRUCTIONS: This scale is made up of a list of statements each of which may or may not be true about you. For each statement check "definitely true" if you are sure it is true about you and "probably true" if you think it is true but are not absolutely certain. Similarly, you should check "definitely false" if you are sure the statement is false and "probably false" is you think it is false but are not absolutely certain.

Definitely False	Probably False	Probably	True	Definitely True
1	2	3	4	5

- 1. If I wanted to go on a trip for a day (e.g., to the mountains, beach, or country) I would have a hard time findingsomeone to go with me
- 2. I feel that there is no one I can share my most private worries and fears with.
- 3. If I were sick, I could easily find someone to help me with my daily chores.
- 4. There is someone I can turn to for advice about handling problems with my family.
- 5. If I decide one afternoon that I would like to go to a movie that evening, I could easily find someone to go with me.
- 6. When I need suggestions on how to deal with a personal problem, I know someone I can turn to.
- 7. I don't often get invited to do things with others.
- 8. If I had to go out of town for a few weeks, it would be difficult to find someone who would look after my houseor apartment (the plants, pets, garden, etc.).
- 9. If I wanted to have lunch with someone, I could easily find someone to join me.

10. If I was stranded 10 miles from home, there is someone I could call who would come and get me.

 $11. \ {\rm If}$  a family crisis arose, it would be difficult to find someone who could give me good advice about how tohandle it.

12. If I needed some help in moving to a new house or apartment, I would have a hard time finding someone to help me.

# Addiction Severity Index (ASI) – 5<sup>th</sup> Edition: Psychiatric Status

How many times have you been treated for any psychological or emotional problems:

P1. \* In a hospital or inpatient setting? \_\_\_\_\_

P2. \* Outpatient/private patient?

P3. Do you receive a pension for a psychiatric disability?

Over the Past 30 Days...Have you had a significant period of time (that was not a direct result of drug/alcohol use) in which you have:

$$0 = No, 1 = Yes$$

P4. Experienced serious depression

Sadness, hopelessness, loss of interest, difficulty with daily functioning

P5. Experienced serious anxiety or tension

Uptight, unreasonably worried, inability to feel relaxed \_\_\_\_\_

P6. Experienced hallucinations

Saw things/heard voices that others didn't see/hear \_\_\_\_\_

P7. Experienced trouble understanding, concentrating, or remembering

P8. Experienced trouble controlling violent behavior including episodes or rage or violence \_\_\_\_

P9. Experienced serious thoughts of suicide \_\_\_\_\_

P10. Attempted suicide \_\_\_\_\_

P11. Been prescribed medication for any psychological or emotional problems

Prescribed for the patient by a physician. Record "Yes" if a medication was prescribed even if the patient is not taking it.

P12. How many days in the past 30 have you experienced these psychological or emotional problems?

P13. How much have you been troubled or bothered by these psychological or emotional problems in the past 30 days?

P14. How important to you now is treatment for these psychological problems?

# APPENDIX C

# Knit R Code for Running SAOM via RSiena

# **Dissertation.Script**

## Ted J. Bobak

# 3/5/2022

#Load necessary packages, if required

LOAD base workspace

```
load(paste(workingDir,
    "/Ted.w123456.RData",
    sep=""))
```

#Create 'RSiena data object' NOTE: The RDO (here, 'dtObj1.PSI') will be directly input to the RSiena modeling function ('siena07') below. It can be used to model the variables we input to it (which, as we have seen, need to have been processed by special RSiena functions first). These variables include: - Changes in the friendship network (fNet0SD) depending on internal network effects (outdegree, reciprocity, etc.), the 'recovery factor' (RF) variable depending on individual characteristics (age, sex, etc.) and the characteristics of those they are "friends" with.

```
dtObj1.PSI <- sienaDataCreate(fNet0SD, advNet0SD, loanNet0SD, RF, RS.in
ResL, ccSD, RS.sex, RS.age, RS.Blk, RS.Hi_PSI)
```

#NOTE: describes the networks, gives summaries of various characteristics, of both networks and other variables, etc. This includes the composition change object
(ccSD). Once that's been created and input to the RSiena Data Object, we can forget about it; composition change is automatically handled thereafter!

```
print01Report(dtObj1.PSI, modelname="Dissertation.5")
```

#NOTE: The 'effects object' essentially contains the model specification for any given estimation run. Several effects are included in the initialized object by default; others need to be added 'manually', which we do further on. Note that the effects object (named 'effObj1.PSI') is a direct function of (i.e. depends completely on) the data object dtObj1.PSI

```
effObj1.PSI <- getEffects(dtObj1.PSI)</pre>
```

##Associated fx doc NOTE: This function creates an html file called 'effObj1.PSI.html', which is VERY IMPORTANT! In fact, keep this file open while specifying a model, or thinking about how to specify one. It contains a complete list of all the effects you can possibly put into the model, given the data object to be used (i.e., the effects list is 'a function of' the RDO).

```
effectsDocumentation(eff0bj1.PSI)
```

There are other parameters available for 'sienaModelCreate', but none are immediately relevant. See the help text or the RSiena manual.

#Add effects

```
effObj1.PSI <- includeEffects(effObj1.PSI, name = "fNet0SD", cycle3, tr
ansTrip, include = F)
effObj1.PSI <- includeEffects(effObj1.PSI, name = "loanNet0SD", cycle3,
transTrip, include = F)
effObj1.PSI <- includeEffects(effObj1.PSI, name = "advNet0SD", cycle3,
transTrip, include = F)
```

```
effObj1.PSI <- includeEffects(effObj1.PSI, simX, name="advNet0SD", type
="eval", interaction1="RS.Hi_PSI", include=T)
```

```
effObj1.PSI <- includeEffects(effObj1.PSI, altX, name="loanNetOSD", typ
e="eval", interaction1="RS.Hi_PSI", include=T)
```

```
effObj1.PSI <- includeEffects(effObj1.PSI, effFrom, name="RF", type="ev
al", interaction1="RS.Blk", include=T)
```

```
effObj1.PSI <- includeEffects(effObj1.PSI, effFrom, name="RF", type="ev
al", interaction1="RS.sex", include=T)
```

```
effObj1.PSI <- includeEffects(effObj1.PSI, effFrom, name="RF", type="ev
al", interaction1="RS.Hi_PSI", include=T)
```

##Look at effects NOTE: You always want to do this before running a model, to make sure you have included all of (but only) the effects you intended.

eff0bj1.PSI

**#RUN MODEL** 

```
Dissertation.5 <- siena07(rfMod1.PSI, data=dtObj1.PSI, effects=effObj1.
PSI, useCluster=T,
```

```
nbrNodes=9, prevAns=Dissertation.4) #use a previous m odel as parameter
```

#Save Progress

A nicely-formatted results table: (you get LaTex if you remove the 'type' parameter) (Normally you'll look at results in the .txt file specified in 'siemaModelCreate' (equivalently, 'sienaAlgorithmCreate'))

```
siena.table(Dissertation.5, type="html")
summary(Dissertation.5)
saveRDS(Dissertation.5, file = "Dissertation.5")
```

#stab creates APA style table

```
stab <- function(object, CI = .95) {</pre>
if (class(object) != "sienaFit") stop("Need sienaFit object")
tmp <- with(object, {</pre>
 tmp <- cbind(</pre>
   effects[, 2, drop = F],
  est = theta,
   se = se,
   z = theta/se,
   p = 2*(1 - pnorm(abs(theta/se))),
   lo = theta + qnorm((1-CI)/2)*se,
  hi = theta + qnorm(CI + (1-CI)/2)*se,
   conv t ratio = tconv);
  names(tmp)[6:7] <- paste0(names(tmp)[6:7], paste0(" ", CI, "%"))</pre>
  attr(tmp, "tconv.max") <- tconv.max;</pre>
  print(tmp);
  cat(paste0("\nMax Overall Convergence t-ratio = ", round(tconv.max, 4
), "\n"));
```

tmp }) }

Next, enter: stab(Dissertation.5) in the console section below

```
Dissertation.5 <- stab(Dissertation.5)</pre>
```