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**INVESTIGATING THE CO-EVOLUTION OF INDIVIDUAL AND
NETWORK-LEVEL RECOVERY CAPITAL: A DYNAMIC SOCIAL
NETWORK ANALYSIS TESTING NETWORK COHESION AND
EXCHANGE THEORIES**

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INVESTIGATING THE CO-EVOLUTION OF INDIVIDUAL AND NETWORK-LEVEL
RECOVERY CAPITAL: A DYNAMIC SOCIAL NETWORK ANALYSIS TESTING
NETWORK COHESION AND EXCHANGE THEORIES

A Dissertation presented in Partial Fulfillment of the
Requirements for the Degree of
Community Psychology – Doctor of Philosophy

By

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August 2021

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Dedication

This dissertation is dedicated to my mother, Soraria Milagros Mejia de Guerrero. Her bravery to immigrate to the United States from the Dominican Republic to pursue of a better life for her and her family allowed me to benefit from many educational opportunities that were not available to her. She always pushed me to do my best and instilled in me the importance of education. She passed a year shy of this work being completed. I hope to continue her legacy by helping other first-generation students like myself achieve their goals, just as she always encouraged me to do. Te quiero mucho mami. Que en paz descanse.

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Biography

The author was born in the Bronx, New York City, New York, on May 11, 1991. She graduated from Jonathan Levin High School in 2009 and received her Bachelor's degree in Psychology from the City College of New York in 2014.

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ABSTRACT

Historically, treatment professionals, researchers, and policymakers widely regarded substance use disorders (SUDs) as acute conditions that patients could “recover” from after a single treatment. Recent efforts have redefined recovery as a lifelong, dynamic process that involves improvements in multiple domains over time. Thus, recovery capital frameworks and theory have gained momentum as a way to operationalize recovery from SUDs. Recovery capital is a multifaceted framework with theoretical underpinnings in the social capital literature that provides a way of conceptualizing and measuring the complexities of the recovery process. While the literature on recovery capital has grown significantly since its conception, the extant research has focused on investigating recovery capital at the individual-level and not on how it is developed contextually. The current longitudinal study sought to advance understanding of how recovery capital is developed using social network analysis while testing network cohesion, social exchange, and generalized exchange theories. Stochastic Actor Oriented Modeling was conducted on individuals recovering from SUDs (N = 627) residing in 42 recovery homes. Findings indicated that while cohesion, social exchanges, and generalized exchanges were prevalent across various types of networks, these network-level effects had no influences on changes in the individual-level of recovery capital. However, a dyadic-level effect was found, indicating that residents’ individual-level recovery capital increased when they were directly connected to those rich in recovery capital. Additionally, compared to men, women had slower increases in their recovery capital over time. The theoretical and practical implications and recommendations for future research are discussed.

Keywords: Substance use disorders, recovery capital, social networks, stochastic actor oriented modeling.

OVERVIEW

Substance use disorders (SUDs) are a significant public health concern, affecting an estimated 10.8% of adults in the United States (Substance Abuse and Mental Health Services Administration [SAMHSA], 2019). These disorders can result in significant impairments to physical and mental health, social, employment, housing, and legal difficulties, disability, or even death (Baliunas et al., 2010; Degenhardt & Hall, 2012; Fergusson, Horwood, Swain-Campbell, 2002; Lange & Hillis, 2001; Rehm et al., 2009; Tiffany et al., 2012; Whiteford et al., 2013). The lack of resources to prevent SUDs and effective recovery support services for those living with SUDs has detrimental effects on individuals, families, communities, and society as a whole, underscoring the importance of identifying the facilitators of long-term recovery.

The term recovery has had various conceptualizations over the years. Historically, SUD treatment professionals, researchers, and policymakers widely regarded SUDs as acute conditions that patients could “recover” from after a single episode of treatment (Dennis & Scott, 2007). Proponents of this acute care approach defined recovery from SUDs as the reduction of substance use or the achievement of abstinence. This definition was inherently problematic given that it ignored whether individuals were improving in other life domains. The acute-care approach to SUDs impacted the types of treatment protocols implemented for patients and the types of research outcomes investigated (Laudet & White, 2008). Additionally, this approach impacted public policy, evident in the inadequate funding allocated towards treatment and recovery support services, the restrictions in the number of treatment days covered by insurance, and the lack of intervention initiatives and long-term systems of care (McLellan et al., 2000).

In recent decades, a growing body of empirical research has affirmed that SUDs are chronic conditions, marked by phases of treatment, recovery, and relapse (Dennis et al., 2007;

Dennis, Foss, & Scott, 2007; Dennis, Scott, Funk, & Foss, 2005; Fowler et al., 2007; Paulus et al., 2005; Scott, Dennis, & Foss, 2005). Accordingly, recovery from SUDs is now widely recognized as a lifelong, dynamic process that can take more than five years before stable recovery can be achieved (Betty Ford Institute [BFI] Consensus Panel, 2007; Dennis et al., 2005; Scott et al., 2005a; Scott et al., 2005b). As a result, previous pathological models of recovery have evolved to a holistic recovery health framework that considers the entirety of a person's well-being and whether they are thriving in different areas (Kelly & Hoepfner, 2015). Reflective of this paradigm shift, SAMHSA updated its definition of recovery to “a process of change through which individuals improve their health and wellness, live a self-directed life, and strive to reach their full potential” (SAMHSA, 2012, pg. 3). Notably, SAMHSA did not include abstinence as a necessary component of recovery. Accompanying these recent efforts to promote a person-centered conceptualization of recovery, there have been calls for rigorous examinations into the processes and mechanisms that help initiate and sustain improvements in multiple domains over time (Cleveland et al., 2021; Kelly et al., 2014).

While many organizations have attempted to define recovery (e.g., see BFI, 2007; SAMHSA, 2012; World Health Organization [WHO], 2016), there is still no universally accepted definition. However, within the SUD literature, recovery capital frameworks and theory (Granfield & Cloud, 1999) have gained momentum as a way to operationalize recovery (Parkin, 2015). Recovery capital (Granfield & Cloud, 1999) is a multifaceted framework with theoretical underpinnings in the social capital literature (Bourdieu, 1980; Coleman, 1988; 1994; Bourdieu and Wacquant, 1992; Portes, 2000; Putnam, 1993) that provides a way of conceptualizing and measuring the complexities of the recovery process. Recovery capital is defined as “the sum total of one's resources [internal and external] that can be brought to bear on the initiation and

maintenance of substance use misuse cessation” (Cloud & Granfield, 2008; pg. 1972). While several highly related models of recovery capital have been proposed (Cloud & Granfield, 2004; 2008; Granfield et al., 1999; 2001), according to White and Cloud (2008), recovery capital can be best categorized into three domains: (1) personal; (2) social; and (3) community. These will be discussed in more detail in later sections.

Many studies provide support for the utility of the recovery capital framework for mapping recovery improvements over time across various domains (Best et al., 2012a; Best et al., 2012b; Best et al., 2015; Best, Vanderplasschen, & Nisic, 2020; Boeri, Lamonica, & Harbry, 2011; Daddow & Broome, 2010; Duffy & Baldwin, 2013; Evans, Li, Buoncristiani, & Hser, 2014; Groshkova, Best, & White, 2011; Gueta & Addad, 2015; Hillios, 2013; Laudet, Morgen, & White, 2006; Laudet, 2013; Laudet et al., 2008; Mawson et al., 2015; Van Melick et al., 2013; Zschau et al., 2016). While the body of literature on recovery capital has grown since it was first conceptualized, the extant research has focused on investigating recovery capital at the individual-level and not on how it is developed contextually.

Recovery is a dynamic process that can be influenced by both individual and social/environmental factors (Cleveland et al., 2021; Granfield & Cloud, 2001; Moos, 2003; Vaillant, 1995), and yet, few studies on recovery capital have measured this interaction, leaving contextual factors largely unaccounted for (Gonzales, Hernandez, Douglas, & Yu, 2015; Reise, Ventura, Nuechterlein, & Kim, 2005; Sterling, Slusher, & Weinstein, 2008; Tucker, Vuchinich, & Gladsjo, 1990; Zschau et al., 2016). The disproportionate attention to the individual level is surprising given that the recovery capital framework recognizes the importance of social and community dynamics (Lyons & Lurigio, 2010). There is a need to incorporate multi-level perspectives that help elucidate the contextual factors that influence recovery capital and

examine how the interdependencies between individuals and their environments can facilitate or hinder its development. Investigations into this area require the utilization of appropriate statistical methodology that allows for these interdependencies and dynamics to be modeled.

Social network analysis provides a robust methodological tool and theoretical foundation for understanding the connections between individuals and their most immediate environment: their social networks (Valente, 2010; Wasserman & Faust, 1994). Stochastic Actor-Oriented Modeling (SAOM) (Snijders, van de Bunt, & Steglich, 2010), a statistical framework for dynamic social network modeling, has several methodological strengths that makes it especially suited for examining how recovery capital is developed through social relationships. With SAOM one could: (1) account for the interdependence between social relationships and individual behavior; (2) examine the co-evolution of network structures and recovery capital overtime; and (3) identify specific network and relational characteristics that facilitate recovery capital. The advantages of using social network analysis to investigate how recovery capital within a social context motivates the present work.

In addition to the aforementioned statistical tools, several network theories provide guidance for the types of social network conditions that can result in the greater generation of recovery capital. These theories include network cohesion theory (Coleman, 1988), social exchange theory (Homans, 1961; Emerson, 1972), and generalized exchange theory (Levi-Strauss, 1949). While these theories have been applied to the study of social capital (Abbott & Freeth, 2008; Adler & Kwon, 2002; Baker & Dutton, 2007; Cook, Cheshire, Rice, & Nakawaga, 2013; Flap, 2002; Krishna, 2000; Koopman, Matta, Scott, & Conlon, 2015; Gargiulo & Benassi, 2000; Molm & Collett, 2007; Moody & Paxton, 2009; Paxton, 1999; Sandefur & Laumann, 1998; Wasko & Faraj, 2005; Wei, Zheng, & Zhang, 2011; Yuan, Gay, & Hembrooke, 2006), no

other study, to my knowledge, has used them in the context of recovery capital. The current work will argue the usefulness of these three theories applied to recovery capital to support the current study's rationale.

The current study seeks to advance our understanding of how recovery capital is developed within a social environment. Through the use of social network analysis, the research presented in this dissertation will elucidate recovery capital trajectories as well as individual-level characteristics and social mechanisms that impact these trajectories. The current study adopts a multi-level perspective in the study of recovery capital, and as such, recovery capital will be examined as an individual-level resource as well as a structural-level resource that is developed through social relationships. The specific aims of the current study are to: (1) investigate the boundary conditions in which network cohesion, social exchange, and generalized exchange theories can be reasonably applied and (2) examine how recovery capital co-evolves with changes in network structures over time. A sub aim of aim two is to identify the network structures that facilitate or hinder recovery capital. In this dissertation, I propose to analyze the co-evolution of recovery capital and network characteristics by hypothesizing the underlying network dynamics utilizing the aforementioned theories as guiding frameworks.

The following section begins with a review of the literature on recovery from SUDs. This will be followed by a review of the theoretical and empirical research on recovery capital. A comprehensive section on social networks that discusses (1) its importance to the study of recovery capital, (2) social network theories providing the foundation for the current work, and (3) a discussion of the utility of the current study's methodology for investigating the phenomena of interest. Subsequently, a discussion on integrating the theoretical foundations and the stochastic-actor oriented model development for the current work will be presented. This will be

followed by a section that discusses the specific population/setting of interest. The introduction concludes with the study's rationale.

LITERATURE REVIEW

Recovery from Substance Use Disorders

SUDs are a chronic health condition with biological, psychological, social, and environmental determinants characterized by impairment to one's functioning due to the recurrent use of alcohol and/or drugs (SAMHSA, 2019; United Nations Office of Drugs and Crime [UNODC], 2020). According to the American Psychiatric Association's (APA) (2013) *Diagnostic and Statistical Manual of Mental Disorders*, 5th edition (DSM-5), underlying symptoms of SUDs include (1) the recurrent use of alcohol and/or drugs despite severe impairment to one's health and failure to meet family, employment, and community obligations, (2) an intense desire or urge to engage in the use of the substance that can occur at any time, (3) continued risky use of the substances in hazardous conditions, and (4) experiencing the need for a greater quantity of the substance to obtain the same effect (tolerance) and the physical and mental health symptoms that occur after eliminating or reducing the use of the substance (withdrawal). These symptoms can be classified as mild, moderate, or severe (APA, 2013).

In the U.S, an estimated 20.3 million people 12 years and older have a SUD (SAMHSA, 2019). Currently, the U.S is facing an opioid use epidemic in which one person dies every 15 minutes of a drug overdose (Centers for Disease Control and Prevention, 2016). According to a report by the UNODC, 162 to 324 million people worldwide engage in substance use, of which approximately 10% (16 to 39 million) will develop a SUD (UNODC, 2012). Global estimates reveal that, overall, only one out of every six people with SUDs receive treatment (UNODC,

2020). This proportion is lower in Latin America and Africa, wherein only one out of 11 and one out of 18 people access treatment, respectively (UNODC, 2020).

Inadequate global resources have been put forth to prevent SUDs and promote recovery, along with the implementation of harmful policies that continue to criminalize those with SUDs (UNODC, 2020). As a consequence, SUDs often intersect with other problems, including incarceration, homelessness, unemployment, chronic health problems, mental illness, and mortality (Fischer & Breakey, 1991; John et al., 2018; Knopf, 2020; Lennox, Zarkin, & Bray, 1996; Marmet et al., 2019; Robertson, Zlotnick, & Westerfelt, 1997; Schulte & Hser, 2013; Schmidt et al., 2018). Given how society fails to properly address SUDs through multifaceted, public health-oriented responses, the overall cost of SUDs is considered to surpass that of many other chronic conditions (International Narcotics Board, 2013; World Health Organization, 2016). Thus, understanding what helps people recover is an important aim.

Despite these alarming statistics, recovery from SUDs is possible, albeit difficult. A survey found that 10% (23 million) of adults in the U.S reported being in remission from SUDs (Office of Alcoholism and Substance Abuse Services, 2012). Studies on treatment and community populations have found that between 58 and 60% of people who met the diagnostic criteria for a SUD at some point in their lifetime enter recovery (Dawson, 1996; Dennis et al., 2005; Kessler, 1994). A 33-year observational study of heroin users found that 60.3% reported episodes of remission that lasted at least a year and 21.4% lasting at least five years (Nosyk et al., 2013). While the first few years in recovery are particularly precarious, once individuals reach a five-year benchmark in recovery, the likelihood that they will meet the criteria for a SUD is significantly reduced (American Society of Addiction Medicine, 2015; Betty Ford Consensus Panel, 2007; Dennis et al., 2007; El-Guebaly, 2012; Finney & Moos, 1991; Flynn, Joe, Broome,

Simson, & Brown, 2003; Moos & Moos, 2006a; Moos & Moos, 2006b; White, 2007; Vaillant, 1996; Vaillant, 2003).

Recovery is not a single event but a lifelong, dynamic process, with most individuals cycling between periods of substance use, abstinence, relapse, and recovery (Galai, Safaean, Vlahov, Bolotin, & Celentano, 2003; Moos et al., 2006a; 2006b; Nosyk et al., 2013; Scott, Foss, Dennis, 2005), with recovery involving being in remission from SUDs and achieving wellness. For instance, in one study of 1,326 individuals with SUDs, 82% transitioned through these stages at least once, while 62% moved through this cycle multiple times (Scott et al., 2005). There are also various pathways into recovery. While some enter recovery after multiple episodes of treatment (Cunningham, 1999a; 1999b; Dennis et al., 2005; Grella & Joshi, 1999; Hser et al., 1997; Scott, Dennis, & Foss, 2005; Scott, Foss, & Dennis, 2005), others enter recovery without the use of formal treatment (Cloud & Granfield, 2001; Moos & Moos, 2006a). Moos et al. (2006a; 2006b) followed individuals with SUDs over 16 years and found that 60% of them had achieved remission without formal treatment. Considering the variety of ways individuals initiate recovery from SUDs, there is a necessity to identify the mechanisms that function as ‘natural reinforcers’ for sustained recovery (Mckay, 2017).

Recovery is more than the resolution of substance use problems; instead, it involves functional improvements and/or thriving in areas negatively impacted by substance use. While the path towards recovery is highly heterogeneous, it is believed to involve the growth of recovery capital. Recovery capital encompasses the various internal and external resources or ‘capital’ that helps individuals initiate and sustain their recovery from SUDs (Granfield et al., 1999). While there are several conceptualizations of recovery, the current study defines recovery as both no longer meeting DSM-5 criteria for SUDs and having greater access to recovery

capital. In the next section, the theoretical and empirical literature on recovery capital will be reviewed while underscoring the need to implement multiple levels of analysis to advance what we know about recovery.

What is Recovery Capital?

The recovery capital framework, which has theoretical underpinnings in the social capital theory literature (Bourdieu, 1980; Bourdieu & Wacquant, 1992; Coleman, 1988; 1994; Portes, 2000; Putnam, 1993), was first proposed by Granfield and Cloud based on their research on individuals that had achieved “natural recovery” without the use of formal treatment or mutual-help programs (Cloud & Granfield, 2001; Granfield & Cloud, 1999). Recovery capital is an ecological framework that delineates resources at the individual, interpersonal, and community levels that can be utilized to overcome substance use related problems and achieve well-being and self-actualization (Cloud & Granfield, 2001; Granfield & Cloud, 1999). These resources can be accumulated or expended and exist on a continuum, ranging from positive internal and external resources that enhance recovery to those that present obstacles that hinder these efforts. It is hypothesized that one’s capacity to “recover” is a function of the type and quality of these sets of resources (Cloud & Granfield, 2008). The relationship between recovery capital and remission from SUD is bidirectional, that is, recovery capital helps individuals achieve remission from SUDs and being in remission helps individuals gain greater access to recovery capital (Cloud & Granfield, 2001). Three primary domains of recovery capital have been proposed: *personal*, *social*, and *community recovery capital*. Each domain will be briefly reviewed below.

Personal recovery capital. The first domain, personal recovery capital are any individual-level characteristics or assets that can be used to sustain recovery from SUDs. There are two forms of personal recovery capital. The first, *physical recovery capital* refers to tangible

resources, including healthcare, financial assets, safe and stable housing, and access to other necessities such as food and transportation. However, it is important to highlight that conceptualizing physical recovery capital at the individual level has limitations. For instance, the lack of access tangible resources such as healthcare, housing, and financial assets is not based on individual deficits but on structural and systemic conditions that prevent individuals from obtaining these resources. The second, *human recovery capital* refers to internal resources and personal attributes, such as one's knowledge, skills, self-appraisal, hopefulness, a sense of purpose, and well-being.

Social recovery capital. *Social recovery capital* refers to the sum of resources that are obtained through one's social networks, and includes material, informational, and emotional social support. It also includes the recovery supportive social norms and expectancies established through social networks that result in pro-recovery behaviors and outcomes.

Community recovery capital. *Community recovery capital* is defined as the community-level resources that support recovery. These resources can include the availability and attendance of community programs that facilitate the resolution of drug problems, such as formal and informal community-based recovery supports, treatment and aftercare services, preventative and early-interventions, and active community efforts to reduce recovery-related stigma. It also involves the cultural norms, values, and beliefs that maximize individual's opportunities for recovery success.

Several studies demonstrate that the presence of personal, social, and community recovery capital is linked to better recovery outcomes for various populations at different stages in their recovery process (Best et al., 2011; 2012a;2012b; 2014; 2015; Boeri et al., 2011; Burns & Marks, 2013; Daddow & Broome, 2010; Duffy & Baldwin, 2013; Evans et al., 2014;

Groshkova, Best, & White, 2013; Gueta et al., 2015; Hillios, 2013; 2014; Jason et al., 2020; Laudet et al., 2006; Laudet & White, 2008; Mawson et al., 2015; Neale et al., 2014). A study of 3,228 U.S participants who were in recovery from SUDs with varying lengths of active addiction and time in recovery found significant improvement across key recovery capital domains, including increases in social support, civic engagement, financial and housing stability, physical and mental health (Laudet, 2013). It is important to note that this study allowed participants to answer questions based on their own definitions of addiction and recovery, so for some recovery involved some substance use while for others, recovery involved complete abstinence. This study was replicated in Canada (McQuaid et al., 2017), Australia (Best, 2015), and the United Kingdom (Best et al., 2015), with similar findings across the major recovery capital domains. While these studies examined the relationship between recovery (e.g. defined as remission from SUDs) and recovery capital as unidirectional (e.g., time in recovery increases one's recovery capital), these relationships are thought to be bidirectional (Granfield & Cloud, 1999). Additionally, the quantity and quality of recovery capital have been found to play a critical role in the successful recovery of people who seek professional treatment, those who utilize a recovery support service, or those who do not seek any assistance (Granfield & Cloud, 1996; 1999; Kaskutas, Bond, & Humphreys, 2002; Moos & Moos, 2006a).

Individual-level recovery capital. In the current study, individual-level recovery capital was measured using a single latent factor (see Jason et al., 2020) comprised of the following resources: quality of life, hope, stress, sense of community, self-esteem, social support, self-efficacy, and income. While these are individual-level resources, the process of increasing recovery capital is inherently social and contextually-based (Cloud & Granfield, 2008). When discussing the importance of social relationships for recovery capital, Granfield and Cloud

(2001) explained “personal problems and their solutions are embedded within a larger structure of social relations and networks. Just as drug use is mediated by the structured relations within which one is embedded, so too are the opportunities for personal change” (pg. 1553). This section will review the literature on each of the latent factor indicators, focusing on how social factors impact these resources.

Quality of life. Quality of life is a measure of a person’s subjective well-being across four areas: social, psychological, physical, and environmental. Quality of life is an important outcome among individuals with SUDs given that it measures four domains of functioning that can be severely impaired by substance abuse (Hubbard, Craddock, & Anderson, 2003; Laudet, 2011; Morgan et al., 2003; Preau et al., 2007; Smith & Larson, 2003; Stein et al., 1998; Volk et al., 1997). For instance, a study reported that the quality of life among those in treatment for drug addiction was as low as or lower than patients with other chronic health conditions such as lung and heart disease and diabetes (Smith & Larson, 2013).

Improvements in quality of life are associated with sustained recovery efforts (Kelly, Greene & Bergman, 2018; Kraemer et al., 2002; Laudet et al., 2006; Laudet & White, 2008; McKay, 2017; Nosyk et al., 2013; Subbaraman & Witbrodt, 2014; Villeneuve et al., 2006). A national study of U.S adults in recovery from alcohol and substance abuse that examined the rate of change in quality of life and other indices of recovery capital as a function of time spent in recovery found steep increases in quality of life during the first six years in recovery, with smaller increases after the six years (Kelly et al., 2018). Laudet, Becker, and White (2009) found that higher quality of life at treatment completion predicted abstinence at a 1 and 2-year follow-up. Laudet and Stanick (2010) found that quality of life satisfaction among polysubstance-dependent individuals after completing outpatient treatment was a significant predictor of

commitment to abstinence, a strong predictor of greater time sober. To date, the longest study of quality of life among those with SUDs assessed participants at 2 and 10 years after their initial substance use treatment (Moos, Finney, & Cronkite, 1990). Among those that remained abstinent at both follow-ups (49% at 2 years and 57% at 10 years), significant improvements in levels of physical, mental, social, and occupational functioning were observed compared to the group that had relapsed. Additionally, the group that went into remission demonstrated similar levels of functioning when compared with a matched community sample with prior history of alcohol dependence. While this study only included individuals with alcohol use disorders and not those that abuse other substances, other studies have found similar improvements in most or all quality of life domains among both alcohol and drug dependent populations (Fassino et al., 2004; Foster, Marshall, & Peters, 2000; Hubbard et al., 2003; Morgan et al., 2003; Villeneuve et al., 2006). Together, these findings suggest that quality of life may be a function of recovery, and thus, higher quality of life may signify having greater recovery capital.

Social factors are known to enhance the quality of life of those recovering from SUDs (Best et al., 2012a; Laudet, Morgen, & White, 2006; Rudolf & Watts, 2002). A study examining the recovery factors that were most strongly associated with quality of life among individuals attempting to overcome their addiction found that quality of life was best predicted by the number of non-users in one's social network and greater engagement in meaningful activities (Best et al., 2012a). A study of residents of substance abuse recovery homes found that social embeddedness was related to higher quality of life (Jason, Stevens, Light, & Doogan, 2020). Mawson et al. (2015) found that environmental quality of life was highly associated with social recovery capital, suggesting that factors such as environmental safety, wages, access to

accommodation and transportation, services, and leisure activities are connected to the availability of social resources.

Hope. Hope is an internal resource that influences the motivation to engage in behaviors that can promote recovery from SUDs (Bradshaw, Shumway, Harris, & Baker, 2013; Bradshaw, Shumway, Wang & Harris, 2014; Bradshaw et al., 2017; Irving, Seidner, Burling, Pagliarini & Robbins-Sisco, 1998; Jackson, Wernicke, & Haaga, 2003; Laudet et al., 2006; Law & Guo, 2012; Rollnick, Morgan, & Heather, 1996; Shumway, Bradshaw, Harris, & Baker, 2013; Stevens, Guerrero, Green, & Jason, 2018). Hope is characterized by three dimensions: (1) the perception of successful *agency*, (2) available *pathways* to achieve one's goals (Snyder et al., 1991), and (3) having opportunities found in their *environmental context* that facilitate goal attainment (Stevens, Buchannan, Ferrari, Jason, & Ram, 2014). Studies have demonstrated the importance of hope at different stages of the recovery process. For instance, high levels of hope is associated with entering SUD treatment (Jackson et al., 2003), greater length of sobriety after treatment (Strack, Carver, & Blaney, 1987), better outpatient treatment outcomes (Sowards, Boyle, & Weissman, 2006), and higher quality of life (Carvajal, Clair, Nash, & Evans, 1998). These findings suggest individuals recovering from SUDs who exhibit high levels of hope are better equipped to navigate challenges and generate more strategies for attaining their goals (Irving et al., 1998). Since hope is also contingent on the opportunities and obstacles present in the environment that either hinder or facilitate goal attainment, contextual factors are important to consider when examining individual levels of hopefulness (Jason, Stevens, & Light, 2016; Stevens et al., 2018). For instance, social recovery capital is an important contextual factor that can contribute to greater hope by providing pathways for overcoming challenges encountered in

recovery, bolstering greater agency perceptions, and providing essential resources that facilitate goal-attainment (Parker et al., 2015).

Stress. Stress is a cited threat to recovery linked to addiction and relapse (Laudet, Magura, Vogel, & Knight, 2004; Laudet & White, 2008; Rhoads, 1983; Titus, Godley, & White, 2007). Once in recovery, this path is often marked by many challenges and obstacles that can generate great levels of stress. However, individuals with greater recovery capital can more effectively manage this stress. Weaver, Turner, and O'Dell (2000) investigated stress and coping strategies among women in recovery and found that their perceived stress across 16 life domains significantly decreased, whereas the stress coping strategies increased from the pre-recovery phase compared to the recovery period. Laudet, et al. (2006) investigated whether recovery capital, measured through social support, spirituality, life meaning, and 12-step affiliation, mitigated the negative effects of stress on quality of life among former polysubstance users in recovery. They found that stress levels decreased significantly as time in recovery increased and that recovery capital did mitigate the negative effects of stress while enhancing quality of life. Similarly, Laudet and White (2008) found that greater time in recovery predicted lower stress and greater quality of life, suggesting that engaging in recovery can lead to improvements in several life functioning domains as well as gain resources that help individuals cope with stress. In sum, stress is an important indicator of recovery capital, with lower stress signifying greater recovery resources.

It is well documented that stress can be buffered by the presence of social support (Barrera, 1988; Cohen & Wills, 1985; Kawachi & Berkman, 2001; Taylor & Aspinwall, 1996) and other resources availed through one's social networks (Iso-Ahola & Park, 1996; Thoits, 2011). One way that social relationships can help reduce stress is by helping individuals

reappraise events or problems in a positive light and by offering solutions to solve their problems (Thoits, 1995). Additionally, social support in the form of emotional guidance and information from others can help individuals cope with stress. The positive effects of social relationships on stress underlie the importance of considering social contextual factors when examining stress among those in recovery.

Sense of community. Sense of community represents a feeling of connectedness and a positive relationship to one's community and social environment (Sarason, 1974). Sarason (1974) first introduced sense of community as "the perception of similarity to others, an acknowledged interdependence with others, a willingness to maintain this interdependence by giving to or doing for others what one expects from them, the feeling that one is part of a larger dependable and stable structure" (p.157). Three domains of PSOC have been proposed that include the *self* (the importance of one's community membership to one's identity), *membership* (the relationship one has with other members of the community), and *entity* (how well the community's mission and purpose resonates with the members) (Jason, Stevens, & Ram, 2015). The current literature on sense of community among individuals in recovery from SUDs highlights several beneficial outcomes related to a higher sense of community (Bahl, Nafstad, Blakar, Landheim, & Brodahl, 2019; Barbieri et al., 2016; Drake, Wallach, & McGovern, 2005; Ferrari, Jason, Olson, Davis, & Alvarez, 2002; Jason, Davis, Ferrari & Bishop, 2001; Kollath-Cattano et al., 2018; Laudet, 2008; Peterson & Reid, 2003; Stevens, Jason, Ferrari, & Hunter, 2010; Stevens, Jason, Ferrari, Olson, & Legler, 2012). For instance, Stevens et al. (2018) found that a higher sense of community and hope were associated with higher quality of life among recovery home residents. This finding suggests contextual factors such as one's sense of community positively influence recovery trajectories.

Self-esteem. Self-esteem is a person's self-reflection of their worth and abilities characterized by two dimensions *self-liking* and *self-competence* (Tafarodi & Milne, 2002). Positive self-esteem is associated with a greater likelihood of sustained recovery (McNeill Brown, Brennan Nanni, & LaBelle, 2020; Richter, Brown, & Mott, 1991). One study found that although significant drops in self-esteem occurred during the first year of recovery, individuals experienced steady increases over time after the first year (Kelly et al., 2018). Social relationships can increase self-esteem by providing positive appraisals, which can help individuals develop positive self-perception and higher confidence in one's abilities to overcome obstacles. For instance, Groshkova et al. (2011) found that greater participation in recovery support groups is linked to a higher quality of life and self-esteem. This suggests that self-esteem can be facilitated through involvement in recovery congruent communities.

Social support. Social support, which embodies resources obtained from social relationships such as the provision of information, tangible resources, emotional guidance, and positive appraisal (McKay, 1984; House, 1981), has been extensively linked to positive recovery outcomes (Brennan & Moos, 1990; El-Bassel, Duan-Rung, & Cooper, 1998; Granfield & Cloud, 2001; Havassy, Hall, & Wasserman, 1991; Humphreys, Moos, & Cohen, 1997; Humphreys, Mankowski, Moos, & Finney, 1999; Humphreys & Noke, 1997; Laudet et al., 2000; Noone, Dua, & Markham, 1999; Rumpf, Bishof, Hapke, Meyer, & John, 2002; Weisner, Delucchi, & Matzger, 2003). A previous study found that one of the strongest predictor of recovery capital was overall social support, with higher social support predicting higher recovery capital (Best et al., 2012b). In another study, recovery capital, as measured by general social support, recovery specific support, affiliation with a sober network, spirituality, and life meaning, buffered the adverse effects of stress on quality of life (Laudet & White, 2008). Laudet et al. (2000) examined

how support for recovery and sources of support influenced the abstinence and mental health of individuals participating in 12-step groups and found that higher social support and greater support sources were related to improved mental health and sustained sobriety.

Self-efficacy. Self-efficacy is a psychological construct that refers to a person's confidence that they can use their resources, skills, and motivation to achieve a desired outcome (Bandura, 1977). Self-efficacy is well supported theoretically and empirically as playing a pivotal role in behavior change (Ajzen & Madden, 1986; Baldwin et al., 2006; Bandura, 1986; Marcus, Selby, Niaura, & Rossi, 1992; Prochaska & DiClemente, 1983; Rosenstock, Strecher, & Becker, 1988; Strecher, McEvoy DeVellis, Becker, & Rosenstock, 1986). Self-efficacy influences how invested individuals are to change their behavior and how persistent they will be in achieving their goals when faced with obstacles (Bandura, 1982; Bandura, 1999). In the realm of substance abuse recovery, abstinence self-efficacy - the belief in one's ability to abstain even in the face of temptation and obstacles – affects several recovery stages, including recovery initiation, recovery attempts after relapse, and long-term recovery maintenance (Bandura, 1999). Studies have found that higher levels of abstinence self-efficacy are associated with not only abstinence but greater recovery success overall (Chavarria, Stevens, Jason, & Ferreri, 2012; Gubi & Marsden-Hughes, 2013; Kadden & Litt, 2011; Kelly, Finney, & Moos, 2005; Laudet et al., 2010; Moos, 2008; Torrecillas, Cobo, Delgado, & Ucles, 2015). In a meta-analysis, Adamson, Sellman, and Frampton (2009) found that abstinence self-efficacy was the strongest predictor of alcohol consumption outcomes out of 31 predictors. Moos et al. (2006) followed individuals in recovery from alcohol use disorders for over sixteen years. Those who achieved remission at the 3-year follow-up reported greater abstinence self-efficacy than those that had not achieved remission. Additionally, those that achieved remission at the 3-year follow-up but relapsed at the

16-year follow up had lower abstinence self-efficacy at the 3-year follow-up. Ilgen, McKellar, and Tiet (2005) studied over 3,000 individuals who completed a substance abuse treatment program and found that a score of 100% on an abstinence self-efficacy scale was the strongest predictor of sobriety at a one-year follow-up. Scott et al. (2005b) conducted a study examining the factors that influence the transitions between relapse, treatment entry, incarceration, and recovery among individuals with SUDs over two years. The study found that those who were most likely to transition into recovery had a higher level of self-efficacy to resist substance use than those who never entered recovery.

Social relationships can help increase individuals' belief that they are capable of maintaining their recovery. As Jill Kiecolt writes, "location in social structure sorts persons into 'contexts of action' which afford different amounts of resources and opportunities for engaging in efficacious action" (1994, pg. 61). This aligns with the view that recovery capital - in the form of self-efficacy - is influenced by the availability of social resources (Granfield & White, 2001). Indeed, participation in peer support groups such as Alcoholic Anonymous has been found to enhance abstinence self-efficacy (Kelly, Hoepfner, Stout, & Pagano, 2012). Additionally, social support has been found to promote abstinence self-efficacy (Stevens, Jason, Ram, and Light, 2015).

Income. Research suggests that income is an important form of physical recovery capital that increases individuals' financial stability, ability to secure a safe and stable living condition, and expand their options for pursuing recovery, such as by making treatment more accessible or making it possible for individuals to move away from areas with high substance availability (Cloud & Granfield, 2008; Gueta et al., 2015). Studies have shown that higher income is associated with higher recovery capital (Sanchez, Sahker, & Arndt, 2020; Whitesock, Zhao,

Goettsch & Hanson, 2018). For instance, Sanchez et al. (2020) found that those who reported income from employment as their primary source had higher recovery capital scores than those who reported other sources. Similarly, a validation study of the Recovery Capital Index found that among 22 recovery capital domains, income was among the four variables most significantly related to recovery capital (Whitesock et al., 2018). Dennis et al. (2007) followed individuals in recovery for a period of eight years and found that income, employment and housing contributed to long-term recovery independent of the type of treatment utilized. Higher-income is also associated with a lower risk of relapse and higher quality of life (Marshall et al., 2014; Panebianco et al., 2016).

Conclusion. In summary, individual-level capital in the form of quality of life, hope, stress, sense of community, self-esteem, social support, self-efficacy, and income have been shown to promote recovery. Notably, these forms of capital, whether internal or external, are facilitated by social relationships highlighting the need to investigate the impact of social network dynamics on recovery capital.

A study by Jason et al. (2020a) calls attention to the importance of considering the social context when examining recovery capital. The study conducted a multi-level confirmatory factor analysis with 602 participants who were residents of 42 substance abuse recovery homes. Findings revealed a single latent factor measuring recovery capital (quality of life, hope, stress, sense of community, self-esteem, social support, self-efficacy, and income) at both the resident and house-level. Notably, the study found that an individual's probability of relapse was predicted by recovery capital at the house-level while the resident-level recovery factor did not predict variations in the relapse rates. These findings suggest that recovery is strongly influenced by those with whom recovering individuals come into regular contact. The current dissertation

aims to build on these findings in two ways: (1) by examining individual-level recovery capital (e.g., as measured by the recovery capital factor) along with network-level recovery capital (described in great detail in subsequent sections); and (2) by investigating *how* recovery capital is developed through social networks using stochastic actor-oriented modeling, with a sub aim being to determine which types of network characteristics facilitate or hinder the development of recovery capital.

An individual-level of analysis currently dominates the research on recovery capital resulting in an overemphasis on how individual actions and behaviors influence recovery outcomes (Boeri, Gardner, Gerken, Ross & Wheeler, 2016; Boeri, Gibson, & Boshears, 2014; Zchau et al., 2016). This single-level approach for measuring recovery capital ignores that recovery occurs within a social context that includes one's social networks (Moos, 2003), thus offering only a limited understanding of this complex and dynamic process. To move past individual-level explanations, we need to examine how individuals interact with their environments to generate greater recovery capital. The following section will provide an overview of the literature on social networks and their importance to the study of recovery capital. The social network theories providing the foundation for the current work will also be discussed.

Social Networks

The study of social network phenomena originated within the field of sociology (Cobb, 1976; Coleman, 1990; Fischer, 1977; Fischer, 1982; Laumann, 1973; Mitchell, 1969; Wasserman & Faust, 1994) and has since been applied to several other disciplines, including engineering, biology, physics, community and organizational psychology, and health and medicine (Albert & Barabasi, 2002; Barabasi, Gulbache, & Loscalzo, 2011; Wellman, 1988; Watts & Strogatz, 1998).

A social network refers to a social structure that is comprised of actors (e.g., the focal social entity), alters (e.g., an actor's social contact), relational ties (e.g., dyadic, triadic, close, distant), and social groupings (e.g., clusters) within a given boundary (e.g., social system/environment). Actors in a network can represent individuals or entities within a larger system (e.g., group, organization, school, program, and other entities). Social networks can also have multiple relational dimensions that can either be hierarchical (e.g., mentorship) or non-hierarchical (e.g., friendships). Social networks thus provide a relational map of all the linkages of an entire social structure.

To fully comprehend what social networks are, it is helpful to understand how it differs from a similar construct: social support. The following section will discuss the fundamental differences between social support and social networks.

Key distinctions between social networks and social support. While social support and social networks both describe processes and functions of social relationships and are often conflated in the literature (Berkman & Glass, 2000), there are fundamental differences between these two constructs. Social support is one of the most important functions of social relationships and define a person's subjective appraisal of how well their support needs are met by their social contacts (Smith & Christakis, 2008). According to the pivotal work by House (1981), social support can come in the form of (1) emotional support; (2) instrumental support; (3) informational support; and (4) appraisal support. These types of social support are outside of the scope of the proposed study, so they will not be discussed further (see House, 1981; Barrera, 1986 for further discussion on the types of social support). A significant difference between social support and social networks is the level of analysis used for each phenomenon. For instance, social support is an individual-level measure that taps into the extent to which

individuals perceive their social relationships to be helpful but does not reveal further insights into the structural characteristics of these relationships. In contrast, social networks are a structural-level measure that provides comprehensive information on all actual ties, relational patterns, and characteristics of a given network. While a social network approach can be used to examine the provision of social support within a network (McLeroy, Gottlieb, & Heaney, 2001), such an approach can also be used to investigate other social functions (e.g., social capital, social influence, diffusion of information and innovation).

The social network approach to research. A social network perspective privileges the relationships over individual actors, ascribing to the view that the whole of a social network exceeds the sum of its parts (Watts, 2004). The perspective holds that actors, their relationships, and their actions are interdependent rather than autonomous (Wasserman et al., 1994). Additionally, linkages between actors are hypothesized to serve as channels for the flow of material (e.g., social support, financial exchange) or non-material (e.g., social conformity, social learning) resources, and these linkages also provide opportunities for or constraints on individual action.

Social network analysis (SNA) comprises theoretical and methodological tools uniquely suited for studying structural and relational occurrences and processes (Wasserman et al., 1994). Specifically, SNA is used to examine the characteristics, patterns, and impact of social relationships. SNA makes it possible to test theories regarding relational processes and how they impact individual and structural outcomes using mathematical and computational models. Another key feature of SNA is the use of graphs as a way to visualize networks that depict the nodes (individual actors) and ties (relationships or interactions) that connect them.

Examples of commonly examined network characteristics include the number of members of a network (network size), the extent to which network members share commonalities on one or multiple dimensions (homogeneity), the extent to which there are direct linkages between egos and alters (density), the extent to which resources and support are both given and received (reciprocity), whether networks involve multiple types of relations between dyads (multiplex), the extent to which the relationships are emotionally close (intensity), the extent to which a relationship serves several functions (complexity), the smallest number of connections separating an ego and an alter (geodesic distance), the extent network connections are dependent on a few actors (centrality), and the tendency for triads to share the same relationship (transitivity) (Smith & Christakis, 2008).

There are two approaches to conducting network studies. The first approach uses egocentric data. Egocentric network methodology involves asking a focal individual to identify and rate their relationships with others in their perceived network (e.g., alters); thus, this approach can only model direct links to a focal individual. Since this data represents an ego's perceived network, it is a limited view of their relational structures. In contrast, whole network studies involve collecting data from all actors in a bounded setting allowing for the analysis of various patterns and structures found in an entire network (Wasserman & Faust, 1994). This approach then allows for the collection of information regarding both direct and indirect ties. Due to data and methodological challenges present when conducting whole network research, these types of studies are rarer than egocentric studies. Conducting a social network analysis with whole network data is critical for an in-depth understanding of how recovery capital is developed in networks. A few studies using whole network data have begun looking at network-level characteristics and how they relate to recovery capital (Jason et al., 2020a; Jason et al.,

2020b; Jason et al., 2020c; Jason et al., 2021; Zchau et al., 2016). This dissertation will build on these studies by testing network dynamics over time by using stochastic actor modeling.

The following section will review the literature on social networks and recovery. An overview of the three social network theories tested in the current study will be discussed. A subsequent section will present the integration of the theoretical foundation and stochastic actor-oriented modeling that were utilized in the current study. Lastly, the introduction will conclude with an overview of the current study.

Social networks and substance use. The impact of social networks on substance use behaviors, including substance use initiation, maintenance, and cessation, is well documented (Dobkin, Civita, Paraherakis, & Gill, 2002; Ellis, Bernichon, Yu, Roberts, & Herrell, 2004; Joe, Broome, Rowan-Szal, & Simpson, 2002; Litt, Kadden, Kabel-Cormier, & Petry, 2007; 2009; Rosenquist, Murabito, Fowler, & Christakis, 2010; Walton, Blow, Bingham, & Chermack, 2003; Weisner et al., 2003; Zywiak et al., 2009). Individuals that are socially connected to others who use substances are more likely to engage in substance use themselves (Hawkins, Catalano, & Miller, 1992). Continued association with other substance-using peers is linked to higher rates of relapse during treatment (Brewer, Catalano, Haggerty, Gainey, & Fleming, 1998; Havassy et al., 1991; Havassy, Wasserman, & Hall, 1995) and after treatment (Latkin, Knowlton, Hoover, & Mandell, 1999). Research investigating the competing effects of social networks and neighborhood characteristics on substance use has found that social networks exert greater influence on individuals' substance use than neighborhood-level factors (Davis & Tunks, 1990; Schroeder et al., 2001). This suggests that one's proximal social environment has a more significant influence on substance-using behaviors than the more distal, social macro-

environment, underscoring the importance of investigating social network dynamics when examining long-term recovery outcomes.

Social networks and recovery capital. The recovery capital framework is theoretically grounded in the social capital theory literature. Social capital refers to the tangible and intangible benefits obtained directly or indirectly through participation in social networks. The work of two prominent social capital theorists, Pierre Bourdieu (1980) and James Coleman (1988; 1990), was particularly influential to the conceptualization of recovery capital. While both theorists share similarities in their views on social capital, their views diverge on whether social capital is a resource that is accrued by the social group or for the members within the group (Lin, 1999). The current study operationalizes recovery capital as both an *individual-level* and a *network-level* resource that is developed through social relationships. The following section provides an overview of Bourdieu and Coleman's theories of social capital to support the utility of applying a multi-level approach to the study of recovery capital.

Social capital theory. While several prominent sociologists and philosophers are credited with describing aspects of social capital, including Karl Marx, Emile Durkheim, David Hume, Edmund Burke, Adam Smith, and de Tocqueville (Portes, 2000; Putnam, 2000), Pierre Bourdieu (1985; 1986), a French sociologist, is the first person to provide a formal conceptualization of social capital. Bourdieu defined social capital as “the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance or recognition” (1985; pg. 248). He proposes that social relationships, whether formal or informal, determine the resources that are available and accessible to each individual, as well as the quality of those resources. Thus, individuals must develop and maintain memberships in social networks to access social capital

(Bourdieu, 1986). While he viewed social capital as developed through social networks, Bourdieu posited social capital was an individual resource external to the network, meaning actors can leave their networks and still hold on to their capital. According to this perspective, social capital entails how resources embedded within a social network are accessed and utilized with respect to some benefit or profit at the individual level (Lin, 1999).

While Bourdieu distinguished between the different types of capital such as physical (e.g., financial resources), human (e.g., assets that reside within individuals such as knowledge, skills, personal attributes) and cultural capital (e.g., assets that derive from contextual factors such as cultural norms that facilitate the development of capital), he argued that all forms of capital were intricately tied to one's social relationships. Social capital can produce what he referred to as a 'multiplication effect' that influences other types of capital. For instance, social relationships can help an individual accumulate economic capital by providing access to jobs or information on generating wealth through investments. Social relationships are also the vehicle that promotes social and cultural norms. Additionally, different types of capital can be traded for each other, and while these transactions may not be immediately mutually beneficial to both parties, they serve as an investment strategy in which actors establish a reliable source of future resources (Portes, 1998).

James Coleman (1988) was an American sociologist who expanded on Bourdieu's social capital theory by incorporating sociological and economic perspectives. In contrast to Bourdieu's view of social capital as an individual-level resource, Coleman viewed social capital as a collective asset existing within the social network structure. As such, Coleman argued that social capital "...is not a single entity, but a variety of different entities having two characteristics in common: They all consist of some aspect of social structure, and they facilitate certain actions of

actors – whether persons or corporate actors - who are within the structure” (1988, pg. 98). In this view, social capital is endogenous to a social structure and not its individual actors. Thus, social capital dissolves when actors exit their networks, wherein both individuals and the overall group lose the capital afforded by that network. Like Bourdieu, Coleman believed that social capital could be used to develop other forms of capital, particularly human capital, which he defined as internal resources such as an individual’s intellect, skills, knowledge, traits, mental and physical health.

This social capital perspective is concerned with the network processes and mechanisms that allow for the creation of capital. According to Coleman, three main forms of social capital include *reciprocity*, *information channels*, and *norms and effective sanctions*. *Reciprocity* when there are mutually beneficial relationships in which an actor reciprocates a favor or what he referred to as a “credit slip” (Coleman, 1988). This type of social capital depends on several conditions, including the trust between network actors that enables these exchanges, the expectation that the favor will be reciprocated in the future, and the obligations actors feel to repay the favor. *Information channels* refer to the paths along relational ties that allows actors to obtain information (Coleman, 1988). This type of social capital depends on whether the information acquired leads to an actionable behavior. Lastly, norms and sanctions are the social mechanisms that facilitate or impede an action resulting in greater capital. All three forms of social capital facilitate specific actions from individuals that allows them to achieve goals that would otherwise be unfeasible for them to accomplish alone.

Overall, the premises that underpin Bourdieu and Coleman’s theories is that social capital is network-based and that relationships are the conduits through which tangible and intangible resources, including personal, social, and community forms of capital are attained. They differ,

however, on their assessment of whether social capital is an individual resource or one embedded in the relational structures of a network. This is a critical area of contention in the social capital literature that continues to be debated today (De Silva, McKenzie, Harpham, & Huttly, 2005; Lin, 1999; Oh, Labianca, & Chung, 2006; Tan, Zhang, & Wang, 2015). In light of these debates, there have been calls for more research on social capital that utilizes SNA to account for the multi-level nature of this phenomena (Capaldo, 2007; Klein, Dansereau, & Hall, 1994; Tan et al., 2015). The same need has been identified within the recovery capital literature (Zschau et al., 2016). While the conceptualization of recovery capital is grounded in both Bourdieu and Coleman's perspectives on social capital (Grandfield & Cloud, 1999; Grandfield & Cloud, 2001; Cloud & Grandfield, 2004), recovery capital has mainly been studied as an individual resource, ignoring the systemic and structural aspects of this resource (Zschau et al., 2016). As a result, the social network dynamics involved in the recovery process are not well understood.

The current study adopts both Bourdieu and Coleman's perspectives by using a multi-level analytic lens that operationalizes recovery capital as an individual and network-level resource. This study aims to offer additional insights into *how* recovery capital is developed through social networks, further elucidating how individuals interact with their social environments to build greater recovery capital. This study also seeks to understand the network conditions that facilitate or hinder the development of recovery capital. The following section provides a review of recovery capital found within networks.

Recovery capital within social networks. Social networks have important implications for recovery capital. For instance, there is considerable evidence that individuals who undergo adaptive changes to their social networks by associating with others who support their recovery have better overall recovery outcomes (Longabaugh, Wirtz, Zywiak, & O'malley, 2010). For

instance, Litt et al. (2007, 2009) conducted a study in which people who completed a detoxification treatment from alcohol were randomly assigned to either usual after-care or to “network support” intervention, which involved adding at least one non-drinking peer to their network. Those in the network support intervention had a 27% increased likelihood of treatment success at their one-year follow-up. Best et al. (2012a) found that a higher number of recovering peers in one’s social network was associated with an enhanced personal and social recovery capital, even after accounting for time in recovery. A study that investigated the recovery capital factors (e.g., physical health, self-esteem, self-efficacy, anxiety, depression) that were most strongly associated with quality of life among individuals recovering from alcohol and heroin addiction found that quality of life was best predicted by the number of non-users in one’s social network and greater engagement in meaningful activities (Best et al., 2012b). Best, McKitterick, Beswick, and Savic (2015) compared the recovery capital for individuals who described themselves as in recovery from SUDs but no longer in treatment to individuals who were currently receiving treatment for their addiction. The study found that those out of treatment were more likely to be involved in a recovery support group and had social networks with more individuals in recovery and fewer individuals who were active users. Additionally, individuals in recovery with these social networks also reported greater quality of life, lower depression and anxiety, and higher social capital than those still in treatment, highlighting that social networks are key mechanisms through which recovery capital is developed. While these studies are informative, they have exclusively focused on social network composition and size and their impact on recovery. Therefore, there is still a lack of knowledge pertaining to the effects of more complex social network dynamics on the development of recovery capital.

A few recent studies have begun to shed light on other network-level characteristics beyond network composition and how they relate to recovery capital. Work in this area has examined recovery capital both at the individual and network-levels. At the network level, advice seeking among individuals residing in recovery homes has been shown to be positively associated with stress at the individual and house-level (Jason et al., 2020b; Jason et al., 2020c). At the individual level, willingness to loan money has been shown to be positively associated with house-level income, social support, self-esteem, quality of life, abstinence self-efficacy, hope, and a sense of community and negatively associated with stress (Jason et al., 2020b; Jason et al., 2020c). These findings suggest that networks where there is a high willingness to share a tangible resource facilitate recovery capital whereas networks high in advice seeking hinder recovery capital. These studies further highlight the importance of measuring both the network level and individual level implications for recovery capital.

The current dissertation seeks to build on this burgeoning area of research by examining how individual and network-level recovery capital is developed over time using stochastic actor-oriented modeling. Before describing the stochastic actor-oriented models that were developed and tested, I provide an overview of the three social network theories that serve as the theoretical foundation for the stochastic models in the following section. The three theories include network cohesion theory (Coleman, 1988), social exchange theory (Homans, 1961; Emerson, 1972), and generalized exchange theory (Levi-Strauss, 1949; Stanzani, 2015). These theories describe structural levels of social capital and propose the different social network mechanisms that facilitate social capital such as the network conditions that enable or hinder its production. This dissertation extends these theories to the study of recovery capital to understand the network conditions that facilitate or hinder recovery capital.

Network-Level Theories of Recovery Capital

Network Cohesion. Network cohesion theory was born out of Coleman's (1988) work on social capital. This theory proposes that cohesive ties are a fundamental means by which social capital is created and maintained. Networks with cohesive ties are characterized as those in which most members are connected either directly or indirectly, have multiple types of social relationships within the group that pull the network together, lack any distinguishable subgroups, and are resistant to being dissolved by the removal of a subset of its members (Moody & White, 2003; White & Harary, 2001). Network density, which is the ratio of observed ties among actors to possible ties, is often used as a proxy for network cohesion (Frank & Yasumoto, 1998; Reagans & McEvily, 2003), with higher levels of density signifying greater levels of social capital exchange (Bodin & Crona, 2009; Burt, 2000; 2001; Coleman, 1988; Marti, Bolibar, & Lozares, 2017).

Network cohesion is thought to engender social capital through several mechanisms. Network cohesion helps foster social norms and sanctions that promote trust and cooperation, which can result in greater resource sharing among actors (Burt & Knez, 1995; Coleman, 1988; Coleman, 1990; Gargiulo & Benassi, 2000; Ingram & Roberts, 2000; Reagans & McEvily, 2003; Uzzi, 1997). Networks are considered to be more effective at generating capital when members abide by these norms in their interactions with other members in the present and trust that others will behave according to the rules established by the group in the future (Uzzi, 1997). Trust that others will honor their obligations engenders a better an environment for the exchanges of resources. Additionally, norms in cohesive networks can mobilize members to share capital through group pressures to provide such capital (Coleman, 1988; 1990; Haines, Beggs, & Hurlbert, 2002; Wellman & Frank, 2001; Wellman & Gulia, 1999). Cohesive ties compared to

weak ties are also characterized by greater emotional intensity and greater investments in social relationships, which have been found to protect against mental illness and general stress (Ferlander, 2007). Network cohesion also facilitates the acquisition and diffusion of information and knowledge (Bodin & Crona, 2009; Ingram et al., 2000; Reagans et al., 2003; Uzzi, 1996) and that information shared among cohesive ties is believed to be of greater quality compared to information shared in networks with more loosely connected actors (Aral & Alstytne, 2011; Uzzi, 1996). Additionally, networks with greater cohesion can result in a more leveled playing field as actors have more equitable access to capital than actors in more loosely connected networks (Wei et al., 2011).

In alignment with Coleman's theory of network cohesion, Moos (2008) hypothesized that the social mechanisms critical to recovery from substance addiction are those found in networks with cohesive ties, such as social bonding, monitoring, and goal direction. More generally, having cohesive ties with others who are supportive of one's recovery can help individuals model recovery-congruent behaviors, learn effective coping skills that can mitigate life stressors, and enhance their self-efficacy, all of which can optimize recovery success (Castonguay & Beutler, 2006; Johnson et al., 2008; Moos, 2008; Oetting & Donnermeyer, 1998; Petraitis, Flay, & Miller, 1995).

A few studies have found associations between positive recovery outcomes and network cohesion. Tucker et al. (2011) found that greater network density among homeless women with SUDs predicted entering treatment for their SUDs, indicating that network cohesion can promote help-seeking behaviors and treatment participation. Min et al. (2013) compared the changes in network density of individuals in substance abuse residential treatment and those in intensive outpatient treatment. Individuals in both treatment modalities experienced an increase in network

density over the 12 months post-treatment, suggesting that greater network density are adaptive network changes that occur with time spent recovery.

Network cohesion may not always yield positive effects on recovery capital. To illustrate, Jason et al. (2020) found that individual's likelihood of relapse was dependent on the recovery capital found in their most proximal social environment. Additionally, survival analysis revealed significant associations between relapse risk and the network densities over two years (Jason et al., 2020c). In particular, denser willingness to loan network was associated with a lower hazard of relapse, whereas a denser advice-seeking network was associated with higher relapse rates (Jason et al., 2020c). Seemingly, network density is not always positively associated with recovery capital, suggesting that network cohesion is highly dependent on the type of network under investigation. Thus, it is imperative to investigate the conditions in which network cohesion results in higher or lower recovery capital.

In summary, there are important social mechanisms that arise in cohesive networks that aid the development of capital through one's relationships. Cohesive ties are posited to be a form of structural capital because they establish norms and sanctions that facilitate trust and cooperation between network members that enhance the availability of resources (Coleman, 1988; Gargiulo et al., 2000). While there are positive findings associated with network cohesion, the available evidence suggests that contingency factors might influence whether or not cohesion results in greater capital. This dissertation hopes to shed light on the conditions in which network closure results in the generation or deterioration of recovery capital.

Social Exchange Theory. Social exchange theory (Blau, 1946; Homans, 1958; 1961; Emerson, 1972; Levine & White, 1961) focuses on the *mutual* 'exchanges' of tangible and intangible capital from one actor to another. These exchanges occur within reciprocal

relationships that are considered a form of social capital (A to B; B to A) (Putnam, 2000). Social exchanges are part of our everyday social lives; as Molm (1997) observes, “much of what we need and value in life (e.g., goods, services, companionship, approval, status, information) can only be obtained from others. People depend on one another for such valued resources, and they provide them to one another through the process of exchange” (pg. 12). While different views of social exchanges have been proposed, these types of interactions are seen as contingent on the actions of another person (Blau, 1964), that is, in a dyadic relationship, actor A’s behavior is reinforced by B’s behavior, and B’s behavior is reinforced A’s behavior in turn.

A basic tenet of social exchange theory is that relationships evolve over time into trusting and mutual commitments, but in order to do so, actors must abide by the rules of exchanges. The most central rule proposed by the theory is the norm of reciprocity. Reciprocity refers to a transactional pattern of interdependent exchanges between dyads (Cropanzano & Mitchell, 2005). For instance, when capital is given to another, the person on the receiving end is expected to respond in kind (Gergen, 1969). Once reciprocation occurs, future rounds of capital exchanges transpire. Gouldner (1960) noted that reciprocity could be understood by examining different processes, including equivalence (the extent to which the capital returned is similar to what was received), immediacy (the time between when the capital is exchanged to when it is repaid), and interest (the motive for making the exchange). Reciprocity is also promoted through cultural mandates that sanction those whom do not comply (Mauss, 1967). Additionally, there is support for the universal tendency for people to reciprocate (Axelrod, 1984; Blau, 1964; Gouldner, 1960; Phan, Sripada, Angstadt, & McCabe, 2010; Tsui & Wang, 2002; Wang, Tsui, Zhang, & Ma, 2003), although there are individual and cultural differences (Eisenberger, Huntington,

Hutchison & Sowa, 1986; Parker, 1998; Rousseau & Schalk, 2000; Shore & Coyle-Shapiro, 2003).

There is strong support for reciprocity in relationship formation and maintenance as well as other behaviors (Gächter & Falk, 2002; Göbel, Vogel, & Weber, 2013; Kahneman, Knetsch, & Thaler, 1986; Surma, 2016). Specifically, reciprocity is shown to be an underlying mechanism for cooperative behaviors (Axelrod & Hamilton, 1981; Fiske, 1991; Nowak, 2006; Ohtsuki & Nowak, 2007; Rand & Nowak, 2013; Santos & Pacheco, 2005; Santos & Pacheco, 2006). For example, several experimental studies examining game theory and reinforcement dynamics show that many people tend to behave conditionally cooperatively, i.e., they reciprocate others' contribution of a good (Croson, 2007; Keser & van Winden, 2000; Sonnemans, Schram, & Offerman, 1999). Wang, Szolnoki, and Perc (2013) studied the outcome of the public goods game on two interdependent networks connected by means of a utility function, which determines how rewards on both networks influence the success of players in each network. They found that network reciprocity spontaneously emerged and contributed to the maintenance of high levels of cooperation even in adverse conditions. Reciprocity thus has important implications for collective actions in settings that depend on collaborative behaviors (e.g., peer to peer support, team production) (Lazega & Pattison, 1999).

Reciprocity has also been studied among those recovering from SUDs. The social exchange of support and knowledge are believed to be central to the therapeutic processes of mutual support groups for individuals with SUDs (Brown et al. 2014). For example, Doogan and Warren (2017) examined the affirmation networks of residents of therapeutic communities where peers are expected to affirm other residents for prosocial behavior and to sanction behaviors that contradict the community's norms. The study found a strong effect size for direct reciprocity,

suggesting that cooperation is high in environments that depend on trusting relationships among peers to operate. A study of ego networks found that individuals who were abstinent post-treatment had support networks that exhibited higher reciprocity than those who relapsed (Panebianco, Gallupe, Carrington, Colozzi, 2016). In a cross-sectional study of recovery homes, Jason et al. (2020d) examined the reciprocity patterns of friendship, willingness to loan, and advice seeking networks. Within the friendship network, reciprocity was high suggesting that mutuality is a norm among residents. Compared to the friendship network, loan and advice seeking networks have far lower reciprocity rates, suggesting that there are fewer instances in which loaning and advice-seeking are bidirectional.

Questions remain regarding reciprocity and the implications for recovery capital. For instance, what happens when there is an increased need for a resource along with a decreased ability to reciprocate within a network, and what impact does the failure to meet exchange demands have on recovery capital? Additionally, some types of reciprocity may be more beneficial than others (Brown, Tang, & Hollman, 2014). Thus, identifying when reciprocation is most beneficial would add substantial value to the recovery capital literature. Longitudinal social network analysis can help answer these questions and can elucidate how reciprocity in networks co-evolves over time with individual recovery-related attitudes and behaviors.

Generalized exchange theory. Generalized exchange theory (Bearman, 1997; Lawler et al., 2000; Levi-Strauss, 1969; Molm & Cook, 1995) emerged as a way of describing exchanges beyond the confinements of dyadic structures. Generalized exchanges require at least three network actors who are involved in two unilateral exchanges where an actor transfers a resource to another and over time receives a resource from a third party actor (A to B; B to C) (Yamagishi & Cook, 1993). Thus, reciprocity is indirect and not mutual (Takahashi, 2000). Unlike direct or

dyadic reciprocity, generalized exchanges are inherently riskier given that reciprocity is not guaranteed and reciprocity via a third party takes longer to be realized. Given the riskier nature of these exchanges and the levels of trust required to engage, Levi-Strauss (1969) argues that indirect exchange systems build stronger bonds and solidarity than directed exchanges. When individuals have a high level of trust or expectancy that others will cooperate, they tend to contribute a higher level to the provision of a collective good than in the absence of such trust (Yamagishi et al., 1993). Ekeh (1974) proposed that dyadic reciprocity and generalized reciprocity produce distinctly different exchanges. For instance, he argued that dyadic exchanges are characterized by a 'quid pro quo' mentality and strict accounting. Conversely, generalized exchanges are characterized by a more collective orientation and reduced emotional tension.

Patterns of generalized exchanges are omnipresent in many types of social networks (Easley & Kleinberg, 2010; Kadushin, 2012; Prell, 2012; Stanca, 2009; Wasserman et al., 1994), including among young children (Chernyak et al., 2019). Research consistently finds that individuals pass help to third parties after receiving help themselves (Nowak, 2006; Stanca, 2009). Both theory and empirical evidence suggest that triadic ties effectively establish norms and provide social support (Centola, 2010; Coleman, 1988; Wellman et al., 2001). Indeed, social support theory predicts that actor A will have stronger social support if B and C are connected (Coleman, 1988). Exchange of feedback between triads is also believed to be more influential than feedback provided between dyads, thus triadic structures may be particularly important for bringing about behavioral change in individuals (Warren et al., 2020a). Network members may be more inclined to seek and accept support in generalized exchange networks, knowing that incidental violations of the norm of reciprocity are permitted and that they can give back at a later point (Ellwardt, Wittek, Hawkley, & Cacioppo, 2020). Similar to direct reciprocity,

generalized reciprocity has been shown to stabilize network cooperation (Herne, Lappalainen & Kestilä-Kekkonen, 2013; Molm et al., 2007; Nowak & Roch, 2007; Stanca, 2009).

Lazega et al. (1999) examined multiplex generalized exchanges and transfers of three types of social resources (e.g., coworkers' goodwill, advice, and friendship) in a corporate law firm and how these exchanges shape participation in collective action while helping mitigate problems associated with status competition. Different patterns of generalized exchanges were observed for each resource type. For instance, goodwill ties appeared to be strongly organized around principles of generalized exchanges, whereas advice and friendship demonstrated patterns of clustering and asymmetrical tie formation. This study suggests that patterns of generalized exchanges differ across network types, raising questions regarding how differences manifest in the context of recovery capital.

The concept of generalized exchanges is highly salient among peer support recovery communities characterized by network members actively giving and receiving support. Warren et al. (2020a) conducted a study to investigate how social networks influence therapeutic community outcomes. The study found that residents who affirm each other are more likely to affirm a third-party actor and exhibit triadic clustering behaviors. Similar patterns were observed in a study by Doogan and Warren (2017) among residents of therapeutic communities, and these patterns were only present between residents but not between residents and staff. Phan and Yarosh (2016) also found support for generalized exchanges within an online peer-support community among people in recovery. Campbell et al. (2019) found that residents of therapeutic communities engaged in triadic ties were at a lower risk of re-incarceration post-treatment. In a replication study, Warren, Campbell, and Cranmer (2020b) found that residents exhibiting greater triadic clustering in two therapeutic communities were at lower risk for re-incarceration,

whereas in one facility, residents exhibiting these types of network connections were at a higher risk of re-incarceration. These studies suggest that generalized exchange networks are critical among members of recovery communities and highlight a need to examine how these networks positively or negatively impact the development of recovery capital.

Yamagishi et al. (1993) and Takahashi (2000) note that particular challenges arise with generalized exchanges. These challenges include the potential for certain actors to exploit the network resources by never reciprocating and the difficulty of establishing norms of generalized exchanges without initial levels of trust. Additionally, in cases where most network actors are not cooperating, non-cooperation provides better individual outcomes than cooperation (Yamagishi et al., 1993). Therefore, it is important to investigate under which conditions generalized exchanges result in greater recovery capital.

In summary, network cohesion, social exchange, and generalized exchange theory provide insights into how recovery capital can be developed with network structures. The current dissertation will first seek to establish the boundary conditions for each network theory presented in this section. Boundary conditions specify the conditions in which theories can be reasonably applied (Foschi, 1998; George & Bennet, 2005). This inquiry could enhance the precision in which these theories predict outcomes. While empirical failures to meet boundary conditions may limit the application of theories, they can also lead to new theoretical advancements (Parks, 2011). Following this work, the study will examine how the network structures described in each theory facilitate or hinder the development of recovery capital using stochastic actor oriented modeling. The following section provides a discussion of this method.

Stochastic actor oriented modeling. A major tenet within the field of community psychology is that the social environment shapes individual behavior and vice versa

(Bronfenbrenner, 1979; Kelly, 2006), yet research that employs statistical frameworks that account for these two-way dynamics are scarce (Neal & Christens, 2014). While commonly used methods within the field, such as multilevel modeling, are helpful for understanding the effect of social context on behavior, this technique cannot account for the mutually reinforcing dynamics of individuals and their environment. In contrast, stochastic actor-oriented modeling (Snijders, 2001; Snijders et al., 2010) can model complex phenomena that involve the co-evolution of individual behaviors and social network structures over time.

The stochastic actor oriented model (SAOM) defines social networks as a group of actors whose relationships evolve based on a probability structure. Actors in a network possess several attributes, including characteristics, attitudes, perceptions, traits, emotions, and behaviors that inform their relationships with others, such as whom to connect with and whom to disconnect from (Kalish, 2020). SAOM evaluates change over time from each actor's perspective with the underlying assumption that actors can change their network structures or their perceptions of their networks. For a mathematical account of SAOM, refer to Snijders (2001) and Snijders et al. (2007; 2010).

SAOM estimate network evolutions by several *effects*, some of which are characteristics of actors which can be fixed effects (e.g., race/ethnicity), time-varying (e.g., attitudes, behaviors), dyads (e.g., distance between them, strength of relationship), or of the entire network structure (e.g., reciprocity, transitivity). These parameter estimates can test the social network theories outlined earlier in this dissertation to examine how individual and network-level recovery capital co-evolve. Each theory outlines a set of rules by which actors abide allowing for inferences regarding causality in the relations between network structures and actor-level effects. These network dynamics were tested on a sample of substance abuse recovery home residents.

Current Study

The current dissertation will utilize a dynamic social network approach to examine how recovery capital is developed through social networks. The study will analyze whole network data of individuals in recovery from SUDs (N = 627) using SAOM. Participants are residents of 42 recovery homes called Oxford House (OH). OH is the largest network of substance use recovery homes, with over 3,000 homes across the United States and over 20,000 residents (Oxford House, 2020). These sex-specific residences usually occupy 6 to 12 individuals. Houses function without any professional staff; instead, members are in charge of all house operations. Individuals can remain in OH for as long as they want, as long as they follow the following rules: maintain abstinence from any alcohol and drug use, pay their fair share of the rent, and follow house rules regarding conduct and assigned tasks/responsibilities (Oxford House Manual, 2019). While previous studies show the benefits of residing in these homes for at least six months (Jason, Davis, & Ferrari, 2007), these types of homes do not work for everyone, and more than 50% of residents have early departures (< 6 months) (Jason et al., 2007). The current study seeks to contribute to the theory and practice by elucidating how network processes such as network cohesion, social exchange, and generalized exchange influence individual-level of recovery capital and identifying the types of housing settings or network configurations most beneficial for residents' recovery.

The current study has two specific aims: (1) investigate the boundary conditions in which network cohesion, social exchange, and generalized exchange theories can be reasonably applied; and (2) examine how recovery capital co-evolves with changes in network structures over time with a sub aim to identify the network structures that facilitate or hinder recovery capital. The network structures under investigation are the extent that networks demonstrate

patterns of network cohesion, social exchanges, and generalized exchanges and how these patterns influence recovery capital. Recovery capital at the individual level was measured using a latent recovery capital factor score (quality of life, hope, stress, sense of community, self-esteem, social support, self-efficacy, and income) (see Jason et al., 2020a), and network level recovery capital was measured by several network metrics, including density, centralization, reciprocity, and transitivity.

Hypotheses development. Network cohesion, social exchange, and generalized exchange theories provide insights on how recovery capital may develop within network structures. Research suggests that the benefits originating from different network structures are contingent on the interplay between individual attributes and the network structures (Latora, Nicosia, & Panzarasa, 2013); thus, specific network configurations may be more optimal for recovery capital under certain conditions than others.

Cohesive networks are thought to foster social norms that promote trust and cooperation among network actors resulting in greater resource sharing (Burt & Knez, 1995; Coleman, 1988; Coleman, 1990; Gargiulo & Benassi, 2000; Ingram & Roberts, 2000; Reagans & McEvily, 2003; Uzzi, 1997). According to the recovery capital framework more highly connected individuals are able to build crucial interpersonal and intrapersonal resources for initiating and sustaining their recovery (Grandfield & Cloud, 2001). While there are positive findings associated with greater network cohesion, these effects appear to be context and time-dependent (Ahuja, 2000; Bodin & Norberg, 2005; Hite & Hesterly, 2001; Peng & Wang, 2013). As an example, both empirical and theoretical work with multi-agent simulations suggests that networks high in network density can result in the homogenization of information, which in turn result in the less efficient use and sharing of resources and/or in a reduced capacity to adapt to network changes (Bodin & Norberg,

2005; Little & McDonald, 2007; Ruef, 2002). These findings align with what Uzzi (1997) referred to as the 'paradox of embeddedness' in which he argued that the positive effects of network cohesion diminish after an optimal threshold is reached. Further, social exchange theory argues that ties in a cohesive network that are not reciprocated will dissolve over time (Hallinan, 1978), arguing that the benefits of cohesive networks are contingent on networks evolving into one's with dyadic reciprocity. Given that actors may face the loss of a resource when they give a form of capital to an alter and receive little or nothing in exchange (Molm et al., 2007), one could expect a lack of reciprocation in cohesive networks will negatively impact recovery capital. For these reasons, the following hypotheses are proposed:

Hypothesis I: The positive impact of network cohesion on recovery capital factor scores will decrease over time in networks low on social exchanges.

Existing research suggests that network centralization can lead to more optimal outcomes than network cohesion, whereas in other circumstances, the inverse is true (Gargiulo et al., 2000). For instance, Tsai and Ghoshal (1998) found that network centralization was positively related to the ability of an organizational unit to exchange and combine their resources more efficiently, and in turn, it resulted in more significant innovation. Therefore, it can be hypothesized that network centralization may result in positive recovery capital outcomes when central individuals high in recovery capital engage in resource sharing. Conversely, those who find themselves highly embedded in networks with low recovery capital may not benefit from the recovery capital at the network level, and instead, maybe more negatively impacted by network cohesion. Therefore, the following hypothesis is proposed:

Hypothesis II: Network centralization will have a positive effect on recovery capital factor scores over time in networks where actors engaged in the resource sharing have higher recovery capital.

Unlike social exchanges that only require the exchanges of resources between two actors, generalized exchange networks are characterized by three or more actors engaged in indirect reciprocity. Since greater time goes on between when an actor first gives a resource to when a third party reciprocates their action, generalized exchanges take longer to be realized than social exchanges. Additionally, since actions are not immediately repaid in generalized exchanges, these networks require higher levels of trust to develop, resulting in stronger bonds and cooperation than social exchange networks (Levi-Strauss, 1969; Yamagishi et al., 1993). Further, unlike social exchange networks characterized by ‘quid pro quo’ exchanges, actors in networks of generalized exchanges are more motivated by the contribution to a greater good rather than obtaining benefits for themselves. Thus, generalized exchange networks are particularly prominent and beneficial in contexts where the pursuit of individual goals requires the cooperation of the whole (Gargiulo et al., 2000). In light of previous theoretical and empirical research on generalized exchange networks, the following hypotheses are made:

Hypothesis III: Generalized exchanges will develop overtime in networks that demonstrate a tendency for network cohesion (e.g., high levels of outgoing ties) and reciprocity beyond the dyadic level.

Hypothesis IV: Generalized exchange networks will have a stronger positive effect on recovery capital factor scores over time compared to social exchange networks.

METHOD

Participants & Procedures. The current longitudinal study included 42 Oxford Houses located in North Carolina, Texas, and Oregon. Data were collected every four months over a 2-year period, for a total of seven waves, from 2015 to 2018. Although seven waves of data were collected, only six waves were included in the current study given the current study's aim to model network dynamics. There were a total of 714 residents who resided in the OHs during the course of the research, of which 666 (93%) agreed to participate in the study. Of those that agreed to participate, 34 had entered into the study during wave 7, and therefore, were excluded from the analyses. An additional 5 participants were excluded due to survey non-responses. This resulted in analyses sample of 627 participants. Of the final sample included in the analyses, 497 (74%) left their Oxford House at some point during the study. The analytic approach explains in detail how data that is missing at random (e.g., wave non-assessments) is handled within SAOM. The analysis sample of 627 was 51% male and 49% female, with a mean age of 37.0 years ($SD = 10.5$). Participants identified as White (78.8%), African American/Black (8.5%), Latinx (10.0%), with all other races accounting for 2.7% of the total sample (Asian American, Alaskan Native, American Indian, and Pacific Islander). In previous analyses, using White as the reference group, the only significant contrast was for Black residents; the contrasts for Latinx and all others were negligible. Accordingly, racial/ethnic contrasts were simplified to not-Black (reference group including White, Latinx, and all other) vs Black in all analyses (see Jason, Guerrero, Bobak, Light & Stoolmiller, 2020).

Participants were part of a larger study that examined the substance use recovery trajectories of OH residents. Residents of participating houses were able to enter the study at any point during the 2-year. Participants completed several measures including, stress, self-esteem, support, abstinence self-efficacy, hope, and social network ratings. Demographic information

were also collected which included time in residence, age, length of sobriety, race/ethnicity, gender, income, and educational level. State organizations helped the field staff assemble lists of residences to approach for the study, and recruitment attempts were made in approximately in the order that resident contact information became available. Member-elected house presidents were asked to introduce the study to residents by reading a description of it from a project provided script during a house meeting. Houses were accepted into the study if the house president and all other members (or all but, at most, one member) agreed to participate. All participants were interviewed by field research staff during individual face-to-face meetings. The interview began with an overview of the study in which participants were told of the voluntary nature of the study and were assured of confidentiality. All participants signed written consent forms. The consent forms granted permission for reassessment every four months over two years. Interviews consisted of only quantitative measures and lasted between 45 to 60 minutes for completion. Each questionnaire was assigned a random identification number to ensure participant confidentiality. Participants were compensated \$20 for completing their interviews. Permission to do this study was obtained by the DePaul University Institutional Review Board (IRB Protocol #LJ072314PSYR9).

Individual Level Recovery Capital Measures. Individual-level recovery capital was measured using a latent recovery capital factor score based on a confirmatory factor analysis of several recovery capital indicators (see Jason et al., 2020a) from a resident's first survey. The recovery factor score ranges from 0 to 7, with 7 signifying the highest recovery capital score. The recovery capital factor score was calculated from the following instruments:

Wages. Wages was calculated using the square root of participants' self-reported employment-based income during the last 30 days were computed by taking the square root to reduce positive skewness. Wages was then used as a continuous variable.

Quality of Life. World Health Organization Quality of Life Assessment-Brief (Quality of Life; WHOQOL Group, 1998) is a 24-item questionnaire that assesses quality of life across four dimensions: social relationships, environment, physical, and psychosocial. This scale has been validated in substance using 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 whole measure for our sample was $.89$.

Abstinence Self-Efficacy. The Drug Taking Confidence Questionnaire (Self-Efficacy; Sklar, Annis, & Turner, 1999) is an 8-item survey that measures self-efficacy in terms of abstinence. Participants are asked to consider eight theoretical high-risk situations and rate how confident they would be of resisting the urge to use a substance given the hypothetical circumstances. For our sample, this measure had good reliability ($\alpha = .95$).

Self-Esteem. The Rosenberg's Self-Esteem Scale (SES; Rosenberg, 1965) was utilized to measure the participant's positive and negative feelings about the self. SES is a widely used 10-item, global self-esteem scale measured on a 4-point Likert Scale ranging from "strongly agree" to "strongly disagree." Items include "I think I have a number of good qualities," "I take a positive attitude toward myself," and "I feel I do not have much to be proud of." The internal reliability for our sample of the SES scale was $.92$.

Stress. The Perceived Stress Scale (PSS; Cohen, Kamarck, & Mermelstein, 1983) was utilized to measure the degree to which situations in participants' lives are appraised as stressful.

PSS consists of four items measured on a 5-point Likert scale ranging from “never” to “very often.” Items include “how often have you felt that you were unable to control the important things in your life?” and “how often have you felt difficulties were piling up so high that you could not overcome them?” The internal reliability of the PSS scale for our sample was .73.

Social Support. The Interpersonal Support Evaluation List (ISEL; Cohen & Wills, 1985) measured three types of actual or perceived social support (tangible, appraisal, and belonging). Tangible support refers to instrumental aid which refers to monetary assistance; appraisal support refers to having someone to talk to about one’s problems; and belonging support refers to the availability of people one can do activities with. 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 ISEL scale was .88 for our sample.

Sense of Community. The Psychological Sense of Community (SOC; Jason, Stevens & Ram, 2015) is a 9-item scale utilized to measure participants’ sense of community. 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, and for our sample, the $\alpha = .91$.

Hope. Snyder’s State Hope Scale (Hope; Snyder et al., 1996) was utilized to measure participants’ current state of hope. The Hope measure contains two subscales: 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 hope scale was analyzed as a whole measure, and for our sample, the $\alpha = .90$.

Network Level Recovery Capital Measures. The *Social Network Instrument* (SNI; Jason & Stevens, 2017) was utilized to capture different measures of network level recovery capital. This instrument has been used in several investigations on the social networks of recovery home residents (Jason, Light, Stevens, & Beers, 2014; Jason et al., 2017; Light et al., 2016). The SNI measures six relationship characteristics, including friendships, willingness to loan money, advice-seeking, help, relationship strength, and frequency of contact. Each social network item was measured on a 5-point likert scale (0-4). *Friendship*, which taps into non-judgmental social support, was determined by asking “How friendly are you with this person?” Ratings ranged from “close friend” to “adversary” (0 = “close friend;” 1 = “friend;” 2 = “acquaintance;” 3 = “stranger;” 4 = “adversary”). *Willingness to loan* asked respondents “If this person asked to borrow money from you, how much would you be willing to lend them?” and the responses ranged from \$0 to \$500 (0 = “\$0;” 1 = “\$10;” 2 = “\$50;” 3 = “\$100;” 4 = “\$500”). Willingness to loan was the only item that was reverse scored. *Advice-seeking* asked respondents “How often do you go to this person for advice on your recovery and other important life issues?” and answers range from very often to never (0 = “very often;” 1 = “quite often;” 2 = “regularly;” 3 = “rarely;” 4 = “never”). *Help*, which measures how likely a person would help an individual, was determined by asking “If this person needed help for a day, how likely would you be to help?” Ratings ranged from very likely to wouldn’t (0 = “very likely;” 1 = “likely;” 2 = “maybe;” 3 = “probably not;” 4 = “wouldn’t”). *Frequency*, which is how frequently a person interacts with an individual, was determined by asking “How often do you have a personal conversation with this person?” Ratings ranged from very often to never (0 = “very often;” 1 = “quite often;” 2 = “Regularly;” 3 = “rarely;” 4 = “never”). Lastly, *strength*, which taps into an individual's perception of the overall quality of their relationship with an individual, was

determined by asking “Overall, how strong would you relate your relationship with this person?” Ratings ranged from very strong to negative (0 = “very strong;” 1 = “strong;” 2 = “weak;” 3 = “none;” 4 = “negative”). Each item in the SNI can be examined separately as different types of networks. The current study only examined the *friendship*, *willingness to loan*, *advice-seeking*, and *helping* networks. These items were selected because they represent a relationship type whereas strength and frequency represent a more general relationship characteristic and not a theoretical relationship dimension. The SNI has a Cronbach’s alpha of .85 and all items contributed positively. A multilevel confirmatory factor analysis of the SNI found an excellent fit and per-item contribution, and neither age nor sex were significantly correlated with this instrument (Jason et al., 2017).

The *friendship*, *willingness to loan*, *advice-seeking* and *helping* item scores were dichotomized in order to indicate the presence or absence of a tie. This is a common step that takes place prior to generating network statistics (Marsden, 2011). A friendship tie was considered present if an actor nominated an alter as a friend or a close friend (scored as 1) and not present if they rated the alter less than a friend (scored as 0). A willingness to loan tie was considered present if an actor was willing to loan actor \$100 or more (scored as 1) and not present if they were willing to loan less than \$100 (scored as 0). An advice-seeking tie was considered present if an actor sought advice from an alter very often or quite often (scored as 1) and not present if they were seeking advice less than quite often (scored as 0). A helping tie was considered present if an actor reported being willing to help an alter very likely and likely (scored as 1) and not present if they were less than likely willing to help (scored as 0).

Analytic Approach. Prior to conducting stochastic actor-oriented modeling, several features of the data were evaluated. First the Moran’s network autocorrelation coefficient was

used to determine if there is an association between the network and the behavioral variable (e.g., recovery capital factor score), which will provide justification for modeling these dynamics using stochastic modeling. The Moran's coefficient uses the correlation in the behavior variable between dyads and the degree to which actors who share a relationship deviate from the average in the network. The coefficient ranges from -1 through +1, with scores closer to -1 indicating the greatest deviation from the network average, scores closer to 0 indicating greater independence from the network average, and scores closer to +1 indicating greater similarity with the network average. Second, the Jaccard index was used to determine if the data are sufficiently informative to allow for the identification of effects by indicating the amount of change and stability in the network from one wave to the next. The Jaccard index is the fraction of relationship nominations among the new, lost, and stable ones between observed data points (the index disregards the stable absence of nominations). Jaccard indices of around 30% to 20% indicate sufficient stability (see Simpkins, Schaefer, Price, & Vest, 2013). Lastly, changes in the recovery capital factor scores were mapped from one wave to the next to evaluate the direction and the strength of the changes among participants.

Stochastic actor-oriented modeling was conducted using the R package RSiena version 4.0 (Ripley et al., 2021). Several relationship types were examined (e.g., friendship, willingness to loan, advice-seeking, and helping) along with structural network effects (these are elaborated on below), individual attributes (age, gender, and race/ethnicity) and behavioral effects (recovery capital factor scores). Individual house networks were pooled into a single longitudinal network where linkages are constrained to occur only within houses, at a given wave. This considers participants as subject to the same social dynamics, conditional on covariates and initial network relationships (Jason et al., 2014). RSiena simulates data across time points by deducing the

observed networks as the cumulating effects of network change mechanisms based on decisions made by individual actors (Veenstra & Steglich, 2012). RSiena models network change mechanisms in a series of steps using a “method of moments” estimation (Ripley et al., 2021). At each step, actors can choose to maintain, dissolve, or create ties to other actors in the network. Next, RSiena conducts repeated imputations via the Robbins–Monro stochastic approximation that allows for the estimation of structural and actor-level effects on network changes over time. The estimation reliability is determined using good convergence statistics such as t-ratios of simulated compared to observed statistics for each predictor (instead of R^2 , AIC , etc.). Good model convergence is determined by t ratio values of .10 or less, with values closer to zero demonstrating better convergence (see Ripley et al., 2021), and when the overall maximum convergence ratio meets the recommended maximum threshold of 0.25 (Ripley et al., 2021). The maximum autocorrelation of successive simulation effect statistics were evaluated within the recommended upper limit of .30 (Ripley et al., 2021). A model selection criteria have not yet been developed (Snijders et al., 2010). Currently, the best way to implement ad hoc stepwise modeling procedures with both forward selection (adding effects) and backwards selection (deleting effects) that are guided by significance tests and convergence statistics (Ripley et al., 2015; Schweinberger, 2012; Snijders et al., 2010). It is also recommended to start with endogenous network effects and then one can add exogenous effects (Ripley et al., 2021). Including many model effects may result in convergence issues, thus if this occurs, the recommendation is to start with endogenous network effects, then one can enter new effects while retaining previously significant effects (Ripley et al., 2021). Non-significant effects can also remain in the model to the extent that convergence statistics are still acceptable. All non-significant effects that were removed from the final models can be found in Appendix B.

RSiena allows up to 20% of missingness in network, covariate, and behavioral data per wave. In the present study, there were less than 20% of missing network data which were due to residents exiting their houses or to non-responses that can be categorized as missing at random, thus, missing data were handled within RSiena using the model-based hybrid imputation method (Ripley et al., 2021). The method is called hybrid because it uses imputed values during the simulation of Markov chains but not during the calculation of the estimates (Zandberg and Huisman, 2019). More specifically, during the simulation of Markov chains between consecutive waves, missing network data at the first observation are set to 0, which assumes that there is no tie present. In subsequent observations, if there is an earlier observation for a tie variable, the previous value is used to impute the current value. However, if there is no previous observed value for a given tie, the value 0 is imputed. A similar strategy is implemented for missing behavior data: if there is previous value of a behavior variable then that value is imputed, if there is no previous value but there is a subsequent value then this is imputed, if there is no previous or subsequent values then the mode of the variable is imputed (Ripley et al., 2021). Following the simulation runs when the simulated and observed data are compared of the subsequent time points, the updated parameters are based on observed data only. Thus, imputed values only effect the simulation phase of the modeling procedures. The default method in RSiena for treating missing data were examined in Zandberg et al. (2019) and Huisman et al. (2008), and were found to provide the best performance when compared to other types of missing data methods.

Stochastic actor-oriented models have several statistical assumptions. The evolution of networks and individual behaviors are represented separately using transition probabilities between probable states. The probable states are all possible configurations of network and individual behaviors combined. Due to the amount of all possible configurations, changes

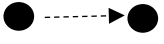
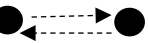
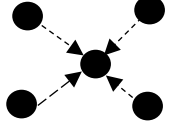

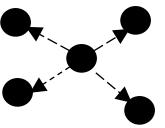
between measurement time points are modeled using a continuous-time Markov process, imputing the likely developmental trajectories between observations or waves. Given that social network data are collected between discrete time points, therefore, failing to capture changes in networks between observations, the assumption underlying the Markov process is that the changes in network ties that are modeled only depend on the current network configuration and not on previous configurations. Another assumption is that actors can only change network ties or one level of behavior, thereby eliminating simultaneous changes. Accordingly, as a continuous-time Markov chain process, the estimated model parameters represent the aggregate series of small changes in network and behaviors over time (Burk, Steglich, & Snijders, 2007; Snijders et al., 2010).

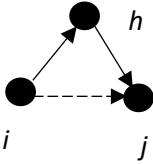
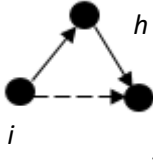
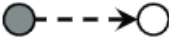
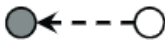
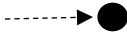
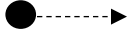
The selection of model parameters were based on several requirements, including: (1) to select effects theoretically relevant to the hypotheses being tested, (2) to capture the structures found in the data, and (3) to keep the models parsimonious. The last two requirements were determined using fit and convergence statistics. The following endogenous network effects were examined: indegree and outdegree effect, density (outdegree), reciprocity, in-degree popularity, out-degree popularity, transitive triplets, and transitive ties. Visual representations and mathematical expressions for each effect can be found in Table 1. *Indegree effect* refers to tendency for actors with more in-going ties to have high values on the recovery capital factor. *Outdegree effect* refers to tendency for actors with more out-going ties to have high values on the recovery capital factor. *Density* describes the overall tendency for actors to extend ties to alters. It measures the overall interconnectedness of the network and is the sum of the directed edges divided by the number of possible directed edges. Since it is a proportion, it is naturally bounded between zero and one. *Reciprocity* describes the tendency for actors to have mutual connections.

Two edges are considered reciprocal if a directed edge goes from node A to node B, and another from B to A. *Centrality* is a measure of the tendency for there to be high concentration of incoming or outgoing ties among key actors. Three network effects were used as proxies for centrality: *in-degree popularity*, *out-degree popularity*, and *out-degree activity*. The *in-degree popularity* effect reflects the tendency of actors who receive many nominations to receive more nominations over time, whereas the *out-degree popularity* effect reflects the tendency of actors with high out-degrees to attract extra incoming ties ‘because’ of their high current out-degrees. The *out-degree activity* effect reflects the tendency of actors who give many nominations to give more nominations over time. These three effects represent a type of network centralization that predict future increases in incoming or outgoing ties among key actors based on initial tie configuration. If significant, these effects would indicate that recovery capital is concentrated among a few actors rather than being more equitably distributed across many. *Transitivity* is a measure of the tendency for relationships to form three-way relationships or triads. Two network effects were used as proxies for transitivity: *transitive triplets*, and *transitive ties*. *Transitive triplets* refers to the tendency that two actors who have tie with a third party will eventually become themselves. More specifically, this effect measures the number of configurations for three actors (i, h, j) in which all three ties are present (e.g. $i \rightarrow j \rightarrow h$; $i \rightarrow h$ or $i \rightarrow h \rightarrow j$; $i \rightarrow j$) (see table 1) (Ripley et al., 2021). The $i \rightarrow j$ tie is increasingly more likely the more indirect two-way paths there are between actors i and j (e.g., $i \rightarrow h \rightarrow j$) (Veenstra, Dijkstra, Steglich, & Van Zalk., 2013). *Transitive ties* is similar to the transitive triplets effect, however, instead of considering for each alter j how many two-paths there are ($i \rightarrow h \rightarrow j$), it only considers whether there is at least one indirect connection. Table 1 reports which effects were used to test each of the study’s four hypotheses.

Ego and alter network selection effects for length of stay in Oxford House was included in the stochastic models, which reflect the effects of length of stay on nominations received or given across each relationship type (e.g., friendship, loaning, helping, and advice-seeking). The effects from length of stay, race/ethnicity, age, and sex on recovery capital were also included in the models as covariates to examine the changes in recovery capital scores over time across demographic groups.

Table 1. Mathematical representation and interpretation of model effects

Network dynamic effect	Mathematical Formula	Graphical Express	RSiena description	Hypothesis
Density (out degree)	$\sum_i x_{ij}$		Actor i extending ties to alter j {density}	Hypothesis I; Hypothesis III
Reciprocity	$\sum_i x_{ij} x_{ji}$		Actor i reciprocating ties to alter j {recip}	Hypothesis I; Hypothesis III
In-degree popularity	$\sum_j x_{ij} \sum_h x_{hj}$		Actors with many incoming ties attract more incoming ties {inPop}	Hypothesis II
Out-degree popularity	$\sum_j x_{ij} \sum_h x_{jh}$		Actors with many outgoing ties attract more incoming ties {outPop}	Hypothesis II
Out-degree activity	X^2_{i+}		Actors with many outgoing ties have more outgoing ties over time {outAct}	Hypothesis II

Transitive triplets	$\sum_h X_{ij} X_{ih} X_{hj}$		Actor i extending ties to alter j to whom he is indirectly tied (via h) {transTrip}	Hypothesis III
Transitive ties	$\sum_j X_{ij} \max_h (X_{ih} X_{hj})$		Actor i extending ties to alter j to whom he is directly and indirectly tied (via h) (one indirect tie suffices) {transTies}	Hypothesis III; Hypothesis IV
Covariate network selection effect				
Covariate ego	$V_i X_i +$		Actor i with higher values on covariate (v) attracts more outgoing ties {egoX}	
Covariate alter	$\sum_j X_{ij} \sum V_j$		Actor i with higher values on covariate (v) attracts more incoming ties {altX}	
Behavioral effects				
Indegree effect	$S_i^{\text{beh}} = \sum_j X_{ji}$		The more incoming ties, the higher the behavior variable becomes overtime {indeg}	Hypothesis I
Outdegree effect	$S_i^{\text{beh}} = \sum_j X_{ij}$		The more outgoing ties, the higher the behavior variable overtime {outdeg}	Hypothesis I

Average alter	$S^{beh}_{i5}(x) = z_i (\sum_j x_{ij} z_j) / (\sum_j x_{ij})$		Actors whose alters have a higher average of the behavior, also have themselves a stronger tendency toward high values on the behavior {avAlt}	Hypothesis II
Reciprocated degree	$S^{beh}_{i18}(x) = z_i \sum_j x_{ij} x_{ji}$		The tendency for reciprocated ties to influence the behavior {recipDeg}	Hypothesis I; Hypothesis IV
Average alter popularity	-1 $S^{beh}_{i23}(x, z) = z_i x_{i+} + \sum_j x_{ij} x_{j+} + z_j$; (and 0 if $x_{i+} = 0$)		Defined by the behavior multiplied by the average behavior of the alters, multiplied by their indegrees {avAltPop}	Hypothesis II
Dense triads	$S^{beh}_{i16}(x) = z_i \sum_{j,h} I[\{x_{ij} + x_{ji} + x_{ih} + x_{hi} + x_{jh} + x_{hj}\} \geq c]$, where c is either 5 or 6		Defined by the behavior multiplied by the number of dense triads {behDenseTriads}	Hypothesis IV
Behavior effect from covariate	$S^{beh}_{i57}(x, z) = z_i v_i$		Main covariate effect on the behavioral variable {effFrom}	

Only uniplex (single network) models were run. Uniplex models ignore mutual dependencies between networks of different relational dimensions (e.g. friendship, willingness to

loan, helping, and advice-seeking) thus presenting dynamics for each individual network when considered on their own, and serving as a point of reference for the multiplex dynamics. While multiplex network analyses could demonstrate the co-evolution of friendship, loan, advice, and helping networks, this type of analysis are not needed to test the study's hypotheses.

RESULTS

Descriptive Statistics. Network descriptive statistics for all four types of networks (e.g. friendship, loaning, and advice-seeking) across the six observations of data are reported in in Table 2, including density, average degree, number of ties, and number of mutual and asymmetric dyads. Given that participants joined or left their recovery home during the course of the study, the number of possible ties vary between measurements. While the current study proposed to analyze helping networks, this network was dropped due to poor convergence.

Table 2. Descriptives of the Friendship, Loaning, and Advice-Seeking Networks

	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6
<i>Friendship Network</i>						
Network characteristics						
Density ^a	0.76	0.81	0.75	0.75	0.79	0.81
Average degree	1.31	0.87	1.16	1.01	1.24	1.17
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
<i>Loaning Network</i>						
Density ^a	0.27	0.30	0.30	0.27	0.29	0.25
Average degree	0.51	0.34	0.51	0.34	0.44	0.37
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
<i>Advice-Seeking Network</i>						
Density ^a	0.37	0.49	0.41	0.45	0.49	0.54
Average degree	0.51	0.49	0.65	0.61	0.77	0.79
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 3 contains information regarding changes in nominations for each network between time points. There are a total of five time lags between all six waves of data. Lag 1 indicates the period between waves 1 and 2, Lag 2 indicates the period between waves 2 and 3, Lag 3 indicates the period between waves 3 and 4, Lag 4 indicates the period between waves 4 and 5, and Lag 5 indicates the period of time between waves 5 and 6. Tie changes are indicated for each time lag that denote changes in values in the tie adjacency matrices for each network. The label the ‘0=>1’ means that a value went from a 0 at one time point to a 1 at the next time point (i.e., a new tie was created); the ‘1=>0’ label means that a value went from a 1 at one time point to a 0 at the next time point (i.e., a tie dissolution); the ‘1=>1’ label means that a value went from a 1 at one time point to a 1 at the next time point (i.e., a stable existing tie).

Table 3. Tie Changes between Observations for Each Network

Lag	1	2	3	4	5
	1 => 2	2 => 3	3 => 4	4 => 5	5 => 6
Friendship Network					
Creating a tie (0 => 1)	317	585	417	618	469
Dissolving a tie (1 => 0)	593	403	513	475	515
Stable tie (1 => 1)	229	143	212	157	261
Hamming distance	73	31	53	36	60
Jaccard Index	0.20	0.13	0.19	0.13	0.21
Loaning Network					
Creating a tie (0 => 1)	139	265	134	212	148
Dissolving a tie (1 => 0)	246	155	243	148	186
Stable tie (1 => 1)	71	55	76	62	85
Hamming distance	97	60	77	62	109
Jaccard Index	0.16	0.12	0.17	0.15	0.20
Advice-Seeking Network					
Creating a tie (0 => 1)	216	343	287	412	383
Dissolving a tie (1 => 0)	229	242	313	296	389
Stable tie (1 => 1)	90	63	94	87	110
Hamming distance	75	50	67	51	133
Jaccard Index	0.17	0.10	0.14	0.11	0.13

The Jaccard index is a measure of network stability between time points which indicates the proportion of stable relations among the number of created, dissolved, and stable relations (Snijders et al., 2010). The proportion of stable relations for each type of network was low (a Jaccard index of at least 0.20 is recommended; Snijders et al., 2010), but this had no consequences for the analyses as all models demonstrated good convergence statistics.

Univariate Stochastic Actor-Oriented Modeling Results

Friendship Network Results. Table 4 shows the model results for the friendship network. Parameter estimates are reported along with their 95% CIs (b=estimate, [95% CI lower, upper]) along with two-tailed p value tests. Parameter estimates were based on 1402 iterations during the estimation routine, with convergence diagnostics, covariance and derivative matrices based on 2403 iterations. The model convergence was acceptable; the overall maximum convergence ratio (a summary measure across effects) was .23 (the conventional cutoff is 0.25; Ripley et al., 2021), and all individual parameter convergence t ratios (the autocorrelation between consecutive iterative estimates, which ideally are near zero) were .09 or less (the conventional cutoff is 0.10; Ripley et al., 2021).

The first part of the SAOM results presented are the network dynamic parameters. Network rate parameters are inter-wave specific estimates of the amount change in each endogenous variable that reflect the number of micro-steps involved in the dynamic simulation with significant parameters confirming sufficient variation for SAOM to explain, but have no substantive significance in the hypotheses testing. The outdegree density effect is primarily an indicator of a tendency toward a certain proportion of non-zero ties in any given network variable. The outdegree density for the friendship parameter (b=-1.00, CI [-0.36, 2.36], $p= 0.15$)

was not significant. This suggests that friendship nominations are common and expected, with an overall probability indistinguishable from 50-50. The positive reciprocity parameter ($b = 1.55$ CI [0.73, 2.38], $p < .001$) means that friendship ties tend to be reciprocal with one-way ties changing to two-way ties overtime. In support of hypothesis III, the transitive triplets parameter was positive and significant ($b = 0.53$ CI [0.24, 0.81], $p < .001$), demonstrating that friendship ties were more likely to be extended to friends of friends. This suggests that friendship networks exhibit a form of generalized exchanges with friendship ties evolving into resource sharing triads. However, the transitive ties parameter was non-significant suggesting that generalized exchanges are contained to those who residents are directly connected to via a third party. The out-degree popularity effect parameter ($b = -0.55$, CI [-0.90, -0.19], $p < .001$) was negative and significant, indicating that actors with many outgoing friendship ties attract less incoming ties overtime. However, the in-degree popularity and out-degree activity parameters were non-significant. Given the negative out-degree parameter and non-significant in-degree popularity and out-degree activity parameters, centralization of resources was not structural tendency for the friendship network. A positive and significant length of stay ego parameter indicated that friendship ties were more likely to be extended by network members who were in their recovery home for a longer length of time. The recovery capital network selection effects were non-significant indicating that residents' level of recovery capital had no bearing on incoming or outgoing friendship nominations.

The behavioral dynamic portion of the model examined predictors of change in the recovery capital factor scores overtime. The linear and quadratic shape effects represent the shape of the recovery capital factor scores distribution. The in degree and out degree as well as the reciprocated effects were non-significant therefore disconfirming hypothesis I. That is,

network cohesion nor social exchanges played a role in changes in the recovery capital scores overtime time. The average alter popularity effect was eliminated from the final model due to poor convergence (see model with eliminated effect in Appendix B) thus hypothesis II was only partially tested. The primary finding for this part of the model is that the average recovery level of ones’ “friends” was predictive of improvements in recovery capital factor scores over time ($b=0.12$, $[0.01, 0.23]$ $p=.03$), partially confirming hypothesis II. The dense triad effect was also eliminated from the final model due to poor convergence (see model with eliminated effect in Appendix B) thus hypothesis IV was only partially tested (see model with eliminated effect in Appendix B). However, the non-significant reciprocated degree parameter suggests that proportion reciprocation in friendship networks had no influence on changes in the recovery capital factor scores over time, disconfirming hypothesis IV.

Table 4. SAOM Results For Friendship Network—Method of Moments estimation

	Parameter	SE	z	p-value	95% CI		t-ratio ^a
	Estimate				Low	High	
Network Dynamics							
1. Friend rate (period 1)	4.66	1.21	3.86	< .001	2.30	7.03	0.002
2. Friend rate (period 2)	3.39	1.17	2.90	< .001	1.10	5.67	-0.02
3. Friend rate (period 3)	3.64	0.90	4.05	< .001	1.88	5.41	-0.05
4. Friend rate (period 4)	3.09	0.96	3.23	< .001	1.21	4.96	-0.01
5. Friend rate (period 5)	5.14	3.41	1.51	0.13	-1.54	11.82	-0.06
6. Friend: outdegree (density)	1.00	0.69	1.44	0.15	-0.36	2.36	0.08
7. Friend: reciprocity	1.55	0.42	3.68	< .001	0.73	2.38	0.08
8. Friend: transitive triplets	0.53	0.14	3.62	< .001	0.24	0.81	0.06
9. Friend: transitive ties	0.18	0.28	0.63	0.53	-0.38	0.74	0.06
10. Friend: in-degree popularity	-0.01	0.15	-0.09	0.93	-0.32	0.29	0.08
11. Friend: out-degree popularity	-0.55	0.18	-3.02	< .001	-0.90	-0.19	0.06
12. Friend: out-degree activity	-0.18	0.11	-1.62	0.10	-0.40	0.04	0.07
Covariate Network Effects							
13. Friend: LOS ^b alter	0.01	0.07	0.15	0.88	-0.12	0.14	0.05
14. Friend: LOS ^b	0.23	0.07	3.24	< .005	0.09	0.37	0.01
15. RCF ^c alter	-0.04	0.09	-0.44	0.66	-0.21	0.13	-0.03

16. RCF ^c ego	0.04	0.09	0.48	0.63	-0.13	0.22	-0.09
Behavior Dynamics							
17. Rate RCF ^c (period 1)	3.76	0.53	7.12	< .001	2.73	4.80	-0.02
18. Rate RCF ^c (period 2)	2.49	0.63	3.93	< .001	1.25	3.73	0.03
19. Rate RCF ^c (period 3)	3.80	0.78	4.89	< .001	2.28	5.33	0.00
20. Rate RCF ^c (period 4)	3.71	0.84	4.42	< .001	2.07	5.36	0.04
21. Rate RCF ^c (period 5)	4.02	0.91	4.40	< .001	2.23	5.81	0.01
22. RCF ^c linear shape	0.46	0.13	3.48	< .001	0.20	0.72	-0.02
23. RCF ^c quadratic shape	-0.14	0.02	-6.53	< .001	-0.18	-0.10	0.05
24. RCF ^c indegree	-0.04	0.11	-0.35	0.72	-0.26	0.18	-0.03
25. RCF ^c outdegree	-0.16	0.14	-1.13	0.26	-0.44	0.12	-0.03
26. RCF ^c average alter	0.12	0.06	2.15	0.03	0.01	0.23	0.01
27. RCF ^c reciprocated degree	0.16	0.20	0.84	0.40	-0.22	0.55	-0.03
Covariate Behavior Effects							
28. RCF ^c : effect from Sex	-0.25	0.09	-2.93	< .005	-0.42	-0.08	-0.03
29. RCF ^c : effect from Age	-0.003	0.003	-1.02	0.31	-0.01	0.00	0.01
30. RCF ^c : effect from Black	0.21	0.12	1.76	0.08	-0.02	0.44	-0.01
31. RCF ^c : effect from LOS ^b	0.02	0.03	0.62	0.54	-0.04	0.09	0.003

Note: ^aRatio of deviations of simulated vs. observed statistics for each effect, calculated in Phase 3 of the *RSiena* model estimation procedure. Conventionally, a *t ratio* value of less than 0.10 indicates good convergence (Ripley et al., 2020). Overall maximum convergence ratio: 0.24. ^bthe log of residents length of stay in their recovery home. ^cRecovery capital factor scores. ^dParameter eliminated from final model.

Loaning Network Results. Table 5 shows the model results for the loaning network.

Parameter estimates are reported along with their 95% CIs (b=estimate, [95% CI lower, upper]) along with two-tailed *p* value tests. Parameter estimates were based on 1263 iterations during the estimation routine, with convergence diagnostics, covariance and derivative matrices based on 2445 iterations. The model convergence was acceptable; the overall maximum convergence ratio (a summary measure across effects) was .24 (the conventional cutoff is 0.25; Ripley et al., 2021), and all individual parameter convergence *t* ratios (the autocorrelation between consecutive iterative estimates, which ideally are near zero) were .09 or less (the conventional cutoff is 0.10; Ripley et al., 2021).

The outdegree density for the loaning parameter ($b=-0.83$, CI $[-1.31, -0.35]$, $p < .001$) was negative and significant, implying both that willingness to loan relationships are quite sparse (well below 50 percent of ties that a value of zero would imply), and that a larger number of such ties for any given individual are unlikely to form overtime. This finding suggests that unlike in the friendship network, cohesion is not at play in the loaning networks. The positive reciprocity parameter ($b= 1.39$, CI $[0.91, 1.87]$, $p < .001$) means that loan ties tend to be reciprocal with one-way loan ties changing to two-way ties overtime. In support of hypothesis III, the transitive triplets parameter was positive and significant ($b = 0.50$ CI $[0.25, 0.76]$, $p < .001$), suggesting that residents show a tendency to share tangible resources with others if they are already willing to loan to someone who loans to this alter. While loaning networks demonstrate tendencies for generalized exchanges, a non-significant transitive ties parameter suggests that generalized exchanges of tangible resources are contained to those who residents are directly connected to via a third party. The out-degree popularity effect parameter ($b= -0.58$, CI $[-0.81, -0.36]$, $p < .001$) was negative and significant, indicating that actors with many outgoing ties attract less incoming ties overtime. However, the in-degree popularity and out-degree activity parameters were non-significant. Given the negative out-degree parameter and non-significant in-degree popularity and out-degree activity parameters, centralization of resources was not structural tendency for the loaning network. No network selection effects were found for willingness to loan based on resident's length of stay or levels of recovery capital factor scores. This indicates that residents' length of stay and level of recovery capital had no bearing on their incoming or outgoing willingness to loan nominations.

The behavioral dynamic portion of the model revealed non-significant effects for the in and out degree parameters as well as the reciprocated degree parameter, therefore disconfirming

hypothesis I. More specifically, network cohesion nor social exchanges in the loaning network had an influence on changes in the recovery capital scores overtime time. The average alter popularity effect was eliminated from the final model due to poor convergence (see model with eliminated effect in Appendix B) thus hypothesis II was only partially tested. The second effect of interest, average alter effect, for testing hypothesis II was included in the final model and was found to be non-significant. The dense triads effect was also non-significant suggesting that generalized exchanges within the loaning network did not impact the changes in recovery capital overtime, disconfirming hypothesis IV.

Table 5. SAOM Results For Loaning Network—Method of Moments estimation

	Parameter	SE	z	p-value	95% CI		t-ratio ^a
	Estimate				Low	High	
Network Dynamics							
1. Loan rate (period 1)	4.31	0.84	5.12	< .001	2.66	5.96	-0.07
2. Loan rate (period 2)	3.38	0.69	4.90	< .001	2.03	4.73	-0.06
3. Loan rate (period 3)	3.26	0.60	5.39	< .001	2.07	4.44	0.01
4. Loan rate (period 4)	3.26	0.68	4.81	< .001	1.93	4.59	0.02
5. Loan rate (period 5)	5.01	1.47	3.40	< .001	2.13	7.90	-0.05
6. Loan: outdegree (density)	-0.83	0.24	-3.38	< .001	-1.31	-0.35	0.00
7. Loan: reciprocity	1.39	0.25	5.65	< .001	0.91	1.87	-0.02
8. Loan: transitive triplets	0.50	0.13	3.88	< .001	0.25	0.76	0.03
9. Loan: transitive ties	0.32	0.19	1.69	0.09	-0.05	0.69	0.04
10. Loan: in-degree popularity	0.10	0.07	1.40	0.16	-0.04	0.25	0.02
11. Loan: out-degree popularity	-0.58	0.11	-5.10	< .001	-0.81	-0.36	0.01
12. Loan: out-degree activity	-0.02	0.06	-0.31	0.76	-0.13	0.09	0.03
Covariate Network Effects							
13. Loan: LOS ^b alter	0.05	0.04	1.26	0.21	-0.03	0.14	0.01
14. Loan: LOS ^b ego	0.00	0.04	-0.09	0.93	-0.09	0.08	-0.04
15. RCF ^c alter	0.10	0.06	1.67	0.10	-0.02	0.21	0.09
16. RCF ^c ego	-0.01	0.05	-0.15	0.88	-0.10	0.09	0.02
Behavior Dynamics							
17. Rate RCF ^c (period 1)	3.67	0.51	7.21	< .001	2.67	4.66	0.01
18. Rate RCF ^c (period 2)	2.50	0.50	5.03	< .001	1.53	3.48	0.02
19. Rate RCF ^c (period 3)	3.66	0.81	4.54	< .001	2.08	5.24	-0.02
20. Rate RCF ^c (period 4)	3.76	0.74	5.10	< .001	2.32	5.21	0.06
21. Rate RCF ^c (period 5)	3.94	0.77	5.15	< .001	2.44	5.44	-0.01
22. RCF ^c linear shape	0.28	0.10	2.67	< .001	0.07	0.48	0.02

23. RCF ^c quadratic shape	-0.13	0.02	-7.19	< .001	-0.17	-0.10	0.03
24. RCF ^c indegree	-0.05	0.07	-0.76	0.45	-0.19	0.08	0.02
25. RCF ^c outdegree	0.06	0.08	0.82	0.41	-0.09	0.22	-0.04
26. RCF ^c average alter	0.15	0.08	1.84	0.07	-0.01	0.32	0.08
27. RCF ^c dense triads	-0.004	0.07	-0.06	0.96	-0.14	0.13	-0.03
28. RCF ^c reciprocated degree	-0.08	0.23	-0.36	0.72	-0.52	0.36	-0.03
<i>Covariate Network Effects</i>							
29. RCF ^c : effect from Sex	-0.26	0.08	-3.17	< .001	-0.42	-0.10	-0.02
30. RCF ^c : effect from Age	0.00	0.00	-0.58	0.56	-0.01	0.005	0.04
31. RCF ^c : effect from Black	0.21	0.12	1.78	0.08	-0.02	0.43	0.00
32. RCF ^c : effect from LOS ^b	0.03	0.03	0.98	0.33	-0.03	0.10	-0.01

Note: ^aRatio of deviations of simulated vs. observed statistics for each effect, calculated in Phase 3 of the *RSiena* model estimation procedure. Conventionally, a *t ratio* value of less than 0.10 indicates good convergence (Ripley et al., 2020). Overall maximum convergence ratio: 0.24. ^bthe log of residents length of stay in their recovery home. ^cRecovery capital factor scores. ^dParameter eliminated from final model.

Advice-Seeking Network Results. Table 6 shows the model results for the loaning network. Parameter estimates are reported along with their 95% CIs (b=estimate, [95% CI lower, upper]) along with two-tailed *p* value tests. Parameter estimates were based on 1167 iterations during the estimation routine, with convergence diagnostics, covariance and derivative matrices based on 2168 iterations. The model convergence was acceptable; the overall maximum convergence ratio (a summary measure across effects) was .24 (the conventional cutoff is 0.25; Ripley et al., 2021), and all individual parameter convergence *t* ratios (the autocorrelation between consecutive iterative estimates, which ideally are near zero) were .07 or less (the conventional cutoff is 0.10; Ripley et al., 2021).

The outdegree density for the advice-seeking parameter (b=-0.57, CI [-1.07, -0.08], *p* = 0.02) was negative and significant, implying both that advice-seeking networks are quite sparse (well below 50 percent of ties that a value of zero would imply), and that a larger number of such ties for any given individual are unlikely to form overtime. This finding suggests that unlike in the friendship network, cohesion is not at play in the advice-seeking networks. The positive

reciprocity parameter ($b = 1.35$, CI [0.87, 1.82], $p < .001$) means that advice-seeking ties tend to be reciprocal with one-way advice-seeking ties changing to two-way ties overtime. The positive and significant transitive triplets parameter ($b = 0.38$ CI [0.18, 0.57], $p < .001$) suggest that seeking advice from another resident is greater if you are connected to someone who also seeks advice from this resident. The transitive ties parameter is also positive and significant ($b = 0.38$ CI [0.18, 0.57], $p < .001$), suggesting that residents show a tendency to seek advice from those they are both directly and indirectly connected to. Together, the transitive triplets and transitive ties parameters provide support for hypothesis III, suggesting that generalized exchangers are particularly prevalent in advice-seeking networks, even more so than in friendship and loaning networks. That is, advice-seeking networks demonstrate tendencies for generalized exchanges even more so than the loaning networks. The out-degree popularity effect parameter ($b = -0.47$, CI [-0.69, -0.24], $p < .001$) was negative and significant, indicating that actors with many outgoing ties attract less incoming ties overtime. No network selection effects were found for advice-seeking based on resident's length of stay or levels of recovery capital factor scores.

The behavioral dynamic portion of the model revealed non-significant effects for the in and out degree parameters as well as the reciprocated degree parameter, therefore disconfirming hypothesis I. More specifically, network cohesion nor social exchanges in the advice-seeking network had an influence on changes in the recovery capital scores overtime time. The average alter popularity effect was eliminated from the final model due to poor convergence (see model with eliminated effect in Appendix B) thus hypothesis II was only partially tested. The second effect of interest, average alter effect, for testing hypothesis II was included in the final model and was found to be non-significant. The average alter effect was positive and significant for the advice-seeking network ($b = 0.15$, CI [0.005, 0.30], $p = 0.04$) partially confirms Hypothesis II.

This finding suggest that the average recovery capital level of those resident’s seek advice from within the recovery home was predictive of improvements in recovery capital scores over time ($b = -0.23$, CI $[-0.38, -0.08]$, $p = 0.04$). The dense triads effect was non-significant suggesting that despite advice-seeking networks demonstrating a strong tendency for generalized exchanges, this structural characteristic did not have an influence on recovery capital factor scores overtime, disconfirming hypothesis IV.

Covariate Behavior Effects. The only covariate behavioral effect to emerge from the analyses was a significant sex effect (see the behavior dynamic component of each model; Tables 4-6). As sex is coded 0 for male and 1 for female, the negative value for this estimate means that men have a tendency to improve on the recovery capital factor scores faster than women. No other behavioral effects from other demographic covariates were found. However, while non-significant, the race parameter was closed to the conventional .05 p value cut off, with Black residents showing greater improvements in their recovery factor scores.

Table 6. Stochastic Actor-Oriented Model Results For Advice-Seeking Network—Method of Moments estimation

	Parameter	SE	z	p-value	95% CI		t-ratio ^a
	Estimate				Low	High	
Network Dynamics							
1. Advice rate (period 1)	2.52	0.54	4.64	< .001	1.45	3.58	-0.04
2. Advice rate (period 2)	2.91	1.02	2.85	< .001	0.91	4.91	0.01
3. Advice rate (period 3)	2.62	0.47	5.62	< .001	1.70	3.53	0.05
4. Advice rate (period 4)	2.28	0.48	4.80	< .001	1.35	3.21	0.04
5. Advice rate (period 5)	7.71	3.08	2.50	0.01	1.66	13.75	0.07
6. Advice: outdegree (density)	-0.57	0.25	-2.26	0.02	-1.07	-0.08	-0.01
7. Advice: reciprocity	1.35	0.24	5.54	< .001	0.87	1.82	-0.02
8. Advice: transitive triplets	0.38	0.10	3.82	< .001	0.18	0.57	-0.05
9. Advice: transitive ties	0.51	0.15	3.37	< .001	0.22	0.81	-0.04
10. Advice: in-degree popularity	-0.06	0.08	-0.77	0.44	-0.21	0.09	-0.03
11. Advice: out-degree popularity	-0.47	0.12	-4.00	< .001	-0.69	-0.24	-0.05
12. Advice: out-degree activity	0.03	0.06	0.43	0.67	-0.09	0.14	-0.02
Covariate Network Effects							
13. Advice: LOS ^b alter	0.01	0.05	0.27	0.79	-0.09	0.11	-0.01

14. Advice: LOS ^b ego	0.06	0.04	1.34	0.18	-0.03	0.14	-0.04
15. RCF ^c alter	0.04	0.07	0.54	0.59	-0.09	0.17	-0.02
16. RCF ^c ego	-0.03	0.06	-0.62	0.54	-0.14	0.07	-0.05
Behavior Dynamics							
17. Rate RCF ^c (period 1)	3.80	0.64	5.97	< .001	2.55	5.05	0.00
18. Rate RCF ^c (period 2)	2.59	0.52	4.97	< .001	1.57	3.61	0.00
19. Rate RCF ^c (period 3)	3.91	0.90	4.36	< .001	2.15	5.67	-0.01
20. Rate RCF ^c (period 4)	3.78	0.82	4.60	< .001	2.17	5.39	-0.01
21. Rate RCF ^c (period 5)	4.08	0.85	4.82	< .001	2.42	5.75	-0.04
22. RCF ^c linear shape	0.22	0.11	2.04	0.04	0.01	0.43	-0.02
23. RCF ^c quadratic shape	-0.14	0.02	-7.85	< .001	-0.17	-0.10	-0.05
24. RCF ^c indegree	0.00	0.08	0.05	0.96	-0.15	0.16	0.01
25. RCF ^c outdegree	-0.02	0.06	-0.38	0.71	-0.15	0.10	-0.02
26. RCF ^c average alter	0.15	0.08	2.02	0.04	0.005	0.30	-0.01
27. RCF ^c dense triads	-0.001	0.03	-0.03	0.98	-0.06	0.05	0.02
28. RCF ^c reciprocated degree	0.04	0.13	0.30	0.77	-0.22	0.30	0.02
Covariate Behavior Effects							
29. RCF ^c : effect from Sex	-0.23	0.08	-3.04	< .001	-0.38	-0.08	0.04
30. RCF ^c : effect from Age	0.00	0.00	-0.76	0.45	-0.01	0.00	-0.06
31. RCF ^c : effect from Black	0.22	0.11	1.95	0.05	0.00	0.45	0.01
32. RCF ^c : effect from LOS ^b	0.02	0.03	0.60	0.55	-0.04	0.08	-0.03

Note: ^aRatio of deviations of simulated vs. observed statistics for each effect, calculated in Phase 3 of the *RSiena* model estimation procedure. Conventionally, a *p* value of less than 0.10 indicates good convergence (Ripley et al., 2020). Overall maximum convergence ratio: 0.24. ^bthe log of residents length of stay in their recovery home. ^cRecovery capital factor scores. ^dParameter eliminated from final model.

Discussion

The current study presents a dynamic social network analysis that investigates how recovery capital is developed through social connections. The study conceptualized recovery capital as both an individual and network-level resource. Network cohesion, social exchange, and generalized exchange theories were tested across different relationship types to examine the interdependence of recovery behaviors and network formation. The current study had two overarching aims: (1) to investigate the boundary conditions in which network cohesion, social exchange, and generalized exchange theories can be reasonably applied; and (2) examine how recovery capital co-evolves with changes in network structures over time, with sub-aim to

identify the network structures that facilitate or hinder recovery capital. It was expected that cohesive networks that failed to evolve into ones rich in social exchanges would be detrimental to recovery capital (Hypothesis I), that network centralization would have a positive effect on recovery capital when actors engaged in the resource sharing had higher recovery capital (Hypothesis II), that generalized exchanges would develop in networks demonstrating reciprocation beyond the dyadic level (Hypotheses III), and lastly, that generalized exchange networks would have a stronger positive effect on recovery capital compared to social exchange networks (Hypothesis IV). Partial support for Hypothesis II and full support for Hypothesis III were found. The following sections synthesize the major findings related to the study's aims, present the theoretical and practical implications, consider the methodological strengths and limitations, and propose future directions.

Aim One: Theoretical Boundary Conditions

The current investigation examined how network cohesion, social exchange, and generalized exchange theories apply to three types of networks, including friendship, willingness to loan, and advice-seeking. The aim was to identify the boundary conditions under which networks structures described in each theory manifest across different relational dimensions. There were a few noteworthy structural differences across the different relationship networks examined. Friendship networks demonstrated a tendency to evolve into cohesive networks. However, this was not the case for loaning and advice-seeking relationships, which demonstrated a lower than 50% probability of ties forming over time, thus suggesting that these networks are quite sparse. Results were consistent with patterns found in a cross-sectional study on friendship, willingness to loan, and advice-seeking networks in recovery homes (Jason et al., 2020d). Given that both loaning and advice-seeking relationships are harder to come by in the recovery home

setting, a possible avenue for future research is to investigate the predictors of acceptance into these networks. All networks demonstrated a tendency towards social exchanges and generalized exchanges. However, advice-seeking networks demonstrated the greatest tendency towards generalized exchanges compared to the other networks, as demonstrated by positive and significant transitive triplets and transitive ties parameters. Furthermore, none of the networks demonstrated tendencies towards network centralization, as shown by the lack of significant positive popularity parameters. Instead, a significant negative out-degree popularity effect revealed that actors with many outgoing ties attract fewer incoming ties over time. One possible explanation for this finding is that actors that indiscriminately extend ties to others may be less attractive to develop ties with. These findings emphasize the importance of considering the context for defining the boundary conditions of each theory to aid the understanding of how the prevalence of specific network structures co-evolve with recovery capital, the second focus of this study.

Aim Two: The Co-Evolution of Recovery Capital and Social Networks

The second aim was to examine how recovery capital co-evolves with changes in network structures over time. Contrary to the study's hypotheses which predicted that network-level structures such as those representing cohesion and resource exchanges would impact recovery capital, no network-level effect emerged from the SAOM analyses. Instead, findings revealed a dyadic-level effect on recovery capital. Specifically, findings suggest that direct connection to friends and seeking advice from those high in recovery capital improved one's recovery over time. The lack of a network-level effect on recovery capital is surprising, given a previous study that found that individuals' probability of relapse was predicted by the average levels of recovery capital of their recovery home peers (Jason et al., 2020a). Nonetheless, the

dyadic effect found is an important one demonstrating that recovery capital is indeed developed through one's social connections, as many theorists have argued (Cleveland et al., 2021; Granfield & Cloud, 2001; Moos, 2003; Vaillant, 1995).

Previous studies have found that denser advice-seeking networks were related to higher stress and relapse among recovery home residents (Jason et al., 2020b; Jason et al., 2020c), yet when examining this dynamic more closely in the current study, seeking advice from those higher in recovery capital contributed to positive changes. These discrepancies can imply that high outgoing advice-seeking ties can signify greater stress and instability among residents at a network-level level. However, at a more granular level, residents who strategically approach other residents with high levels of recovery capital can directly benefit from their peers' capital (Jason, Lynch, et al., 2021). This demonstrates that the characteristics of the advice-giver matter. Such findings reveal the importance of disentangling the network and dyadic level when studying recovery capital and social networks.

Implications for theory, research, and practice. The findings from the current study serve to inform the study of recovery capital and social networks and provide important implications for mental health professionals and community-based programs serving those with SUDs. Our findings suggest that recovery capital may be enhanced through direct connections with peers rich in recovery capital - and this appears to be one of the most important value-derived from living in recovery homes settings. The practical implications include the need to ensure that houses have a good mix of individuals, both high and low in recovery capital, to ensure that residents most in need can access needed resources from their peers.

It was found that men improved their recovery capital factors scores faster than women. This finding further reflects the disparities that exist among women in recovery from SUDs when

compared to men. For instance, women in recovery often face more significant barriers to treatment, greater disruptions to social relationships, face greater stigma related to their substance use, and more trauma (Laudet, 2013; Sutherland, Cook, & Hernandez, 2009). These social disadvantages are further compounded at the intersection of their many identities (e.g., race/ethnicity, sexual orientation, gender identities, and mental health status) (Crenshaw, 1990). As such, there is a greater need to create appropriate community-based supports that help build their recovery capital. Additionally, only one study on recovery capital has primarily focused on women's experiences (Gueta & Addad, 2015), presenting an area in need of greater research.

Despite the lack of network-level effects in the results, there might be other recovery benefits from the network structures examined. For instance, Moos (2008) and Vaillant (2005) hypothesized that the social mechanisms most critical to recovery from SUDs are those found in cohesive networks, such as social bonding, monitoring, and goal direction. More generally, having cohesive ties with others who are supportive of one's recovery can help individuals model recovery-congruent behaviors, and learn effective coping skills that can mitigate life stressors, and build one's feelings of self-efficacy, all of which can optimize recovery success (Castonguay & Beutler, 2006; Oetting & Donner meyer, 1998; Petraitis, Flay, & Miller, 1995). More research is warranted to examine how networks may impact other recovery-supportive processes.

Strengths, Limitations and Future Directions. The current study has several strengths worth highlighting. First, this study made several contributions to the theoretical understanding of how recovery capital is gained through social connections. At its core, this study attempted to promote our understanding of recovery capital as both an individual and network-level construct that is both developed within and between individuals. Second, the study's design used a

dynamic social network approach to network analysis. Further, the completeness of the current data and the number of networks examined over six waves of data are strengths of this investigation. Data were collected from 85% of the participants, with complete participation from all members of most of the homes in the sample. The small amount of missing data provides some confidence that the results of this study are meaningful.

The findings of this study must be considered in light of several methodological limitations. While the homes included in the study were located in three states from three different regions (e.g., North West, South East, and South West) of the US, it is unclear whether these findings can generalize to other Oxford Houses in other regions of the US. Further, the sample is demographically homogenous, with the vast majority of participants being White. However, participant's racial and ethnic breakdowns were comparable to national estimates of the overall Oxford House population (Oxford House, 2020) and of the broader United States population with substance use disorders (Grisgsby & Howard, 2019; Witbrodt, Mulia, Zemore, & Kerr, 2014) and thus do not represent a sampling bias. While racial and ethnic differences across rates of SUDs are modest (SAMHSA, 2018), racial and ethnic minorities are disproportionately impacted by the negative consequences of substance use due to systemic discrimination (Acevedo et al., 2012; Algeria et al., 2004; Bluthenthal, Jacobson, & Robinson, 2007; Centers for Disease Control and Prevention, 2017a; 2017b; Davis & Ancis, 2012; Guerrero et al., 2013; Knighton et al., 2018; Lappan, Brown, & Hendricks, 2020; Le Cook et al., 2011; Mays, Jones, Delany-Brumsey, Coles, & Cochran, 2018; Saloner & Le Cook, 2013; Wells, 2001). Future studies on racial and ethnic minorities with SUDs are warranted for reducing health disparities and ensuring equitable recovery outcomes.

Findings may not be representative of other types of recovery homes. Recovery homes are the largest residential community-based option for individuals recovering from SUDs (Jason, Wiedbusch, Bobak, & Taullahu, 2020). Whereas most recovery homes are run by professional staff, Oxford Houses are entirely peer-run with house members managing all house operations, including financial obligations, house maintenance, rule enforcement, and behavioral management. Therefore, the organizational characteristics of Oxford Houses such as its peer-run model may influence how relationships form in the homes which suggests that Oxford House networks may differ from those formed in staff governed recovery homes. Future research can expand on the current study by comparing how networks form and evolve overtime in Oxford Houses versus traditional homes and its influence on recovery capital.

Another limitation of the study include the methodological disadvantages of conducting longitudinal social network analyses on small networks. While the study sample included 627 residents over six observations, the number of ties is much fewer than that of a single network comprised of the same number of actors. While an unrestricted network of 627 actors would potentially have 393,129 ties per wave ($627 \times 627 = 393,129$), the restricted networks of 627 actors bounded by a recovery home examined in the study resulted in a total number of 5,389 ties of per observation. This possibly prevented the examination of more complex models, such as those testing the interaction effects of average alter popularity which did not make it to any of the final models. While the effects of reciprocated degree and dense triads were tested, these were not statistically significant. Nonetheless, analyzing the small bounded networks of individuals in recovery was important to the study's aim to investigate how their most proximal social environments influences their recovery trajectories. However, increasing the number of networks in future studies can aid the investigation of more complex models.

While a significant percentage of participants (74%) exited their recovery home throughout the study, the current study only examined data collected during residents' stay in their recovery homes and not when they transitioned out of their homes. Future studies can augment the findings by examining outcomes after individuals exit their homes.

Social networks are complex and multidimensional; therefore, combining multiple methods in social network research can help account for these intricacies in future investigations. For instance, quantitative and qualitative methodology can be merged in social network analyses to provide a more nuanced understanding of individual's social context and the mechanisms behind network change (Bolibar, 2016; Rice & Yoshioka-Maxwell, 2015), and such a mixed-method approach has been increasingly used in social network research (Froehlich, Van Waes, & Schafer, 2020; Henwood et al., 2015; Nooraie, Lohfeld, Marin, Hanneman & Dobbins, 2017). A mixed-method study can augment the information obtained through quantitative social network instruments by helping elucidate the nature and quality of the relationships under investigation in greater detail thus enhancing the explanatory power and resulting knowledge of the findings (Bolibar, 2016; Bryman, 2008; Hollstein, 2014; Nooraie et al., 2021).

Future research would benefit from utilizing network visualization to provide a dynamic representation of the SAOM results (see Adams & Schaefer, 2018). Network visualizations are particularly helpful in understanding the unobserved process that unfold between waves of observed data referred to as 'micro steps,' which is when actors have the opportunity to change their outgoing ties or change their behavior (e.g., increasing or decreasing one level).

The studies proposed a multi-level framework of recovery capital that can also be extended to other subpopulations within the substance use recovery community to examine whether there are consistencies or discrepancies between our sample of Oxford House residents

and those utilizing different recovery support services or those who do not utilize any services. These subpopulations may have different access to resources and network support, thus offering greater insights into a broader range of recovery trajectories.

Conclusion

Social networks represent individuals' most proximal social environment and thus play an important role in developing recovery capital. This study presents new research beginning to model the co-evolution of social network dynamics and recovery capital trajectories for those with SUDs. Insights into the social dynamics that predict individuals' positive recovery course helps facilitate future theoretical developments and empirical investigations on the social ecology of recovery.

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APPENDICES

APPENDIX A
Measures

Oxford House Member Social Network Instrument

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 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?

\$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 4

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 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?
\$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 8

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 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?

1. Not at all
2. A little
3. Moderately
4. Mostly
5. Completely

11. Are you able to accept your bodily appearance?

1. Not at all
2. A little
3. Moderately
4. Mostly
5. Completely

12. Have you enough money to meet your needs?

1. Not at all
2. A little
3. Moderately
4. Mostly
5. Completely

13. How available to you is the information that you need in your day-to-day life?

1. Not at all
2. A little
3. Moderately
4. Mostly
5. Completely

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

1. Not at all
2. A little
3. Moderately
4. Mostly
5. Completely

15. How well are you able to get around?

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

16. How satisfied are you with your sleep?

1. Very dissatisfied
2. Dissatisfied

3. Neither satisfied nor dissatisfied
 4. Satisfied
 5. Very satisfied
17. How satisfied are you with your ability to perform your daily living activities?
1. Very dissatisfied
 2. Dissatisfied
 3. Neither satisfied nor dissatisfied
 4. Satisfied
 5. Very satisfied
18. How satisfied are you with your capacity for work?
1. Very dissatisfied
 2. Dissatisfied
 3. Neither satisfied nor dissatisfied
 4. Satisfied
 5. Very satisfied
19. How satisfied are you with yourself?
1. Very dissatisfied
 2. Dissatisfied
 3. Neither satisfied nor dissatisfied
 4. Satisfied
 5. Very satisfied
20. How satisfied are you with your personal relationships?
1. Very dissatisfied
 2. Dissatisfied
 3. Neither satisfied nor dissatisfied
 4. Satisfied
 5. Very satisfied
21. How satisfied are you with your sex life?
1. Very dissatisfied
 2. Dissatisfied
 3. Neither satisfied nor dissatisfied
 4. Satisfied
 5. Very satisfied
22. How satisfied are you with the support you get from your friends?
1. Very dissatisfied
 2. Dissatisfied
 3. Neither satisfied nor dissatisfied
 4. Satisfied
 5. Very satisfied
23. How satisfied are you with the conditions of your living place?
1. Very dissatisfied
 2. Dissatisfied
 3. Neither satisfied nor dissatisfied
 4. Satisfied
 5. Very satisfied
24. How satisfied are you with your access to health services?
1. Very dissatisfied
 2. Dissatisfied
 3. Neither satisfied nor dissatisfied

- 4. Satisfied
- 5. Very satisfied

25. How satisfied are you with your transport?

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

Never	Almost never	Sometimes	Fairly often	Very often
1	2	3	4	5

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 _____

Psychological Sense of Community Scale. Respondents answer whether they Strongly Disagree, Disagree, Slightly Disagree, Slightly Agree, Agree, or Strongly Agree with the questions 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" if 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 finding someone 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 house or 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. If a family crisis arose, it would be difficult to find someone who could give me good advice about how to handle 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

APPENDIX B
Models with Eliminated Parameters

Table 7. Stochastic Actor-Oriented Model Results For Friendship Network—Method of Moments estimation

	Parameter	SE	z	p-value	95% CI		<i>t</i> -ratio ^a
	Estimate				Low	High	
Network Dynamics							
1. Friend rate (period 1)	3.61	2.17	1.67	0.10	-0.64	7.86	-1.35
2. Friend rate (period 2)	4.30	2.54	1.69	0.09	-0.68	9.29	0.18
3. Friend rate (period 3)	3.88	1.22	3.19	< .001	1.50	6.27	-0.11
4. Friend rate (period 4)	2.92	2.60	1.12	0.27	-2.18	8.01	-0.40
5. Friend rate (period 5)	6.60	3.25	2.03	0.04	0.24	12.96	0.02
6. Friend: outdegree (density)	1.25	0.91	1.37	0.17	-0.54	3.03	0.60
7. Friend: reciprocity	1.68	0.44	3.80	< .001	0.81	2.55	0.44
8. Friend: transitive triplets	0.65	0.17	3.87	< .001	0.32	0.98	0.59
9. Friend: transitive ties	0.21	0.29	0.73	0.46	-0.35	0.78	0.69
10. Friend: in-degree popularity	-0.02	0.23	-0.09	0.93	-0.47	0.42	0.45
11. Friend: out-degree popularity	-0.70	0.30	-2.32	0.02	-1.30	-0.11	0.38
12. Friend: out-degree activity	-0.21	0.12	-1.70	0.09	-0.45	0.03	0.61
13. Friend: LOS ^b alter	-0.01	0.09	-0.17	0.86	-0.18	0.15	-0.39
14. Friend: LOS ^b ego	0.22	0.11	1.96	0.05	0.00	0.43	0.07
15. RCF ^c alter	-0.05	0.10	-0.50	0.62	-0.25	0.15	-0.01
16. RCF ^c ego	0.07	0.14	0.54	0.59	-0.20	0.35	0.43
Behavior Dynamics							
17. Rate RCF ^c (period 1)	5.22	3.11	1.68	0.09	-0.88	11.32	-0.04
18. Rate RCF ^c (period 2)	2.58	1.68	1.53	0.13	-0.73	5.88	-0.59
19. Rate RCF ^c (period 3)	3.78	2.54	1.49	0.14	-1.19	8.76	-0.88
20. Rate RCF ^c (period 4)	5.38	1.33	4.03	< .001	2.76	7.99	-0.50
21. Rate RCF ^c (period 5)	3.32	2.00	1.66	0.10	-0.60	7.24	-1.17
22. RCF ^c linear shape	1.96	5.02	0.39	0.70	-7.87	11.80	0.20
23. RCF ^c quadratic shape	-0.40	1.00	-0.40	0.69	-2.36	1.55	0.03
24. RCF ^c indegree	0.37	1.21	0.31	0.76	-2.01	2.76	0.99
25. RCF ^c outdegree	-0.96	2.91	-0.33	0.74	-6.66	4.73	0.22
26. RCF ^c average alter	-0.88	2.54	-0.35	0.73	-5.86	4.09	-1.42
27. RCF ^c ave. alter x pop. alter ^d	59.89	105.0	0.57	0.57	-145.95	265.72	-1.30
28. RCF ^c reciprocated degree	0.66	2.10	0.32	0.75	-3.45	4.77	0.53
29. RCF ^c : effect from Sex	-1.48	4.11	-0.36	0.72	-9.53	6.58	-0.35
30. RCF ^c : effect from Age	-0.01	0.03	-0.43	0.67	-0.08	0.05	-0.58
31. RCF ^c : effect from Black	1.06	2.79	0.38	0.70	-4.40	6.53	1.25
32. RCF ^c : effect from LOS ^b	0.09	0.24	0.38	0.70	-0.38	0.56	-0.66

Note: ^aRatio of deviations of simulated vs. observed statistics for each effect, calculated in Phase 3 of the *RSiena* model estimation procedure. Conventionally, a *p* value of less than 0.10 indicates good convergence (Ripley et al., 2020). Overall maximum convergence ratio: 5.34. ^bthe log of residents length of stay in their recovery home. ^cRecovery capital factor scores. ^dParameter eliminated from final model.

Table 8. Stochastic Actor-Oriented Model Results For Friendship Network—Method of Moments estimation

	Parameter		<i>p</i> -value	95% CI		<i>t</i> -ratio ^a	
	Estimate	SE		Low	High		
Network Dynamics							
1. Friend rate (period 1)	4.65	1.14	4.07	0.00	2.41	6.89	-0.04
2. Friend rate (period 2)	3.32	1.31	2.53	0.01	0.75	5.89	-0.02
3. Friend rate (period 3)	3.67	1.10	3.35	< .001	1.52	5.82	-0.06
4. Friend rate (period 4)	3.14	0.83	3.79	< .001	1.52	4.77	-0.01
5. Friend rate (period 5)	4.94	3.59	1.37	0.17	-2.10	11.99	-0.13
6. Friend: outdegree (density)	0.77	0.73	1.05	0.29	-0.66	2.19	0.13
7. Friend: reciprocity	1.64	0.52	3.14	< .001	0.61	2.66	0.09
8. Friend: transitive triplets	0.48	0.16	3.01	< .001	0.17	0.80	0.19
9. Friend: transitive ties	0.20	0.29	0.71	0.48	-0.36	0.77	0.13
10. Friend: in-degree popularity	0.03	0.19	0.16	0.87	-0.34	0.40	0.19
11. Friend: out-degree popularity	-0.58	0.23	-2.56	0.01	-1.03	-0.14	0.16
12. Friend: out-degree activity	-0.14	0.14	-0.99	0.32	-0.40	0.13	0.23
13. Friend: LOS ^b alter	0.02	0.10	0.24	0.81	-0.17	0.22	0.07
14. Friend: LOS ^b ego	0.23	0.08	2.99	< .005	0.08	0.38	0.08
15. RCF ^c alter	-0.02	0.09	-0.25	0.80	-0.20	0.16	0.18
16. RCF ^c ego	0.05	0.08	0.59	0.56	-0.11	0.21	0.17
Behavior Dynamics							
17. Rate RCF ^c (period 1)	3.76	0.65	5.76	< .001	2.48	5.04	-0.04
18. Rate RCF ^c (period 2)	2.45	0.43	5.65	< .001	1.60	3.30	-0.07
20. Rate RCF ^c (period 3)	3.71	0.73	5.10	< .001	2.28	5.13	-0.04
21. Rate RCF ^c (period 4)	3.69	0.89	4.15	< .001	1.95	5.44	-0.06
22. Rate RCF ^c (period 5)	4.14	1.22	3.40	< .001	1.75	6.52	0.19
23. RCF ^c linear shape	0.60	0.26	2.35	0.02	0.10	1.11	0.11
24. RCF ^c quadratic shape	-0.14	0.02	-7.05	< .001	-0.18	-0.10	-0.19
25. RCF ^c indegree	-0.06	0.13	-0.46	0.64	-0.32	0.20	0.10
26. RCF ^c outdegree	-0.19	0.14	-1.37	0.17	-0.45	0.08	0.07
27. RCF ^c average alter	0.12	0.06	2.20	0.03	0.01	0.23	-0.07
28. RCF ^c dense triads ^d	0.03	0.03	0.76	0.45	-0.04	0.09	0.02
29. RCF ^c reciprocated degree	0.12	0.17	0.72	0.47	-0.21	0.45	0.07

30. RCF ^c : effect from Sex	-0.26	0.10	-2.69	0.01	-0.44	-0.07	0.13
31. RCF ^c : effect from Age	0.00	0.00	-0.96	0.34	-0.01	0.00	0.03
32. RCF ^c : effect from Black	0.18	0.12	1.50	0.13	-0.06	0.42	-0.18
33. RCF ^c : effect from LOS ^b	0.02	0.03	0.73	0.47	-0.04	0.09	-0.02

Note: ^aRatio of deviations of simulated vs. observed statistics for each effect, calculated in Phase 3 of the *RSiena* model estimation procedure. Conventionally, a *p* value of less than 0.10 indicates good convergence (Ripley et al., 2020). Overall maximum convergence ratio: 0.69. ^bthe log of residents length of stay in their recovery home. ^cRecovery capital factor scores. ^dParameter eliminated from final model.

Table 9. Stochastic Actor-Oriented Model Results For Loaning Network—Method of Moments estimation

	Parameter	SE	z	<i>p</i> -value	95% CI		<i>t</i> -ratio ^a
	Estimate				Low	High	
Network Dynamics							
1. Loan rate (period 1)	4.09	1.34	3.04	< .001	1.45	6.72	-0.44
2. Loan rate (period 2)	2.87	0.81	3.56	< .001	1.29	4.45	-0.54
3. Loan rate (period 3)	3.97	0.88	4.53	< .001	2.25	5.68	0.94
4. Loan rate (period 4)	3.83	1.28	2.98	< .001	1.31	6.35	0.81
5. Loan rate (period 5)	6.33	1.32	4.80	< .001	3.74	8.92	0.96
6. Loan: outdegree (density)	-1.23	0.27	-4.63	< .001	-1.76	-0.71	-1.68
7. Loan: reciprocity	1.42	0.30	4.78	< .001	0.84	2.00	-1.51
8. Loan: transitive triplets	0.41	0.13	3.18	< .001	0.16	0.67	-0.54
9. Loan: transitive ties	0.53	0.19	2.83	< .001	0.16	0.89	-0.44
10. Loan: in-degree popularity	0.17	0.08	2.05	0.04	0.01	0.34	-0.48
11. Loan: out-degree popularity	-0.58	0.13	-4.37	< .001	-0.84	-0.32	-0.85
12. Loan: out-degree activity	0.02	0.06	0.26	0.79	-0.11	0.14	-1.16
13. Loan: LOS ^b alter	0.00	0.04	-0.08	0.94	-0.09	0.08	-1.56
14. Loan: LOS ^b ego	-0.03	0.04	-0.72	0.47	-0.12	0.05	-1.92
15. RCF ^c alter	0.27	0.07	3.79	< .001	0.13	0.41	2.26
16. RCF ^c ego	-0.08	0.06	-1.22	0.22	-0.21	0.05	-0.39
Behavior Dynamics							
17. Rate RCF ^c (period 1)	7.70	2.16	3.56	< .001	3.47	11.94	-0.19
18. Rate RCF ^c (period 2)	5.42	1.44	3.76	< .001	2.60	8.25	0.83
19. Rate RCF ^c (period 3)	6.09	1.63	3.73	< .001	2.89	9.29	-0.30
20. Rate RCF ^c (period 4)	9.54	3.39	2.82	< .001	2.91	16.18	1.24
21. Rate RCF ^c (period 5)	7.61	1.31	5.81	< .001	5.04	10.17	-0.69
22. RCF ^c linear shape	0.76	0.26	2.93	< .001	0.25	1.26	-0.34
23. RCF ^c quadratic shape	-0.22	0.07	-3.10	< .001	-0.35	-0.08	-0.71
24. RCF ^c indegree	-0.34	0.19	-1.77	0.08	-0.71	0.04	-1.36
25. RCF ^c outdegree	0.11	0.19	0.58	0.56	-0.26	0.49	-1.30

26. RCF ^c average alter	0.81	0.51	1.58	0.11	-0.20	1.81	0.38
27. RCF ^c average alter popularity ^d	-83.72	86.33	-0.97	0.33	-252.92	85.48	1.10
28. RCF ^c reciprocated degree	0.16	0.37	0.44	0.66	-0.57	0.89	-0.37
29. RCF ^c : effect from Sex	-0.31	0.13	-2.44	< .001	-0.56	-0.06	0.10
30. RCF ^c : effect from Age	0.00	0.00	0.40	0.69	-0.01	0.01	1.58
31. RCF ^c : effect from Black	0.02	0.16	0.13	0.90	-0.29	0.33	-1.68
32. RCF ^c : effect from LOS ^b	0.08	0.05	1.72	0.09	-0.01	0.17	0.90

Note: ^aRatio of deviations of simulated vs. observed statistics for each effect, calculated in Phase 3 of the *RSiena* model estimation procedure. Conventionally, a *p* value of less than 0.10 indicates good convergence (Ripley et al., 2020). Overall maximum convergence ratio: 7.35. ^bthe log of residents length of stay in their recovery home. ^cRecovery capital factor scores. ^dParameter eliminated from final model.

Table 10. Stochastic Actor-Oriented Model Results For Advice-Seeking Network—Method of Moments estimation

	Parameter	SE	z	<i>p</i> -value	95% CI		<i>t</i> -ratio ^a
	Estimate				Low	High	
Network Dynamics							
1. Advice rate (period 1)	2.58	0.38	6.81	< .001	1.84	3.32	0.18
2. Advice rate (period 2)	2.89	0.73	3.96	< .001	1.46	4.32	0.01
3. Advice rate (period 3)	2.61	0.62	4.23	< .001	1.40	3.82	-0.03
4. Advice rate (period 4)	2.28	0.63	3.62	< .001	1.05	3.52	0.03
5. Advice rate (period 5)	7.61	48.83	0.16	0.88	-88.09	103.32	0.01
6. Advice: outdegree (density)	-0.57	0.36	-1.61	0.11	-1.27	0.13	-0.09
7. Advice: reciprocity	1.35	0.34	3.94	< .001	0.68	2.02	-0.06
8. Advice: transitive triplets	0.37	0.23	1.62	0.11	-0.08	0.83	-0.17
9. Advice: transitive ties	0.53	0.75	0.70	0.49	-0.95	2.00	-0.11
10. Advice: in-degree popularity	-0.06	0.10	-0.57	0.57	-0.25	0.14	-0.11
11. Advice: out-degree popularity	-0.46	0.26	-1.76	0.08	-0.98	0.05	-0.12
12. Advice: out-degree activity	0.02	0.22	0.10	0.92	-0.41	0.46	-0.16
13. Advice: LOS ^b alter	0.01	0.22	0.07	0.95	-0.41	0.44	0.01
14. Advice: LOS ^b ego	0.05	0.42	0.13	0.90	-0.78	0.89	-0.14
15. RCF ^c alter	0.04	0.09	0.44	0.66	-0.13	0.21	-0.06
16. RCF ^c ego	-0.04	0.06	-0.59	0.55	-0.16	0.09	-0.11
Behavior Dynamics							
17. Rate RCF ^c (period 1)	4.52	1.33	3.39	< .001	1.90	7.13	-0.07
18. Rate RCF ^c (period 2)	2.85	0.61	4.72	< .001	1.67	4.04	-0.05
19. Rate RCF ^c (period 3)	4.42	0.70	6.30	< .001	3.05	5.80	-0.08

20. Rate RCF ^c (period 4)	5.00	1.19	4.20	< .001	2.67	7.34	-0.04
21. Rate RCF ^c (period 5)	4.53	17.39	0.26	0.79	-29.56	38.61	0.04
22. RCF ^c linear shape	0.16	0.43	0.36	0.72	-0.69	1.01	-0.03
23. RCF ^c quadratic shape	-0.14	0.05	-2.72	< .001	-0.24	-0.04	0.01
24. RCF ^c indegree	0.01	0.09	0.13	0.89	-0.17	0.20	0.01
25. RCF ^c outdegree	0.01	0.13	0.05	0.96	-0.25	0.26	0.02
26. RCF ^c average alter	0.16	0.45	0.36	0.72	-0.73	1.05	0.01
27. RCF ^c average alter popularity ^d	3.54	126.57	0.03	0.98	-244.53	251.60	-0.03
28. RCF ^c reciprocated degree	0.00	0.13	0.00	< .001	-0.25	0.25	0.01
29. RCF ^c : effect from Sex	-0.27	0.37	-0.73	0.47	-1.01	0.46	-0.01
30. RCF ^c : effect from Age	0.00	0.01	-0.27	0.79	-0.02	0.01	0.07
31. RCF ^c : effect from Black	0.26	0.12	2.08	0.04	0.01	0.50	0.07
32. RCF ^c : effect from LOS ^b	0.03	0.03	0.84	0.40	-0.03	0.08	0.10

Note: ^aRatio of deviations of simulated vs. observed statistics for each effect, calculated in Phase 3 of the *RSiena* model estimation procedure. Conventionally, a *p* value of less than 0.10 indicates good convergence (Ripley et al., 2020). Overall maximum convergence ratio: 0.41. ^bthe log of residents length of stay in their recovery home. ^cRecovery capital factor scores. ^dParameter eliminated from final model.

APPENDIX C

R Code for Creating the Social Network Data Objects and Stochastic Actor Oriented Models using *RSiena*

```
install.packages("devtools")
install.packages("data.table")
install.packages("keyring")
install.packages("blastula")
```

```

install.packages("tidyverse")
install.packages("dplyr")
install.packages("naniar")
install.packages("network")
install.packages("sna")
install.packages("RHNetTools")
install.packages("Matrix")
install.packages("JMLUtils")
install.packages("haven")
install.packages("RSienaTest")

##To install RSiena
install.packages("RSienaTest", dependencies = TRUE, repos="http://R-Forge.R-project.org")

#Load Packages
library("devtools")
library("data.table")
library("keyring")
library("blastula")
library("tidyverse")
library("dplyr")
library("naniar")
library("network")
library("sna")
library("RHNetTools")
library("Matrix")
library("JMLUtils")
library("haven")
library("RSienaTest")

##Create a superset of participants in waves 1-6 from the survey data
sids2Include <- survey.w1_7.mike %>% pull(SID) %>% unique() %>% sort()
longTB.net.w1_6 <- bind_rows(longTB.net.w1, longTB.net.w2,
                           longTB.net.w3, longTB.net.w4,
                           longTB.net.w5, longTB.net.w6) %>%
  filter(SID %in% sids2Include) %>%
  arrange(WID, SID, AltID)
...

#Check network stats
longTB.net.w1_6 %>% group_by(WID) %>%
  summarize(n=n())

#Check count of residents by house by wave
houseCt1_6 <- makeCountByHouseByWave(longTB.net.w1_6)
min(houseCt1_6$Count)
houseCt1_6 %>% filter(Count>2) %>% pull(HID) %>% length()

```

```

#Find participants that are not rated by others in the network data
sidsOnly <- c(errorListw4[[4]]$SID, errorListw5[[4]]$SID,
             errorListw6[[4]]$SID) %>% unique() %>% sort()

longTB.net.w1_6 %>% filter(WID==4 & AltID==6024)
longTB.net.w1_6 %>% filter(WID==5 & AltID==1081)
longTB.net.w1_6 %>% filter(WID==6 & AltID %in% c(1105, 1156, 1207, 1256,
                                             3048, 5026, 5068, 6014))
longTB.net.w1_6.1 <- longTB.net.w1_6 %>%
  filter(!(WID==4 & SID==6024) &
         !(WID==5 & SID==1081) &
         !(WID==6 & SID %in% c(1105, 1156, 1207, 1256,
                               3048, 5026, 5068, 6014)))

#Find other non-participants
w6Alt <- longTB.net.w1_6.1 %>% filter(WID==6) %>% pull(AltID) %>% unique() %>%
sort
w6S <- longTB.net.w1_6.1 %>% filter(WID==6) %>% pull(SID) %>% unique() %>% sort
w6Rmv <- w6Alt %w/o% w6S

#Create an edgelist of network data waves 1-6
```{r}
longTB.net.w1_6.2 <- longTB.net.w1_6.1 %>%
 filter(!(WID==6 & AltID %in% w6Rmv))
```

#Creates friendship network set
```{r}
fNet <- makeNetworkSet(longTB.net.w1_6.2, pWavVec=c(1,2,3,4,5,6),
 pTypNet = "FR",
 pTypOut = "MX",
 pTHold = -2, #Friend or close friend
 pHID = TRUE,
 includeAltID = FALSE)
```

#Create loaning network set
```{r}
loanNet <- makeNetworkSet(longTB.net.w1_6.2, pWavVec=c(1,2,3,4,5,6),
 pTypNet = "LO",
 pTypOut = "MX",
 pTHold = 4, #at least $100
 pHID = TRUE,
 includeAltID = FALSE)
```

#Create advice-seeking network set

```



```

```{r}
advNet <- makeNetworkSet(longTB.net.w1_6.2, pWavVec=c(1,2,3,4,5,6),
 pTypNet = "AD",
 pTypOut = "MX",
 pTHold = -2, #Very often or quite often
 pHID = TRUE,
 includeAltID = FALSE)
...

#Create helping network set
```{r}
helpNet <- makeNetworkSet(longTB.net.w1_6.2, pWavVec=c(1,2,3,4,5,6),
  pTypNet = "HE",
  pTypOut = "MX",
  pTHold = -2, #Likely or Very Likely
  pHID = TRUE,
  includeAltID = FALSE)
...

#Check if all network sets consist of n=627
```{r}
length(fNet[[7]]$SID)
length(loanNet[[7]]$SID)
length(advNet[[7]]$SID)
length(helpNet[[7]]$SID)
length(cfNet[[7]]$SID)
...

```{r}
all.equal(fNet[[7]]$SID, loanNet[[7]]$SID)
all.equal(loanNet[[7]]$SID, advNet[[7]]$SID)
all.equal(fNet[[7]]$SID, unique(fNet[[7]]$SID))
all.equal(helpNet[[7]]$SID, unique(helpNet[[7]]$SID))
all.equal(cfNet[[7]]$SID, unique(fNet[[7]]$SID))
...

```{r}
sids2Exclude <- sids2Include %w/o% fNet[[7]]$SID
...

Pick out the 627 individuals in the analyses from survey data (recovery capital variables)
```{r}
survey.w1_6 <- survey.w1_7.mike %>%
  filter(WID<7 & !(SID %in% sids2Exclude))
...

#Add structural zeros to the network sets
```{r}
fNet0 <- s0Fill(fNet)
loanNet0 <- s0Fill(loanNet)
advNet0 <- s0Fill(advNet)

```

```

helpNet0<- s0Fill(helpNet)
```
Convert to type dgTMatrix (sparse triplets)
```{r}
fNet0.sp <- fNet0[c(1:6)] %>%
 lapply(function(x) as(x,"dgTMatrix"))
advNet0.sp <- advNet0[c(1:6)] %>%
 lapply(function(x) as(x,"dgTMatrix"))
loanNet0.sp <- loanNet0[c(1:6)] %>%
 lapply(function(x) as(x,"dgTMatrix"))
helpNet0.sp <- helpNet0[c(1:6)] %>%
 lapply(function(x) as(x,"dgTMatrix"))
cfNet0.sp <- cfNet0[c(1:6)] %>%
 lapply(function(x) as(x,"dgTMatrix"))
```
#Check the networks
Check and see if a network looks more or less OK.
```{r}
fNet0[[1]][1:20, 1:20]
```
```{r}
helpNet0[[1]][1:20, 1:20]
```
#Create array tables
```{r}
helpNet0.ar <- array(
 unlist(lapply(helpNet0.sp, as.matrix)),
 dim=c(nrow(helpNet0.sp[[1]]), nrow(helpNet0.sp[[1]]), 6))
```
```{r}
fNet0.ar <- array(
 unlist(lapply(fNet0.sp, as.matrix)),
 dim=c(nrow(fNet0.sp[[1]]), nrow(fNet0.sp[[1]]), 6))
```
```{r}
advNet0.ar <- array(
 unlist(lapply(advNet0.sp, as.matrix)),
 dim=c(nrow(advNet0.sp[[1]]), nrow(advNet0.sp[[1]]), 6))
```
```{r}
loanNet0.ar <- array(
 unlist(lapply(loanNet0.sp, as.matrix)),
 dim=c(nrow(loanNet0.sp[[1]]), nrow(loanNet0.sp[[1]]), 6))
```

```

```

#Input survey data with recovery capital variable and covariates
```{r}
fxcovs <- survey.w1_6 %>% select(SID, WID, sex, race, age, region,
 inResMo1, inResMoLn1, exit_type,
 left_reason) %>%
group_by(SID) %>%
summarize (sex=max(sex, na.rm=T),
 race=max(race, na.rm=T),
 age=max(age, na.rm=T),
 region=max(region, na.rm=T),
 inResMo1=max(inResMo1, na.rm=T),
 inResMoLn1 = max(inResMoLn1, na.rm=T),
 exitTp=max(exit_type, na.rm=T),
 whyLeft=max(left_reason, na.rm=T)
) %>%
naniar::replace_with_na_all(condition = ~.x == "-Inf") %>%
mutate(sex=ifelse(!is.na(sex), sex-1, NA),
 region=ifelse(!is.na(region), region-1, NA),
 raceBNB=ifelse(race==2,1,0))
The above operation is necessary because 'max' returns -Inf
if the values it's trying to test are all NA
```

```

Check the distribution of the recovery factor, in order to help determine which cut points should be used to score it.

```

```{r}
hist(survey.w1_6 %>% filter(WID==1) %>% pull(recFacTV))
```

#Recode the recovery capital variable to a 7 point likert
```{r}
tv.recfac <- survey.w1_6 %>% select(SID, WID, recFacTV) %>%
mutate(w="w") %>%
pivot_wider(names_from=c(w, WID),
 values_from=recFacTV) %>%
#Creates four values
mutate(w1=ifelse(!is.na(w_1), cut(w_1, breaks=c(-Inf, -1, 0, 1, Inf)), NA),
 w2=ifelse(!is.na(w_2), cut(w_2, breaks=c(-Inf, -1, 0, 1, Inf)), NA),
 w3=ifelse(!is.na(w_3), cut(w_3, breaks=c(-Inf, -1, 0, 1, Inf)), NA),
 w4=ifelse(!is.na(w_4), cut(w_4, breaks=c(-Inf, -1, 0, 1, Inf)), NA),
 w5=ifelse(!is.na(w_5), cut(w_5, breaks=c(-Inf, -1, 0, 1, Inf)), NA),
 w6=ifelse(!is.na(w_6), cut(w_6, breaks=c(-Inf, -1, 0, 1, Inf)), NA),
) %>%
select(w1:w6) %>%
as.matrix()
```

```

```

#Create RSiena data objects for analysis
```{r}
fNet0SD <- sienaDependent(fNet0.sp, sparse=T)
advNet0SD <- sienaDependent(advNet0.sp, sparse=T)
loanNet0SD <- sienaDependent(loanNet0.sp, sparse=T)
helpNet0SD <- sienaDependent(helpNet0.sp, sparse=T)
RFD <- sienaDependent(RFD, type="behavior")
```

```{r}
helpNet0SD <-sienaDependent(helpNet0.ar)
```{r}
fNet0SD <- sienaDependent(fNet0.ar)
```

```{r}
loanNet0SD <- sienaDependent(loanNet0.ar)
```

```{r}
advNet0SD <- sienaDependent(advNet0.ar)
```

#####SAOM Script
##Friendship Model

```{r}
packages <- c("data.table", "tidyverse", "keyring", "blastula",
             "dtplyr", "naniar",
             "network", "sna", "RHNetTools", "Matrix", "RSienaTest",
             "JMLUtils", "haven", "xtable")
if(length(setdiff(packages, rownames(installed.packages))) > 0) {
  lapply(packages, library, character.only = TRUE)
}
# If necessary (RSienaTest is not on Cran):
#install.packages("RSienaTest", repos="http://R-Forge.R-project.org")
workingDir <- here::here()
```

##Create RSiena data object for the Friendship network

```{r}
dtObj1 <- sienaDataCreate(fNet0SD, RFD, RS.sex, RS.age, RS.Blk, RS.inResL, ccSD)
```

```{r}
print01Report(dtObj1, modelname="RFNetModels_1")
```

#Create effect objects
```{r}
effObj1.16 <- getEffects(dtObj1)

```



```

        behModelType=c(RFD=1)
    )
...
```{r}
rfMod1.27 <- sienaModelCreate(projname="RFNetModels.results.FR",
 useStdInits=F,
 dolby=T,
 maxlike = F,
 modelType = c(fNet0SD=1),
 behModelType=c(RFD=1)
)
...
```{r}
rfMod1.28 <- sienaModelCreate(projname="RFNetModels.results.FR",
    useStdInits=F,
    dolby=T,
    maxlike = F,
    modelType = c(fNet0SD=1),
    behModelType=c(RFD=1)
)
...
```{r}
rfMod1.29 <- sienaModelCreate(projname="RFNetModels.results.FR",
 useStdInits=F,
 dolby=T,
 maxlike = F,
 modelType = c(fNet0SD=1),
 behModelType=c(RFD=1)
)
...
```{r}
effObj1.16 <- includeEffects(effObj1.16, transTies, transTrip, inPop, outPop, outAct)
...
```{r}
effObj1.17 <- includeEffects(effObj1.17, transTies, transTrip, inPop, outPop, outAct)
...
```{r}
effObj1.18 <- includeEffects(effObj1.18, transTies, transTrip, inPop, outPop, outAct)
...
```{r}
effObj1.19 <- includeEffects(effObj1.19, transTies, transTrip, inPop, outPop, outAct)
...
```{r}
effObj1.20 <- includeEffects(effObj1.20, transTies, transTrip, inPop, outPop, outAct)
...
```{r}

```

```

effObj1.16 <- includeEffects(effObj1.16, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RS.inResL")
effObj1.16 <- includeEffects(effObj1.16, effFrom, name="RFD", type="eval",
 interaction1="RS.inResL")
effObj1.16 <- includeEffects(effObj1.16, effFrom, name="RFD", type="eval",
 interaction1="RS.sex")

effObj1.16 <- includeEffects(effObj1.16, avAlt, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.16 <- includeEffects(effObj1.16, totAlt, name="RFD", type="eval",
 interaction1="fNet0SD", include = F)

effObj1.16 <- includeEffects(effObj1.16, effFrom, name="RFD", type="eval",
 interaction1="RS.Blk")
effObj1.16 <- includeEffects(effObj1.16, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RFD", include = F)
effObj1.16 <- includeEffects(effObj1.16, indeg, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.16 <- includeEffects(effObj1.16, outdeg, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.16 <- includeEffects(effObj1.16, avAlt, name="RFD", type="eval",
 interaction1="fNet0SD", include = F)

effObj1.16 <- includeEffects(effObj1.16, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RS.age", include =F)
effObj1.16 <- includeEffects(effObj1.16, effFrom, name="RFD", type="eval",
 interaction1="RS.age")

```

```{r}
effObj1.17 <- includeEffects(effObj1.17, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RS.inResL")
effObj1.17 <- includeEffects(effObj1.17, effFrom, name="RFD", type="eval",
 interaction1="RS.inResL")
effObj1.17 <- includeEffects(effObj1.17, effFrom, name="RFD", type="eval",
 interaction1="RS.sex")

effObj1.17 <- includeEffects(effObj1.17, avAlt, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.17 <- includeEffects(effObj1.17, totAlt, name="RFD", type="eval",
 interaction1="fNet0SD", include = F)

```

```

effObj1.17 <- includeEffects(effObj1.17, effFrom, name="RFD", type="eval",
 interaction1="RS.Blk")
effObj1.17 <- includeEffects(effObj1.17, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RFD", include = T)
effObj1.17 <- includeEffects(effObj1.17, indeg, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.17 <- includeEffects(effObj1.17, outdeg, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.17 <- includeEffects(effObj1.17, avAlt, name="RFD", type="eval",
 interaction1="fNet0SD", include = T)

effObj1.17 <- includeEffects(effObj1.17, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RS.age", include =F)
effObj1.17 <- includeEffects(effObj1.17, effFrom, name="RFD", type="eval",
 interaction1="RS.age")

effObj1.17 <- includeEffects(effObj1.17, recipDeg, name="RFD", type="eval",
 interaction1="fNet0SD", include = F)
effObj1.17 <- includeEffects(effObj1.17, avAltPop, name="RFD", type="eval",
 interaction1="fNet0SD", include = F)
effObj1.17 <- includeEffects(effObj1.17, behDenseTriads, name="RFD", type="eval",
 interaction1="fNet0SD", include = F)

...

```{r}
effObj1.18 <- includeEffects(effObj1.18, egoX, altX, name="fNet0SD", type="eval",
  interaction1="RS.inResL")
effObj1.18 <- includeEffects(effObj1.18, effFrom, name="RFD", type="eval",
  interaction1="RS.inResL")
effObj1.18 <- includeEffects(effObj1.18, effFrom, name="RFD", type="eval",
  interaction1="RS.sex")

effObj1.18 <- includeEffects(effObj1.18, avAlt, name="RFD", type="eval",
  interaction1="fNet0SD")
effObj1.18 <- includeEffects(effObj1.18, totAlt, name="RFD", type="eval",
  interaction1="fNet0SD", include = F)

effObj1.18 <- includeEffects(effObj1.18, effFrom, name="RFD", type="eval",
  interaction1="RS.Blk")
effObj1.18 <- includeEffects(effObj1.18, egoX, altX, name="fNet0SD", type="eval",
  interaction1="RFD", include = T)
effObj1.18 <- includeEffects(effObj1.18, indeg, name="RFD", type="eval",

```



```

        interaction1="fNet0SD")
effObj1.18 <- includeEffects(effObj1.18, outdeg, name="RFD", type="eval",
        interaction1="fNet0SD")
effObj1.18 <- includeEffects(effObj1.18, avAlt, name="RFD", type="eval",
        interaction1="fNet0SD", include = T)

effObj1.18 <- includeEffects(effObj1.18, egoX, altX, name="fNet0SD", type="eval",
        interaction1="RS.age", include =F)
effObj1.18 <- includeEffects(effObj1.18, effFrom, name="RFD", type="eval",
        interaction1="RS.age")

effObj1.18 <- includeEffects(effObj1.18, recipDeg, name="RFD", type="eval",
        interaction1="fNet0SD")

effObj1.18 <- includeEffects(effObj1.18, recipDeg, name="RFD", type="eval",
        interaction1="fNet0SD", include = T)
effObj1.18 <- includeEffects(effObj1.18, avAltPop, name="RFD", type="eval",
        interaction1="fNet0SD", include = F)
effObj1.18 <- includeEffects(effObj1.18, behDenseTriads, name="RFD", type="eval",
        interaction1="fNet0SD", include = F)

...

``{r}
effObj1.19 <- includeEffects(effObj1.19, egoX, altX, name="fNet0SD", type="eval",
        interaction1="RS.inResL")
effObj1.19 <- includeEffects(effObj1.19, effFrom, name="RFD", type="eval",
        interaction1="RS.inResL")
effObj1.19 <- includeEffects(effObj1.19, effFrom, name="RFD", type="eval",
        interaction1="RS.sex")

effObj1.19 <- includeEffects(effObj1.19, avAlt, name="RFD", type="eval",
        interaction1="fNet0SD")
effObj1.19 <- includeEffects(effObj1.19, totAlt, name="RFD", type="eval",
        interaction1="fNet0SD", include = F)

effObj1.19 <- includeEffects(effObj1.19, effFrom, name="RFD", type="eval",
        interaction1="RS.Blk")
effObj1.19 <- includeEffects(effObj1.19, egoX, altX, name="fNet0SD", type="eval",
        interaction1="RFD", include = T)
effObj1.19 <- includeEffects(effObj1.19, indeg, name="RFD", type="eval",
        interaction1="fNet0SD")
effObj1.19 <- includeEffects(effObj1.19, outdeg, name="RFD", type="eval",
        interaction1="fNet0SD")

```

```

effObj1.19 <- includeEffects(effObj1.19, avAlt, name="RFD", type="eval",
                             interaction1="fNet0SD", include = T)

effObj1.19 <- includeEffects(effObj1.19, egoX, altX, name="fNet0SD", type="eval",
                             interaction1="RS.age", include =F)
effObj1.19 <- includeEffects(effObj1.19, effFrom, name="RFD", type="eval",
                             interaction1="RS.age")

effObj1.19 <- includeEffects(effObj1.19, recipDeg, name="RFD", type="eval",
                             interaction1="fNet0SD")

effObj1.19 <- includeEffects(effObj1.19, recipDeg, name="RFD", type="eval",
                             interaction1="fNet0SD", include = T)
effObj1.19 <- includeEffects(effObj1.19, avAltPop, name="RFD", type="eval",
                             interaction1="fNet0SD", include = T)
effObj1.19 <- includeEffects(effObj1.19, behDenseTriads, name="RFD", type="eval",
                             interaction1="fNet0SD", include = F)

...

```{r}
effObj1.20 <- includeEffects(effObj1.20, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RS.inResL")
effObj1.20 <- includeEffects(effObj1.20, effFrom, name="RFD", type="eval",
 interaction1="RS.inResL")
effObj1.20 <- includeEffects(effObj1.20, effFrom, name="RFD", type="eval",
 interaction1="RS.sex")

effObj1.20 <- includeEffects(effObj1.20, avAlt, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.20 <- includeEffects(effObj1.20, totAlt, name="RFD", type="eval",
 interaction1="fNet0SD", include = F)

effObj1.20 <- includeEffects(effObj1.20, effFrom, name="RFD", type="eval",
 interaction1="RS.Blk")
effObj1.20 <- includeEffects(effObj1.20, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RFD", include = T)
effObj1.20 <- includeEffects(effObj1.20, indeg, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.20 <- includeEffects(effObj1.20, outdeg, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.20 <- includeEffects(effObj1.20, avAlt, name="RFD", type="eval",
 interaction1="fNet0SD", include = T)

effObj1.20 <- includeEffects(effObj1.20, egoX, altX, name="fNet0SD", type="eval",

```

```

 interaction1="RS.age", include =F)
effObj1.20 <- includeEffects(effObj1.20, effFrom, name="RFD", type="eval",
 interaction1="RS.age")

effObj1.20 <- includeEffects(effObj1.20, recipDeg, name="RFD", type="eval",
 interaction1="fNet0SD")

effObj1.20 <- includeEffects(effObj1.20, recipDeg, name="RFD", type="eval",
 interaction1="fNet0SD", include = T)
effObj1.20 <- includeEffects(effObj1.20, avAltPop, name="RFD", type="eval",
 interaction1="fNet0SD", include = F)
effObj1.20 <- includeEffects(effObj1.20, behDenseTriads, name="RFD", type="eval",
 interaction1="fNet0SD", include = T)

...

```{r}
mod1.25 <- siena07(rfMod1.25, data=dtObj1, effects=effObj1.16, useCluster=T,
        nbrNodes=7) #prevAns=mod1.12)
...

```{r}
mod1.26 <- siena07(rfMod1.26, data=dtObj1, effects=effObj1.17, useCluster=T,
 nbrNodes=7, prevAns=mod1.25)
...

```{r}
mod1.27 <- siena07(rfMod1.27, data=dtObj1, effects=effObj1.18, useCluster=T,
        nbrNodes=7, prevAns=mod1.26)
...

```{r}
mod1.28 <- siena07(rfMod1.28, data=dtObj1, effects=effObj1.19, useCluster=T,
 nbrNodes=7, prevAns=mod1.26)
...

##Create RSiena data object for the Loaning network

```{r}
dtObj3 <- sienaDataCreate(loanNet0SD, RFD, RS.sex, RS.age, RS.Blk, RS.inResL, ccSD)
...

```{r}
print01Report(dtObj3, modelname="RFNetModels_3")
...

#Create effect objects
```{r}
effObj3.16 <- getEffects(dtObj3)
...

```{r}

```

```

effObj3.17 <- getEffects(dtObj3)
```
```{r}
effObj3.18 <- getEffects(dtObj3)
```
```{r}
effObj3.19 <- getEffects(dtObj3)
```
```{r}
effObj3.20 <- getEffects(dtObj3)
```
```{r}
effectsDocumentation(effObj3.16)
```
```{r}
effectsDocumentation(effObj3.17)
```
```{r}
effectsDocumentation(effObj3.18)
```
```{r}
effectsDocumentation(effObj3.19)
```
```{r}
effectsDocumentation(effObj3.20)
```
#The model
```{r}
rfMod3.25 <- sienaModelCreate(projname="RFNetModels.results.LO",
 useStdInits=T,
 dolby=T,
 maxlike = F,
 modelType = c(loanNet0SD=1),
 behModelType=c(RFD=1)
)
```
```{r}
rfMod3.26 <- sienaModelCreate(projname=" RFNetModels.results.LO ",
 useStdInits=F,
 dolby=T,
 maxlike = F,
 modelType = c(loanNet0SD=1),
 behModelType=c(RFD=1)
)

```



```

effObj1.16 <- includeEffects(effObj1.16, effFrom, name="RFD", type="eval",
 interaction1="RS.inResL")
effObj1.16 <- includeEffects(effObj1.16, effFrom, name="RFD", type="eval",
 interaction1="RS.sex")

effObj1.16 <- includeEffects(effObj1.16, avAlt, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.16 <- includeEffects(effObj1.16, totAlt, name="RFD", type="eval",
 interaction1="fNet0SD", include = F)

effObj1.16 <- includeEffects(effObj1.16, effFrom, name="RFD", type="eval",
 interaction1="RS.Blk")
effObj1.16 <- includeEffects(effObj1.16, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RFD", include = F)
effObj1.16 <- includeEffects(effObj1.16, indeg, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.16 <- includeEffects(effObj1.16, outdeg, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.16 <- includeEffects(effObj1.16, avAlt, name="RFD", type="eval",
 interaction1="fNet0SD", include = F)

effObj1.16 <- includeEffects(effObj1.16, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RS.age", include =F)
effObj1.16 <- includeEffects(effObj1.16, effFrom, name="RFD", type="eval",
 interaction1="RS.age")

...

```{r}
effObj1.17 <- includeEffects(effObj1.17, egoX, altX, name="fNet0SD", type="eval",
  interaction1="RS.inResL")
effObj1.17 <- includeEffects(effObj1.17, effFrom, name="RFD", type="eval",
  interaction1="RS.inResL")
effObj1.17 <- includeEffects(effObj1.17, effFrom, name="RFD", type="eval",
  interaction1="RS.sex")

effObj1.17 <- includeEffects(effObj1.17, avAlt, name="RFD", type="eval",
  interaction1="fNet0SD")
effObj1.17 <- includeEffects(effObj1.17, totAlt, name="RFD", type="eval",
  interaction1="fNet0SD", include = F)

effObj1.17 <- includeEffects(effObj1.17, effFrom, name="RFD", type="eval",
  interaction1="RS.Blk")

```

```

effObj1.17 <- includeEffects(effObj1.17, egoX, altX, name="fNet0SD", type="eval",
  interaction1="RFD", include = T)
effObj1.17 <- includeEffects(effObj1.17, indeg, name="RFD", type="eval",
  interaction1="fNet0SD")
effObj1.17 <- includeEffects(effObj1.17, outdeg, name="RFD", type="eval",
  interaction1="fNet0SD")
effObj1.17 <- includeEffects(effObj1.17, avAlt, name="RFD", type="eval",
  interaction1="fNet0SD", include = T)

effObj1.17 <- includeEffects(effObj1.17, egoX, altX, name="fNet0SD", type="eval",
  interaction1="RS.age", include =F)
effObj1.17 <- includeEffects(effObj1.17, effFrom, name="RFD", type="eval",
  interaction1="RS.age")

effObj1.17 <- includeEffects(effObj1.17, recipDeg, name="RFD", type="eval",
  interaction1="fNet0SD", include = F)
effObj1.17 <- includeEffects(effObj1.17, avAltPop, name="RFD", type="eval",
  interaction1="fNet0SD", include = F)
effObj1.17 <- includeEffects(effObj1.17, behDenseTriads, name="RFD", type="eval",
  interaction1="fNet0SD", include = F)

...

```{r}
effObj1.18 <- includeEffects(effObj1.18, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RS.inResL")
effObj1.18 <- includeEffects(effObj1.18, effFrom, name="RFD", type="eval",
 interaction1="RS.inResL")
effObj1.18 <- includeEffects(effObj1.18, effFrom, name="RFD", type="eval",
 interaction1="RS.sex")

effObj1.18 <- includeEffects(effObj1.18, avAlt, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.18 <- includeEffects(effObj1.18, totAlt, name="RFD", type="eval",
 interaction1="fNet0SD", include = F)

effObj1.18 <- includeEffects(effObj1.18, effFrom, name="RFD", type="eval",
 interaction1="RS.Blk")
effObj1.18 <- includeEffects(effObj1.18, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RFD", include = T)
effObj1.18 <- includeEffects(effObj1.18, indeg, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.18 <- includeEffects(effObj1.18, outdeg, name="RFD", type="eval",

```

```

 interaction1="fNet0SD")
effObj1.18 <- includeEffects(effObj1.18, avAlt, name="RFD", type="eval",
 interaction1="fNet0SD", include = T)

effObj1.18 <- includeEffects(effObj1.18, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RS.age", include =F)
effObj1.18 <- includeEffects(effObj1.18, effFrom, name="RFD", type="eval",
 interaction1="RS.age")

effObj1.18 <- includeEffects(effObj1.18, recipDeg, name="RFD", type="eval",
 interaction1="fNet0SD")

effObj1.18 <- includeEffects(effObj1.18, recipDeg, name="RFD", type="eval",
 interaction1="fNet0SD", include = T)
effObj1.18 <- includeEffects(effObj1.18, avAltPop, name="RFD", type="eval",
 interaction1="fNet0SD", include = F)
effObj1.18 <- includeEffects(effObj1.18, behDenseTriads, name="RFD", type="eval",
 interaction1="fNet0SD", include = F)

```

```{r}
effObj1.19 <- includeEffects(effObj1.19, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RS.inResL")
effObj1.19 <- includeEffects(effObj1.19, effFrom, name="RFD", type="eval",
 interaction1="RS.inResL")
effObj1.19 <- includeEffects(effObj1.19, effFrom, name="RFD", type="eval",
 interaction1="RS.sex")

effObj1.19 <- includeEffects(effObj1.19, avAlt, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.19 <- includeEffects(effObj1.19, totAlt, name="RFD", type="eval",
 interaction1="fNet0SD", include = F)

effObj1.19 <- includeEffects(effObj1.19, effFrom, name="RFD", type="eval",
 interaction1="RS.Blk")
effObj1.19 <- includeEffects(effObj1.19, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RFD", include = T)
effObj1.19 <- includeEffects(effObj1.19, indeg, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.19 <- includeEffects(effObj1.19, outdeg, name="RFD", type="eval",
 interaction1="fNet0SD")
effObj1.19 <- includeEffects(effObj1.19, avAlt, name="RFD", type="eval",
 interaction1="fNet0SD", include = T)

```



```

effObj1.19 <- includeEffects(effObj1.19, egoX, altX, name="fNet0SD", type="eval",
 interaction1="RS.age", include =F)
effObj1.19 <- includeEffects(effObj1.19, effFrom, name="RFD", type="eval",
 interaction1="RS.age")

effObj1.19 <- includeEffects(effObj1.19, recipDeg, name="RFD", type="eval",
 interaction1="fNet0SD")

effObj1.19 <- includeEffects(effObj1.19, recipDeg, name="RFD", type="eval",
 interaction1="fNet0SD", include = T)
effObj1.19 <- includeEffects(effObj1.19, avAltPop, name="RFD", type="eval",
 interaction1="fNet0SD", include = T)
effObj1.19 <- includeEffects(effObj1.19, behDenseTriads, name="RFD", type="eval",
 interaction1="fNet0SD", include = F)

...

```{r}
effObj1.20 <- includeEffects(effObj1.20, egoX, altX, name="fNet0SD", type="eval",
  interaction1="RS.inResL")
effObj1.20 <- includeEffects(effObj1.20, effFrom, name="RFD", type="eval",
  interaction1="RS.inResL")
effObj1.20 <- includeEffects(effObj1.20, effFrom, name="RFD", type="eval",
  interaction1="RS.sex")

effObj1.20 <- includeEffects(effObj1.20, avAlt, name="RFD", type="eval",
  interaction1="fNet0SD")
effObj1.20 <- includeEffects(effObj1.20, totAlt, name="RFD", type="eval",
  interaction1="fNet0SD", include = F)

effObj1.20 <- includeEffects(effObj1.20, effFrom, name="RFD", type="eval",
  interaction1="RS.Blk")
effObj1.20 <- includeEffects(effObj1.20, egoX, altX, name="fNet0SD", type="eval",
  interaction1="RFD", include = T)
effObj1.20 <- includeEffects(effObj1.20, indeg, name="RFD", type="eval",
  interaction1="fNet0SD")
effObj1.20 <- includeEffects(effObj1.20, outdeg, name="RFD", type="eval",
  interaction1="fNet0SD")
effObj1.20 <- includeEffects(effObj1.20, avAlt, name="RFD", type="eval",
  interaction1="fNet0SD", include = T)

effObj1.20 <- includeEffects(effObj1.20, egoX, altX, name="fNet0SD", type="eval",
  interaction1="RS.age", include =F)
effObj1.20 <- includeEffects(effObj1.20, effFrom, name="RFD", type="eval",

```

```

        interaction1="RS.age")

effObj1.20 <- includeEffects(effObj1.20, recipDeg, name="RFD", type="eval",
        interaction1="fNet0SD")

effObj1.20 <- includeEffects(effObj1.20, recipDeg, name="RFD", type="eval",
        interaction1="fNet0SD", include = T)
effObj1.20 <- includeEffects(effObj1.20, avAltPop, name="RFD", type="eval",
        interaction1="fNet0SD", include = F)
effObj1.20 <- includeEffects(effObj1.20, behDenseTriads, name="RFD", type="eval",
        interaction1="fNet0SD", include = T)

...

```{r}
mod1.25 <- siena07(rfMod1.25, data=dtObj1, effects=effObj1.16, useCluster=T,
 nbrNodes=7) #prevAns=mod1.12)
...

###Final Friendship Model
```{r}
mod1.26 <- siena07(rfMod1.26, data=dtObj1, effects=effObj1.17, useCluster=T,
        nbrNodes=7, prevAns=mod1.25)
...

```{r}
mod1.27 <- siena07(rfMod1.27, data=dtObj1, effects=effObj1.18, useCluster=T,
 nbrNodes=7, prevAns=mod3.26)
...

```{r}
mod1.28 <- siena07(rfMod1.28, data=dtObj1, effects=effObj1.19, useCluster=T,
        nbrNodes=7, prevAns=mod1.26)
...

##Create RSiena data object for the Friendship network

```{r}
dtObj3 <- sienaDataCreate(loanNet0SD, RFD, RS.sex, RS.age, RS.Blk, RS.inResL, ccSD)
...

```{r}
print01Report(dtObj3, modelName="RFNetModels_3")
...

#Create effect objects
```{r}
effObj3.16 <- getEffects(dtObj3)
...

```{r}
effObj3.17 <- getEffects(dtObj3)

```

```

...
```{r}
effObj3.18 <- getEffects(dtObj3)
...
```{r}
effObj3.19 <- getEffects(dtObj3)
...
```{r}
effObj3.20 <- getEffects(dtObj3)
...
```{r}
effectsDocumentation(effObj3.16)
...
```{r}
effectsDocumentation(effObj3.17)
...
```{r}
effectsDocumentation(effObj3.18)
...
```{r}
effectsDocumentation(effObj3.19)
...
```{r}
effectsDocumentation(effObj3.20)
...
#The model

```{r}
rfMod3.25 <- sienaModelCreate(projname="RFNetModels.results.LO",
 useStdInits=T,
 dolby=T,
 maxlike = F,
 modelType = c(loanNet0SD=1),
 behModelType=c(RFD=1)
)
...

```{r}
rfMod3.26 <- sienaModelCreate(projname="RFNetModels.results.LO",
                             useStdInits=F,
                             dolby=T,
                             maxlike = F,
                             modelType = c(loanNet0SD=1),
                             behModelType=c(RFD=1)
                             )
...

```

```

```{r}
rfMod3.27 <- sienaModelCreate(projname="RFNetModels.results.LO",
 useStdInits=F,
 dolby=T,
 maxlike = F,
 modelType = c(loanNet0SD=1),
 behModelType=c(RFD=1)
)
...
```{r}
rfMod3.28 <- sienaModelCreate(projname="RFNetModels.results.LO",
  useStdInits=F,
  dolby=T,
  maxlike = F,
  modelType = c(loanNet0SD=1),
  behModelType=c(RFD=1)
)
...
```{r}
rfMod3.29 <- sienaModelCreate(projname="RFNetModels.results.LO",
 useStdInits=F,
 dolby=T,
 maxlike = F,
 modelType = c(loanNet0SD=1),
 behModelType=c(RFD=1)
)
...
```{r}
effObj3.16 <- includeEffects(effObj3.16, transTies, transTrip, inPop, outPop, outAct)
...
```{r}
effObj3.17 <- includeEffects(effObj3.17, transTies, transTrip, inPop, outPop, outAct)
...
```{r}
effObj3.18 <- includeEffects(effObj3.18, transTies, transTrip, inPop, outPop, outAct)
...
```{r}
effObj3.19 <- includeEffects(effObj3.19, transTies, transTrip, inPop, outPop, outAct)
...
```{r}
effObj3.20 <- includeEffects(effObj3.20, transTies, transTrip, inPop, outPop, outAct)
...
```{r}
effObj3.16 <- includeEffects(effObj3.16, egoX, altX, name="loanNet0SD", type="eval",
 interaction1="RS.inResL")
effObj3.16 <- includeEffects(effObj3.16, effFrom, name="RFD", type="eval",

```

```

 interaction1="RS.inResL")
effObj3.16 <- includeEffects(effObj3.16, effFrom, name="RFD", type="eval",
 interaction1="RS.sex")

effObj3.16 <- includeEffects(effObj3.16, avAlt, name="RFD", type="eval",
 interaction1="loanNet0SD")
effObj3.16 <- includeEffects(effObj3.16, totAlt, name="RFD", type="eval",
 interaction1="loanNet0SD", include = F)

effObj3.16 <- includeEffects(effObj3.16, effFrom, name="RFD", type="eval",
 interaction1="RS.Blk")
effObj3.16 <- includeEffects(effObj3.16, egoX, altX, name="loanNet0SD", type="eval",
 interaction1="RFD", include = F)
effObj3.16 <- includeEffects(effObj3.16, indeg, name="RFD", type="eval",
 interaction1="loanNet0SD")
effObj3.16 <- includeEffects(effObj3.16, outdeg, name="RFD", type="eval",
 interaction1="loanNet0SD")
effObj3.16 <- includeEffects(effObj3.16, avAlt, name="RFD", type="eval",
 interaction1="loanNet0SD", include = F)

effObj3.16 <- includeEffects(effObj3.16, egoX, altX, name="loanNet0SD", type="eval",
 interaction1="RS.age", include = F)
effObj3.16 <- includeEffects(effObj3.16, effFrom, name="RFD", type="eval",
 interaction1="RS.age")
...

`` {r}
effObj3.17 <- includeEffects(effObj3.17, egoX, altX, name="loanNet0SD", type="eval",
 interaction1="RS.inResL")
effObj3.17 <- includeEffects(effObj3.17, effFrom, name="RFD", type="eval",
 interaction1="RS.inResL")
effObj3.17 <- includeEffects(effObj3.17, effFrom, name="RFD", type="eval",
 interaction1="RS.sex")

effObj3.17 <- includeEffects(effObj3.17, avAlt, name="RFD", type="eval",
 interaction1="loanNet0SD")
effObj3.17 <- includeEffects(effObj3.17, totAlt, name="RFD", type="eval",
 interaction1="loanNet0SD", include = F)

effObj3.17 <- includeEffects(effObj3.17, effFrom, name="RFD", type="eval",
 interaction1="RS.Blk")
effObj3.17 <- includeEffects(effObj3.17, egoX, altX, name="loanNet0SD", type="eval",
 interaction1="RFD", include = F)

```

```

effObj3.17 <- includeEffects(effObj3.17, indeg, name="RFD", type="eval",
 interaction1="loanNet0SD")
effObj3.17 <- includeEffects(effObj3.17, outdeg, name="RFD", type="eval",
 interaction1="loanNet0SD")
effObj3.17 <- includeEffects(effObj3.17, avAlt, name="RFD", type="eval",
 interaction1="loanNet0SD", include = F)

effObj3.17 <- includeEffects(effObj3.17, egoX, altX, name="loanNet0SD", type="eval",
 interaction1="RS.age", include =F)
effObj3.17 <- includeEffects(effObj3.17, effFrom, name="RFD", type="eval",
 interaction1="RS.age")
...

```{r}
effObj3.18 <- includeEffects(effObj3.18, egoX, altX, name="loanNet0SD", type="eval",
  interaction1="RS.inResL")
effObj3.18 <- includeEffects(effObj3.18, effFrom, name="RFD", type="eval",
  interaction1="RS.inResL")
effObj3.18 <- includeEffects(effObj3.18, effFrom, name="RFD", type="eval",
  interaction1="RS.sex")

effObj3.18 <- includeEffects(effObj3.18, avAlt, name="RFD", type="eval",
  interaction1="loanNet0SD")
effObj3.18 <- includeEffects(effObj3.18, totAlt, name="RFD", type="eval",
  interaction1="loanNet0SD", include = F)

effObj3.18 <- includeEffects(effObj3.18, effFrom, name="RFD", type="eval",
  interaction1="RS.Blk")
effObj3.18 <- includeEffects(effObj3.18, egoX, altX, name="loanNet0SD", type="eval",
  interaction1="RFD", include = T)
effObj3.18 <- includeEffects(effObj3.18, indeg, name="RFD", type="eval",
  interaction1="loanNet0SD")
effObj3.18 <- includeEffects(effObj3.18, outdeg, name="RFD", type="eval",
  interaction1="loanNet0SD")
effObj3.18 <- includeEffects(effObj3.18, avAlt, name="RFD", type="eval",
  interaction1="loanNet0SD", include = T)

effObj3.18 <- includeEffects(effObj3.18, egoX, altX, name="loanNet0SD", type="eval",
  interaction1="RS.age", include =F)
effObj3.18 <- includeEffects(effObj3.18, effFrom, name="RFD", type="eval",
  interaction1="RS.age")

effObj3.18 <- includeEffects(effObj3.18, recipDeg, name="RFD", type="eval",

```

```

        interaction1="loanNet0SD", include = T)
effObj3.18 <- includeEffects(effObj3.18, avAltPop, name="RFD", type="eval",
        interaction1="loanNet0SD", include = F)
effObj3.18 <- includeEffects(effObj3.18, behDenseTriads, name="RFD", type="eval",
        interaction1="loanNet0SD", include = F)
...

```{r}
effObj3.19 <- includeEffects(effObj3.19, egoX, altX, name="loanNet0SD", type="eval",
 interaction1="RS.inResL")
effObj3.19 <- includeEffects(effObj3.19, effFrom, name="RFD", type="eval",
 interaction1="RS.inResL")
effObj3.19 <- includeEffects(effObj3.19, effFrom, name="RFD", type="eval",
 interaction1="RS.sex")

effObj3.19 <- includeEffects(effObj3.19, avAlt, name="RFD", type="eval",
 interaction1="loanNet0SD")
effObj3.19 <- includeEffects(effObj3.19, totAlt, name="RFD", type="eval",
 interaction1="loanNet0SD", include = F)

effObj3.19 <- includeEffects(effObj3.19, effFrom, name="RFD", type="eval",
 interaction1="RS.Blk")
effObj3.19 <- includeEffects(effObj1.19, egoX, altX, name="loanNet0SD", type="eval",
 interaction1="RFD", include = T)
effObj3.19 <- includeEffects(effObj1.19, indeg, name="RFD", type="eval",
 interaction1="loanNet0SD")
effObj3.19 <- includeEffects(effObj1.19, outdeg, name="RFD", type="eval",
 interaction1="loanNet0SD")
effObj3.19 <- includeEffects(effObj1.19, avAlt, name="RFD", type="eval",
 interaction1="loanNet0SD", include = T)

effObj3.19 <- includeEffects(effObj1.19, egoX, altX, name="loanNet0SD", type="eval",
 interaction1="RS.age", include =F)
effObj3.19 <- includeEffects(effObj1.19, effFrom, name="RFD", type="eval",
 interaction1="RS.age")

effObj3.19 <- includeEffects(effObj1.19, recipDeg, name="RFD", type="eval",
 interaction1="loanNet0SD")

effObj3.19 <- includeEffects(effObj3.19, recipDeg, name="RFD", type="eval",
 interaction1="loanNet0SD", include = T)
effObj3.19 <- includeEffects(effObj1.19, avAltPop, name="RFD", type="eval",
 interaction1="fNet0SD", include = T)
effObj3.19 <- includeEffects(effObj1.19, behDenseTriads, name="RFD", type="eval",

```

```

interaction1="fNet0SD", include = F)

...

```{r}
effObj3.20 <- includeEffects(effObj3.20, egoX, altX, name="loanNet0SD", type="eval",
  interaction1="RS.inResL")
effObj3.20 <- includeEffects(effObj3.20, effFrom, name="RFD", type="eval",
  interaction1="RS.inResL")
effObj3.20 <- includeEffects(effObj3.20, effFrom, name="RFD", type="eval",
  interaction1="RS.sex")

effObj3.20 <- includeEffects(effObj3.20, avAlt, name="RFD", type="eval",
  interaction1="loanNet0SD")
effObj3.20 <- includeEffects(effObj3.20, totAlt, name="RFD", type="eval",
  interaction1="loanNet0SD", include = F)

effObj3.20 <- includeEffects(effObj3.20, effFrom, name="RFD", type="eval",
  interaction1="RS.Blk")
effObj3.20 <- includeEffects(effObj3.20, egoX, altX, name="loanNet0SD", type="eval",
  interaction1="RFD", include = T)
effObj3.20 <- includeEffects(effObj3.20, indeg, name="RFD", type="eval",
  interaction1="loanNet0SD")
effObj3.20 <- includeEffects(effObj3.20, outdeg, name="RFD", type="eval",
  interaction1="loanNet0SD")
effObj3.20 <- includeEffects(effObj3.20, avAlt, name="RFD", type="eval",
  interaction1="loanNet0SD", include = T)

effObj3.20 <- includeEffects(effObj3.20, egoX, altX, name="laonNet0SD", type="eval",
  interaction1="RS.age", include =F)
effObj3.20 <- includeEffects(effObj3.20, effFrom, name="RFD", type="eval",
  interaction1="RS.age")

effObj3.20 <- includeEffects(effObj3.20, recipDeg, name="RFD", type="eval",
  interaction1="loanNet0SD")

effObj3.20 <- includeEffects(effObj3.20, recipDeg, name="RFD", type="eval",
  interaction1="loanNet0SD", include = T)
effObj3.20 <- includeEffects(effObj3.20, avAltPop, name="RFD", type="eval",
  interaction1="loanNet0SD", include = F)
effObj3.20 <- includeEffects(effObj3.20, behDenseTriads, name="RFD", type="eval",
  interaction1="loanNet0SD", include = T)

...

```



```

```{r}
mod3.25 <- siena07(rfMod3.25, data=dtObj3, effects=effObj3.16, useCluster=T,
 nbrNodes=7) #prevAns=mod3.12)
...

```{r}
mod3.26 <- siena07(rfMod3.26, data=dtObj3, effects=effObj3.17, useCluster=T,
  nbrNodes=7, prevAns=mod3.25)
...

```{r}
mod3.27 <- siena07(rfMod3.27, data=dtObj3, effects=effObj3.18, useCluster=T,
 nbrNodes=7, prevAns=mod3.26)
...

```{r}
mod3.28 <- siena07(rfMod3.28, data=dtObj3, effects=effObj3.19, useCluster=T,
  nbrNodes=7, prevAns=mod3.26)
...

##Script for advice-seeking model

```{r}
dtObj4 <- sienaDataCreate(advNet0SD, RFD, RS.sex, RS.age, RS.Blk, RS.inResL, ccSD)
...

```{r}
effObj4.1 <- getEffects(dtObj4)
...

```{r}
effObj4.16 <- getEffects(dtObj4)
...

```{r}
effObj4.17 <- getEffects(dtObj4)
...

```{r}
effObj4.18 <- getEffects(dtObj4)
...

```{r}
effObj4.19 <- getEffects(dtObj4)
...

```{r}
effObj4.20 <- getEffects(dtObj4)

```

```

...
```{r}
rfMod4.26 <- sienaModelCreate(projname="RFNetModels.results.AD",
  useStdInits=F,
  dolby=T,
  maxlike = F,
  modelType = c(advNet0SD=1),
  behModelType=c(RFD=1)
)
...

```{r}
rfMod4.27 <- sienaModelCreate(projname="RFNetModels.results.AD",
 useStdInits=F,
 dolby=T,
 maxlike = F,
 modelType = c(advNet0SD=1),
 behModelType=c(RFD=1)
)
...

```{r}
rfMod4.28 <- sienaModelCreate(projname="RFNetModels.results.AD",
  useStdInits=F,
  dolby=T,
  maxlike = F,
  modelType = c(advNet0SD=1),
  behModelType=c(RFD=1)
)
...

```{r}
rfMod4.29 <- sienaModelCreate(projname="RFNetModels.results.AD",
 useStdInits=F,
 dolby=T,
 maxlike = F,
 modelType = c(advNet0SD=1),
 behModelType=c(RFD=1)
)
...

```{r}
effObj4.17 <- includeEffects(effObj4.17, egoX, altX, name="advNet0SD", type="eval",
  interaction1="RS.inResL")
effObj4.17 <- includeEffects(effObj4.17, effFrom, name="RFD", type="eval",
  interaction1="RS.inResL")
effObj4.17 <- includeEffects(effObj4.17, effFrom, name="RFD", type="eval",
  interaction1="RS.sex")

```

```

effObj4.17 <- includeEffects(effObj4.17, avAlt, name="RFD", type="eval",
  interaction1="advNet0SD")
effObj4.17 <- includeEffects(effObj4.17, totAlt, name="RFD", type="eval",
  interaction1="advNet0SD", include = F)

effObj4.17 <- includeEffects(effObj4.17, effFrom, name="RFD", type="eval",
  interaction1="RS.Blk")
effObj4.17 <- includeEffects(effObj4.17, egoX, altX, name="advNet0SD", type="eval",
  interaction1="RFD", include = F)
effObj4.17 <- includeEffects(effObj4.17, indeg, name="RFD", type="eval",
  interaction1="advNet0SD")
effObj4.17 <- includeEffects(effObj4.17, outdeg, name="RFD", type="eval",
  interaction1="advNet0SD")
effObj4.17 <- includeEffects(effObj4.17, avAlt, name="RFD", type="eval",
  interaction1="advNet0SD", include = F)

effObj4.17 <- includeEffects(effObj4.17, egoX, altX, name="advNet0SD", type="eval",
  interaction1="RS.age", include = F)
effObj4.17 <- includeEffects(effObj4.17, effFrom, name="RFD", type="eval",
  interaction1="RS.age")

...

```{r}
effObj4.18 <- includeEffects(effObj4.18, egoX, altX, name="advNet0SD", type="eval",
 interaction1="RS.inResL")
effObj4.18 <- includeEffects(effObj4.18, effFrom, name="RFD", type="eval",
 interaction1="RS.inResL")
effObj4.18 <- includeEffects(effObj4.18, effFrom, name="RFD", type="eval",
 interaction1="RS.sex")

effObj4.18 <- includeEffects(effObj4.18, avAlt, name="RFD", type="eval",
 interaction1="advNet0SD")
effObj4.18 <- includeEffects(effObj4.18, totAlt, name="RFD", type="eval",
 interaction1="advNet0SD", include = F)

effObj4.18 <- includeEffects(effObj4.18, effFrom, name="RFD", type="eval",
 interaction1="RS.Blk")
effObj4.18 <- includeEffects(effObj4.18, egoX, altX, name="advNet0SD", type="eval",
 interaction1="RFD", include = T)
effObj4.18 <- includeEffects(effObj4.18, indeg, name="RFD", type="eval",
 interaction1="advNet0SD")

```

```

effObj4.18 <- includeEffects(effObj4.18, outdeg, name="RFD", type="eval",
 interaction1="advNet0SD")
effObj4.18 <- includeEffects(effObj4.18, avAlt, name="RFD", type="eval",
 interaction1="advNet0SD", include = T)

effObj4.18 <- includeEffects(effObj4.18, egoX, altX, name="advNet0SD", type="eval",
 interaction1="RS.age", include =F)
effObj4.18 <- includeEffects(effObj4.18, effFrom, name="RFD", type="eval",
 interaction1="RS.age")

effObj4.18 <- includeEffects(effObj4.18, recipDeg, name="RFD", type="eval",
 interaction1="advNet0SD", include = T)
effObj4.18 <- includeEffects(effObj4.18, avAltPop, name="RFD", type="eval",
 interaction1="advNet0SD", include = F)
effObj4.18 <- includeEffects(effObj4.18, behDenseTriads, name="RFD", type="eval",
 interaction1="advNet0SD", include = F)

...
`` {r}
effObj4.19 <- includeEffects(effObj4.19, egoX, altX, name="advNet0SD", type="eval",
 interaction1="RS.inResL")
effObj4.19 <- includeEffects(effObj4.19, effFrom, name="RFD", type="eval",
 interaction1="RS.inResL")
effObj4.19<- includeEffects(effObj4.19, effFrom, name="RFD", type="eval",
 interaction1="RS.sex")

effObj4.19 <- includeEffects(effObj4.19, avAlt, name="RFD", type="eval",
 interaction1="advNet0SD")
effObj4.19 <- includeEffects(effObj4.19, totAlt, name="RFD", type="eval",
 interaction1="advNet0SD", include = F)

effObj4.19 <- includeEffects(effObj4.19, effFrom, name="RFD", type="eval",
 interaction1="RS.Blk")
effObj4.19 <- includeEffects(effObj4.19, egoX, altX, name="advNet0SD", type="eval",
 interaction1="RFD", include = T)
effObj4.19 <- includeEffects(effObj4.19, indeg, name="RFD", type="eval",
 interaction1="advNet0SD")
effObj4.19 <- includeEffects(effObj4.19, outdeg, name="RFD", type="eval",
 interaction1="advNet0SD")
effObj4.19 <- includeEffects(effObj4.19, avAlt, name="RFD", type="eval",
 interaction1="advNet0SD", include = T)

```

```

effObj4.19 <- includeEffects(effObj4.19, egoX, altX, name="advNet0SD", type="eval",
 interaction1="RS.age", include =F)
effObj4.19 <- includeEffects(effObj4.19, effFrom, name="RFD", type="eval",
 interaction1="RS.age")

effObj4.19 <- includeEffects(effObj4.18, recipDeg, name="RFD", type="eval",
 interaction1="advNet0SD", include = T)
effObj4.19 <- includeEffects(effObj4.18, avAltPop, name="RFD", type="eval",
 interaction1="advNet0SD", include = T)
effObj4.19 <- includeEffects(effObj4.18, behDenseTriads, name="RFD", type="eval",
 interaction1="advNet0SD", include = F)

...
```{r}
effObj4.20 <- includeEffects(effObj4.20, egoX, altX, name="advNet0SD", type="eval",
  interaction1="RS.inResL")
effObj4.20 <- includeEffects(effObj4.20, effFrom, name="RFD", type="eval",
  interaction1="RS.inResL")
effObj4.20<- includeEffects(effObj4.20, effFrom, name="RFD", type="eval",
  interaction1="RS.sex")

effObj4.20 <- includeEffects(effObj4.20, avAlt, name="RFD", type="eval",
  interaction1="advNet0SD")
effObj4.20 <- includeEffects(effObj4.20, totAlt, name="RFD", type="eval",
  interaction1="advNet0SD", include = F)

effObj4.20 <- includeEffects(effObj4.20, effFrom, name="RFD", type="eval",
  interaction1="RS.Blk")
effObj4.20 <- includeEffects(effObj4.20, egoX, altX, name="advNet0SD", type="eval",
  interaction1="RFD", include = T)
effObj4.20 <- includeEffects(effObj4.20, indeg, name="RFD", type="eval",
  interaction1="advNet0SD")
effObj4.20 <- includeEffects(effObj4.20, outdeg, name="RFD", type="eval",
  interaction1="advNet0SD")
effObj4.20 <- includeEffects(effObj4.20, avAlt, name="RFD", type="eval",
  interaction1="advNet0SD", include = T)

effObj4.20 <- includeEffects(effObj4.20, egoX, altX, name="advNet0SD", type="eval",
  interaction1="RS.age", include =F)
effObj4.20 <- includeEffects(effObj4.20, effFrom, name="RFD", type="eval",

```

```
interaction1="RS.age")
```

```
effObj4.20 <- includeEffects(effObj4.20, recipDeg, name="RFD", type="eval",
  interaction1="advNet0SD", include = T)
```

```
effObj4.20 <- includeEffects(effObj4.20, avAltPop, name="RFD", type="eval",
  interaction1="advNet0SD", include = F)
```

```
effObj4.20 <- includeEffects(effObj4.20, behDenseTriads, name="RFD", type="eval",
  interaction1="advNet0SD", include = T)
```

```
...
```

```
```{r}
```

```
mod4.26 <- siena07(rfMod4.26, data=dtObj4, effects=effObj4.17, useCluster=T,
 nbrNodes=7, prevAns=mod4.11)
```

```
...
```

```
```{r}
```

```
mod4.27 <- siena07(rfMod4.27, data=dtObj4, effects=effObj4.18, useCluster=T,
  nbrNodes=7, prevAns=mod4.26)
```

```
...
```

```
```{r}
```

```
mod4.28 <- siena07(rfMod4.28, data=dtObj4, effects=effObj4.19, useCluster=T,
 nbrNodes=7, prevAns=mod4.27)
```

```
...
```

```
```{r}
```

```
mod4.29 <- siena07(rfMod4.29, data=dtObj4, effects=effObj4.20, useCluster=T,
  nbrNodes=7, prevAns=mod4.27)
```

```
...
```