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Coordination of Care in Substance Abuse Treatment: An Interorganizational Perspective

Author
Spear, Suzanne Evelyn

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Coordination of Care in Substance Abuse Treatment:

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by

Suzanne Evelyn Spear

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ABSTRACT OF THE DISSERTATION

Coordination of Care in Substance Abuse Treatment: An Interorganizational Network Perspective

by

Suzanne Evelyn Spear

Doctor of Philosophy in Public Health

University of California, Los Angeles, 2012

Professor Steven P. Wallace, Chair

The high cost of detoxification (detox) services and health risks associated with continued substance abuse make readmission to detox an important indicator of poor performance for substance abuse treatment systems. One major service gap in the continuum of care for substance use disorders associated with readmissions is not transitioning patients to rehabilitation after a detox service. This study examined the problem of detox readmissions from an interorganizational network perspective. There were four aims: 1) determine the extent to which detox patients transfer to rehabilitation within 14 days of discharge from a detox service, 2) map the linkages between treatment programs, 3) test the impact of detox programs' network ties on their patients' odds of readmission to a detox service within one year, and 4) evaluate the utility of patient transfer rates as a county-level performance measure for detox. Data are from the California Outcomes Measurement System. I used admission and discharge data for all patients treated in 2008-2009 in 32 counties to map linkages between treatment programs and measure structural features of detox programs' local networks using social network analysis. I used multi-level analysis to predict the odds of patient readmissions to detox. Contextual predictors included out-degree (number of out-going ties to other programs) and efficiency (proportion of direct ties within a network that are "non-redundant"). The total number of patients in the dataset was 150,955, including 25,423 detox patients. Approximately 28% of detox patients transferred to some form of rehabilitation care after detox. Transitioning from detox to rehabilitation within 14 days of discharge was associated with lower odds of readmissions (for residential detox: OR .48, 95% CI .40, .57; for narcotic treatment detox: OR .25, 95% CI .19, .32). Network efficiency was associated with lower odds of readmission (for residential detox: OR .25, 95% CI .08, .83; for narcotic treatment detox: OR .34, 95% CI .14, .82). Detox programs with greater efficiency are able to access diverse referral resources. The findings from this study support the use of detox-to-treatment transfer rates as a performance measure for treatment systems.

The dissertation of Suzanne Evelyn Spear is approved.

Michael S. Goldstein

Richard Darrel Grannis

Hector P. Rodriguez

May Choo-Wang

Steven P. Wallace, Committee Chair

University of California, Los Angeles

2012

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

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CURRICULUM VITAE

Education

2007-2012	Ph.D., Community Health Sciences, UCLA Fielding School of Public Health
1993-1996	M.S., Urban Studies, University of New Orleans
1988-1992	B.A., Anthropology, New York University
1996	2-month internship, World Health Organization, Eastern Mediterranean Region, Egypt.

Professional Experience

2012	Graduate Student Researcher, UCLA Fielding School of Public Health, Division of Cancer Prevention and Control Research
2011-2012	Pre-Doctoral Fellow (NRSA F31), UCLA School of Public Health, Department of Community Health Sciences
2010-2011	Graduate Student Researcher, UCLA Substance Abuse Programs, Semel Institute, Department of Psychiatry
2008-2011	Pre-Doctoral Fellow (NRSA T32), UCLA Substance Abuse Programs, Semel Institute, Department of Psychiatry
2000-2008	Project Director, UCLA Substance Abuse Programs, Semel Institute, Department of Psychiatry
2000	Field Supervisor, RAND Santa Monica
1998-1999	Project Coordinator, Louisiana State University, Department of Public Health
1997-1998	Program Evaluator, New Orleans Crescent City Peace Alliance, National Funding Collaborative for Violence Prevention

Awards

2012	Dean's Outstanding Student Award in Community Health Sciences, UCLA Fielding School of Public Health
2011	National Institute on Drug Abuse (NIDA) Travel Award for Junior Investigators, Addiction Health Services Research Conference
2011	Ruth L. Kirschstein National Research Service Awards, Pre-Doctoral Fellowship (F31), National Institute on Drug Abuse
2011	Dissertation Year Award, UCLA
2010	Women & Sex/Gender Junior Investigator Travel Award, College on Problems of Drug Dependence Annual Meeting
2010	Samuel J. Tibbett's Fellowship, UCLA School of Public Health
2009	National Institute on Drug Abuse (NIDA), Director's Travel Award, College on Problems of Drug Dependence Annual Meeting
2008-2011	Pre-doctoral fellowship, National Institute on Drug Abuse (Kirschstein-NRSA), UCLA Substance Abuse Programs, Semel Institute, Department of Psychiatry
2008	Edward Schwartz Scholarship, UCLA School of Public Health
2007	Dr. Ursula Mandel Scholarship, UCLA
1995	Student Planning Award, University of New Orleans, College of Urban and Public Affairs

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CHAPTER 1

INTRODUCTION

I. Background to the Problem

Health problems today require multiple services, the provision of which exceeds the capacity and resources of a single person, organization, or sector (Lasker, Weiss, & Miller, 2001). Substance abuse treatment, to be effective, requires not only behavioral counseling and, in some cases, pharmacotherapy to help patients refrain from substance abuse, but also a range of other services including transportation, medical care, mental health therapy, housing assistance, and employment assistance (National Institute on Drug Abuse, 2009). Integration of services is also needed within the treatment sector to provide a continuum of care from more intensive services in the early phase of recovery to less intensive services and ongoing support in later stages of recovery. According to standards developed by the American Society of Addiction Medicine, patients with substance use disorders require different levels of care over time, depending on the severity of their disorders, that range from intensive forms of care such as detoxification and residential treatment to less intensive services provided on an outpatient basis (Mee-Lee, 2007). Recent research, however, suggests that treatment services today are delivered mainly in single episodes, e.g., 30-day residential program, rather than as a continuum of care (Mark, Vandivort-Warren, & Montejano, 2006; McLellan, Lewis, O'Brien, & Kleber, 2000).

There are real-world constraints to organizing treatment as a continuum of care. The availability of residential treatment has been greatly reduced by managed care organizations seeking to reduce costs. Residential treatment today comprises less than 10% of all treatment services (McLellan, 2008). Other barriers to providing a continuum of care have to do with health insurance coverage. Patients may lack health coverage or have coverage that does not include substance abuse treatment (Mark, Dilonardo, Chalk, & Coffey, 2003).[1] In addition, co-payments for substance abuse treatment may be unaffordable for patients who have coverage for substance abuse treatment. In the case of detoxification (detox), insurance companies may pay for detox as a separate service from counseling and other forms of non-medical treatment, which creates fragmentation in care (Center for Substance Abuse Treatment, 2006).

One major service gap in the continuum of care for substance use disorders is the engagement of patients in treatment or rehabilitation after an initial detox service (McLellan, Weinstein, Shen, Kendig, & Levine, 2005). Detox is a short-term treatment service used to systematically withdraw individuals from substances and stabilize them. Detox programs treat patients who are in a state of crisis because they are experiencing severe withdrawal symptoms or significant emotional instability. Detox services are provided in inpatient, residential, or outpatient settings.

Withdrawal from drugs like alcohol and opiates that cause physical dependence can be severe. Symptoms associated with alcohol withdraw include vomiting and nausea, insomnia, anxiety, depression, sweats, and rapid heart rate. Severe cases of alcohol withdrawal or delirium tremens, can lead to hallucinations, agitation, and seizures. Withdrawal from alcohol can be life threatening if not managed properly (Center for Substance Abuse Treatment, 2006). Opiate withdrawal is also very uncomfortable, but not life threatening. Symptoms of opiate withdrawal include anxiety, muscle aches, vomiting, diarrhea, and abdominal cramping (ibid).

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[1] I use the term "patients" in this dissertation because many individuals in medically-managed detox programs come into contact with clinicians, e.g., physicians and nurses. The term "clients"; however, is more common in the substance abuse treatment field. The use of the term "patients" is also a philosophical statement because I wish to emphasize the role of mainstream healthcare professionals in treating individuals with substance use disorders.

Detox is not considered to be a treatment for substance dependence (Center for Substance Abuse Treatment, 2006). Detox can have short-term benefits such as abstinence and reduced criminal activity (Stein, Kogan, & Sorbero, 2009). The benefits of detox, however, do not endure because detox services do not address the psychosocial and behavioral issues related to addiction. National performance standards for addiction treatment indicate that patients should initiate treatment within 14 days of discharge from detox (Garnick, Lee, Horgan, Acevedo, & Washington Circle Public Sector Workgroup, 2009). At the point of discharge from detox, patients are at high risk of relapse and, therefore, vulnerable to system failures. Patients leave detox with a reduced tolerance to alcohol or drugs. As a result, detox can increase patients' risk of mortality from an overdose if patients do not transition to treatment after discharge (Strang et al., 2003).

There are other consequences to not engaging patients in rehabilitation. In California, detox patients have the highest rates of emergency room visits (20.8%) and overnight hospital stays (6.1%) compared with patients treated in substance abuse treatment facilities. Rates of infection with hepatitis C range from 10-20% in this population, indicating that these patients also have high needs for ancillary health care and prevention services (Rawson, Gonzales, Brecht, Crèvecoeur-MacPhail, & Hemberg, 2008). Continuity of service between detox and substance abuse treatment is seen as an important means for reducing readmission to expensive forms of treatment such as inpatient detox, increasing retention in less intensive forms of treatment such as outpatient care, increasing availability of detox for more individuals in need, and ensuring patients are served at the appropriate level of care (Mark, et al., 2006; McLellan, Weinstein, Shen, Kendig, & Levine, 2005).

Continuity of service for patients leaving detox is a major challenge for the substance abuse treatment system (Carrier et al., 2011; Dennis & Scott, 2007; Garnick, et al., 2009; McLellan, Weinstein, et al., 2005).[2] Multiple admissions to detox are common. One study found that 11.3% of patients who receive detox recycle back into detox two or three times, a situation that indicates the chronic nature of addiction, but also inadequate care and inefficient use of public resources (McLellan, Weinstein, et al., 2005). Research has shown that only 23% of detox admissions in California lead to rehabilitation. As such, the substance use disorder treatment community has begun to emphasize both the provision and measurement of continuity of service.

The present study examines the question of whether readmission rates to detox are associated with the connections detox programs have to treatment programs. No studies to date have looked at the role of interorganizational networks in relation to substance abuse treatment performance. In this study, I use administrative data from the California Outcomes Measurement System (CalOMS) to measure interorganizational networks and test the influence of network structure on readmissions to detox. Interorganizational networks are created from patient transfers. Patient transfers are the sequences of services patients receive that are documented by admission and discharge records. The ties between providers are delineated according to how patients transfer from one service provider to another within a 14-day period (Garnick, et al., 2009). Observing the pathways of patients from series of admissions and discharges to and from treatment providers enables assessing the patterns of care received by detox patients as well as the social structures in which treatment providers operate. The population of interest for this

[2] I use the term "continuity of service" to refer to a continuum of care in substance abuse treatment from one level of care to another. Many treatment providers cannot provide multiple levels of care and would need to coordinate with other providers to offer continuity of service.

study are patients who received detox services from 2008 to 2009. The data for this study come from 32 counties in California.

The inspiration for this study comes from the literature on interorganizational relationships and services integration in the health and human services field (Morrissey, Johnsen, & Calloway, 1997; Provan & Milward, 1995; Rosenheck et al., 2002; Van de Ven & Walker, 1984). Interorganizational relationships and cooperative arrangements between health and human service providers are associated with improved access to care, enhanced service quality, and reduced costs (Alter & Hage, 1993; Provan & Milward, 1995; Rogers & Whetten, 1982). Integrated networks of service agencies are thought to be more effective at providing a complex array of services (Alter & Hage, 1993; Provan & Milward, 2001). The effects of interorganizational relationships and patient outcomes have been studied in the mental health services area (Heflinger, 1996; Morrissey, et al., 1997; Provan, Huang, & Milward, 2009) and in the area of HIV prevention (Thomas, Isler, Carter, & Torrone, 2007).

II. Study Aims

This study has four aims. These aims are both descriptive and analytical.

1. *Define the typical care delivery patterns of detox patients over one year (2008-2009).* The study determines the type of care received by detox patients after their initial detox service. The type of services included in CalOMS includes general treatment modalities such as detox, residential treatment, and outpatient treatment. Of particular interest are transfers to some form of rehabilitation care after detox. I examine transfers to treatment from detox in relation to patient characteristics such as socio-demographics, severity of drug problem, and

detox setting, i.e., residential detox or medically-managed outpatient detox for opiate patients.

2. *Map the interorganizational networks among all providers in 32 counties.*

In order to measure the impacts of provider networks on readmissions to detox, I used social network analysis to map provider networks and measure network structure. Networks are created using all types of patient transfers, not only those involving detox services. The main analysis focuses on the ego-networks of detox programs. Ego-networks include the links between detox programs and their contacts, as well as the links among detox programs' contacts. In addition to the analysis of the ego-networks, I also summarize basic network features for county networks. County networks include all ties between programs within each county. Over 96% of all ties are between programs within the same county.

3. *Determine whether interorganizational networks influence readmission to detox, net of individual and organizational factors.*

The main goal of this study is to use the contextual information from the network analysis to examine whether network structure influences detox readmissions. Detox readmission within one year of the index detox service is the outcome of interest.

Prior research has identified an array of patient-level factors associated with detox readmissions, as well as a number of program-level factors such as program size and proximity to treatment centers. I first test the relationships between readmission to detox and patient-level factors identified in the literature as salient predictors of detox readmissions.

Next, I include those patient-level factors in a multi-level analysis that also includes a measure of network structure at the program level.

4. *Evaluate the utility of patient transfer rates as a county-level performance measure for detoxification care.*

This aim is exploratory and meant to inform public policy around performance measurement of detox services at the county level. Because state agencies such as the California Department of Alcohol and Drug Programs fund counties to provide treatment services, there is interest in the performance of treatment systems at the county level. The California Department of Alcohol and Drug Programs is presently considering the use of performance measures for substance abuse treatment recommended by the Washington Circle Group, a group of national experts in substance abuse policy and research focused on the development of national performance measures (Urada, Fan, & Rawson, 2010). The performance measure related to detox is the proportion of detox patients that transfer to a treatment service within 14 days (Garnick, et al., 2009). Entry into rehabilitation after detox is associated with lower rates of readmissions to detox (Center for Substance Abuse Treatment, 2006; Mark, Vandivort-Warren, & Montejano, 2006; McLellan, Weinstein, et al., 2005). As part of this aim, I also explore county network characteristics associated with transfer rates. Of particular interest is identifying network structures associated with high transfer rates.

III. Dissertation Organization

Chapter 2 provides a brief overview of the substance abuse treatment system and the role of detox as an entry point into treatment. Because this dissertation concerns evaluation of treatment systems, I describe common outcomes studied in substance abuse treatment research and discuss how evaluation research in this field has evolved to include a focus on treatment processes and program performance.

Chapter 3 describes the theoretical perspectives that shaped my thinking about coordination of care within the substance abuse treatment field. The theoretical grounding on which I base this study is that substance abuse treatment systems can be defined as networks of interacting organizations. The networks in this study are based on patient transfers, which essentially tell us about provider linkages from the patient perspective. Programs are tied to one another because they treated the same patient. Network theory explores how network structure impacts the availability of resources and performance of individuals and organizations. In this study, I apply structural hole theory, which was developed by the sociologist Ronald Burt from the University of Chicago. Structural hole theory suggests that individuals and organizations gain competitive advantage in their work through access to outside contacts (Burt, 2000). Structural hole theory is based on some of the same thinking underlying Mark Granovetter's "weak ties" theory. "Weak ties" are arm's length ties such as acquaintances and people that one interacts with only occasionally. Weak ties can provide useful information that is not immediately available to actors and their close ties (Granovetter, 1973). Underlying these two theories is the conceptualization of relationships as resources and networks as a form of social capital. Applying this concept to the problem of detox readmissions, I explore whether having ties to treatment programs that have connections beyond the detox programs' ego-networks provides patients with access to a wider range of treatment options. A diverse set of referral options may facilitate transitional care from detox to treatment programs.

In chapter 4, I describe the dataset, the sample, the hypotheses driving the study, and the methods that I used to analyze the data. There were three main components to this research. First, there was the network analysis phase in which I coded the transfers between programs and quantified structural features of local networks using social network analysis. The second component involved qualitative interviews with a small sample of treatment professionals to learn about their referral procedures and relationships. The third component was the use of multi-level analyses to test my hypotheses about network structure and readmissions to detox.[3]

Chapter 5 introduces the patients and providers in what is really a story about what kind of care detox patients receive in California. These are heterogeneous groups. I explain the differences between the two main types of detox services in the publicly funded treatment sector: residential detox and detox that takes place in narcotic treatment programs that administer opiate replacement medications for opiate dependence (NTP detox). I present a comparison of detox patients who transferred to treatment after their initial detox with patients who did not transfer to treatment. Chapter 6 presents the network analysis, including the process of defining the boundaries of patient transfer networks.

Chapter 7 presents the main analyses that I conducted to predict readmissions to detox. I present two preliminary analyses. First is an analysis exploring associations between patient characteristics and transfers from detox to treatment. Next is an analysis of patient attributes that

[3] There was an element of grounded theory to this work. While I had a general frame of reference when I started this study, the network analysis work led to new insights and theoretical questions. Doing the interviews with treatment professionals gave me insights into the problem that I did not have when I started. The process led me to some new ideas that I tested out through trial and error.

predict readmissions. I present the results from the main analyses, incorporating both patient- and program-level predictors, i.e., network measures.

In Chapter 8, I present findings from an exploratory analysis of county networks, which includes aggregate network measures based on the ties of all the programs within each of the 32 counties included in the main study. I explore whether transfer rates, based on the proportion of detox patients that are transferred to treatment, correlate with structural features of networks such as the mean number of ties, centralization of patient transfer activity around a few programs, and cohesion within small clusters of programs.

Chapter 9 includes a discussion of the results. I compare my results to other studies on the topic and highlight the contributions this research makes to the substance abuse treatment field as well as to network theory. I end the chapter with a review of the limitations and strengths of the study, as well as the implications for future research.

CHAPTER 2

LITERATURE REVIEW

I. Brief Overview of the Substance Abuse Treatment System

Substance abuse treatment can best be defined as a collection of behavioral and medical interventions that help individuals stop using alcohol and drugs, prevent relapse, and improve their overall functioning. The majority of treatment services involve assessments of substance use disorders and psychosocial needs, behavioral counseling, and social support. Pharmacotherapy is an important component of the treatment of certain substance use disorders, but is not widely available in publicly funded treatment programs (National Institute on Drug Abuse, 2009). Some treatment programs are able to provide ancillary services such as transportation, medical care, mental health therapy, housing assistance, and employment assistance within their program or through referrals to other service agencies. Treatment is provided in inpatient, residential, and outpatient settings. Inpatient treatment is medically managed by physicians and nurses and can take place in hospitals or free-standing residential facilities. Residential treatment may involve medically managed services, but most often is provided by drug treatment counselors. Outpatient treatment consists of clinics that provide counseling and educational services, as well as medication-based programs such as methadone clinics. The type of treatment that people receive depends on their primary drug problem, the severity of their condition, available resources, and individual characteristics, e.g., age, gender, and special needs.

The treatment sector consists of mostly small, non-profit organizations providing a range of specialized services (Chalk, 2010; Wells, Lemak, & D'Aunno, 2005). Of 12,000 treatment programs in the U.S., almost two-thirds have less than 60 clients in treatment at any one time and over one-third treat fewer than 200 patients per year (Chalk, 2010). These organizations provide diverse treatment modalities such as detoxification, residential treatment, outpatient counseling, and pharmacotherapy such as methadone and other opiate replacement therapies. Consistent with the reputation of most health and human service sectors, addiction treatment is viewed as a fragmented system with little coordination among treatment programs and limited integration with other health and human services (Wells, Lemak, & D'Aunno, 2005).

Detox is a short-term service that helps patients withdraw from alcohol and/or drugs in a safe and humane manner. Detox functions to stabilize patients, assess the severity of their substance use disorders, and prepare patients for entry into rehabilitation (Center for Substance Abuse Treatment, 2006). As such, detox is often a patient's first exposure to the substance abuse treatment system.

Approximately 23% of all treatment admissions in the United States are for detox. Approximately 17% of all treatment admissions in California in 2008-2009 were for detoxification (Rawson, et al., 2008). The most common drug problems treated in detox are alcohol, opiates, and cocaine. Patients also enter detox programs for marijuana and other opiate use. The most difficult withdrawal is from alcohol, opioids, and sedatives/tranquilizers because these drugs cause physical dependence. Cocaine, methamphetamine, and marijuana users can experience serious emotional and physiological symptoms that require stabilization. Withdrawal symptoms typically begin 8-30 hours after a person's last use (Center for Substance Abuse Treatment, 2006).

Detox is an acute form of care that is delivered in diverse settings and with different levels of intensity. Inpatient and residential detox programs typically last less than one week (Center for Substance Abuse Treatment, 2006). Patients with severe withdrawal or intoxication are treated on an inpatient basis in hospitals or free-standing facilities. In an inpatient setting, patients receive 24-hour care by physicians, nurses, and other clinicians. Patients with less severe conditions may receive detox treatment in residential facilities, which may have or may not have medical monitoring (Center for Substance Abuse Treatment, 2006).

In addition to rest, detox often involves the use of medications to relieve pain and other side effects of withdrawal. For example, methadone is commonly used to detox patients from heroin. Methadone is an opiate replacement therapy because it acts on the same opioid receptors in the brain and mimics the effects of heroin and other opioids. Methadone is administered to patients to prevent symptoms of withdrawal and reduce cravings for heroin (Center for Substance Abuse Treatment, 2006). Methadone doses are given daily and patients are regularly monitored by medical professionals. Benzodiazepines (sedatives) such as lozarepam are given to patients going through withdrawal from alcohol. Benzodiazepines are used to treat anxiety, insomnia, and seizures (Myrick & Anton, 1998).

Many residential detox programs use a "social model" of treatment that does not involve medications. "Social model" programs are focused on "resocializing" individuals to accept responsibility for their actions and develop new patterns of behavior (National Institute on Drug Abuse, 2009). Because patients live together in a 24-hour residential facility (or "therapeutic community"), they are exposed to social influence and social modeling from counselors and peers, who are also recovering from alcohol or drug dependence. Abstinence from alcohol and drugs is the goal of most treatment programs, including residential treatment, and strictly enforced.

Unlike social model programs, outpatient, medication-based programs do not require abstinence. Narcotic treatment programs (NTP) administer opioid agonist medications such as methadone to patients with opiate dependence. NTP programs are most often located in outpatient methadone clinics where patients can continue to receive methadone as part of a long-term maintenance program. NTP detox programs typically last 28 days, but can be extended to 180 days in some cases (Center for Substance Abuse Treatment, 2006).

II. Substance Abuse Treatment Services Research: Evolving Concepts

Traditionally, the most common treatment outcomes examined in the substance abuse treatment research field are abstinence, reduction in alcohol and drug use, reduction in criminal behavior (arrests, incarceration), employment, improvement in physical and mental health, and stronger social and family ties. Outcome studies commonly focus on single treatment episodes and compare patient status before treatment with their status post-treatment. Completion is considered an indicator of treatment success because of the more favorable outcomes associated with retention in treatment (Prendergast, Podus, & Chang, 2000).

Several large treatment outcome studies have shown that individuals who participate in treatment do better than those who do not receive treatment or who drop out prematurely. From 1969, with the start of the Drug Abuse Reporting Program (DARP), through the 1970s with the Treatment Outcome Prospective Study (TOPS), and into the 1980s with the Drug Abuse Treatment Outcome Studies (DATOS), large evaluation studies have tracked thousands of treatment patients over time, typically between 1 and 5 years after treatment discharge (Hubbard, Craddock, & Anderson, 2003). These national studies included patients who received treatment in multiple settings, including outpatient methadone maintenance treatment, long-term residential, and outpatient drug free treatment. DARP and TOPS found large decreases in opioid use and criminal involvement in the first year after treatment. These positive outcomes were found to persist for 3 to 5 years after treatment in some patients (Hubbard, et al., 2003).

The individual benefits of treatment have significant public health benefits when seen from the population level (Babor, Stenius, & Romelsjo, 2008). Drug use is associated with mortality and morbidity, risk of contracting infectious diseases, and crime (Degenhardt et al., 2010; Farabee, Prendergast, & Cartier, 2002; World Health Organization, 2011). A meta-analysis of comparison group studies found significant reductions in drug use and crime among treatment participants irrespective of treatment modality (Prendergast, Podus, Chang, & Urada, 2006).

In a meta-analysis of mortality due to heroin and other opioid use, Degenhardt et al. (2010), found that across 57 cohorts, the standardized mortality ratio was 14.66. Standardized mortality ratios (SMR) compare the observed number of deaths in a sample to the expected number of deaths for people of the same age and gender in the general population. An SRM over 1 indicates higher mortality in the sample compared with the general population. Engagement in treatment was found by Degenhardt et al. (2010) to be protective; heroin and other opioid users who were not in treatment at the time of the study had a crude mortality rate 2.38 times that of individuals in treatment. Most deaths in the sample were due to drug overdoses.

Substance abuse treatment can also reduce patients' risks of infectious diseases. Authors of the DATOS study note that reductions in heroin use due to methadone treatment reflects reductions in HIV risk because of declines in injection drug use and improvements to immune system functioning (Hubbard, et al., 2003). A study by Metzger, Woody, McLellan, et al. (1993)

followed a sample of heroin users who received methadone maintenance therapy and a matched sample of heroin users who did not receive treatment. The authors tracked the samples for seven years and tested participants for HIV every six months. After seven years, the rate of HIV in the treatment group was 21% and 51% in the comparison group.

One of the best predictors of patient improvement found in the DARP and TOPS studies was retention in treatment. A minimum threshold for the emergence of patient improvement was found to be three months (Hubbard, Craddock, Flynn, Anderson, & Etheridge, 1997). The two studies found positive outcomes for methadone, long-term residential, and outpatient. The DATOS study found a similar pattern with greater retention predicting better outcomes (Hubbard, et al., 1997). Long-term residential treatment stood out as having a significant relationship with reduced drug use, illegal activity, and employment. Heroin users treated in methadone maintenance made significant reductions in their drug use. After more than one year on methadone, the odds of continuing heroin among patients were .29 (Hubbard, et al., 2003).

Addiction as a Chronic Illness

The relationship between treatment retention and reduction in drug use suggests that recovery from addiction is a long-term process for many people. Individuals can frequently sustain positive outcomes after treatment for up to 12 months, but ongoing care is needed to mitigate the risk of relapse (McLellan, et al., 2000). Longitudinal natural history studies have documented that individuals with a history of addiction experience repeated cycles of remission and resumption over time (Hser, Hoffman, Grella, & Anglin, 2001). Neuroscientists have found that repeated exposure to drugs creates long-term changes in the brain that persist long after people stop using drugs (National Institute on Drug Abuse, 2009). Hence, the treatment field has begun to recognize over the course of the past decade that acute or short-term treatments are inadequate for treating the chronic nature of addiction.

A leading researcher in the drug abuse treatment field, and former Deputy of the U.S. Office of National Drug Control Policy, A. Thomas McLellan is known for organizing evidence on the chronic nature of addiction into what is known in the field as the chronic illness model of addiction. In a paper published in 2000, McLellan et al. (2000) reported on research comparing addiction to well-known chronic medical conditions such as diabetes, hypertension, and asthma. McLellan et al. (2000) found similarities between addiction and these conditions with respect to their biological basis, genetic heritability, role of personal responsibility, and treatment response. Periodic relapse to drug use after a period of sustained abstinence, McLellan et al. discovered, could be compared to poor adherence to medications by people with asthma, diabetes, and hypertension. Current addiction treatment standards conceptualize addiction as a chronic condition that requires initiation and engagement in rehabilitative care in addition to ongoing monitoring and support to maintain treatment effects (Godley, Godley, Dennis, Funk, & Passetti, 2007; McKay, 2001; McLellan, McKay, Forman, Cacciola, & Kemp, 2005).

A Focus on Treatment Processes

As evidence accumulated in support of addiction treatment, the emphasis for program evaluation evolved from one of examining treatment outcomes to one concerned with understanding the effective elements of treatment. In other words, how does treatment work? Given evidence of the chronic nature of addiction, researchers and policy makers began to examine treatment processes such as engagement in treatment and retention in treatment over time. Retention or length of participation in treatment is considered the most robust predictors of treatment benefits (Simpson, 2004).

The model of effective treatment disseminated by the National Institute on Drug Abuse identifies the major clinical domains of treatment such as assessment, behavioral therapies, pharmacotherapies, and continuing care through social support activities, e.g., Alcoholics Anonymous. In this model, the effectiveness of treatment is assumed to be impacted by the availability of additional support services that enable and reinforce an individual's recovery such as medical care, mental health therapy, and job training (National Institute on Drug Abuse, 2009).

Substance abuse treatment takes place in organizational settings. Organizational environments impact the behavior of staff and the treatment of patients (Moos & Moos, 1998). The influence of organizational characteristics on the quality of care has been extensively studied by D. Dwayne Simpson and his colleagues at Texas Christian University (TCU). The TCU model describes the phases of treatment. Simpson's model starts with the "inputs" to treatment, which are individual and program attributes. These inputs influence recovery processes, which he defines as early engagement, early recovery, and stabilized recovery. Treatment or recovery processes lead to post-treatment outcomes such as abstinence or reduced drug use, no criminal activity, and improved social relations. Treatment outcomes are reinforced by self-help recovery groups. Recovery support networks like Alcoholics Anonymous or other self-help groups are commonly described as social supports that help individuals maintain recovery after treatment.

Simpson emphasizes that treatment is more than a set of clinical interventions. Organizational environments, Simpson and colleagues explain, impact the success of patients in treatment (Broome, Flynn, Knight, & Simpson, 2007). Simpson's model focuses on the organizational environment and clinical processes within treatment programs. The TCU model links program attributes such as financial resources, human resources (e.g., staff training), organizational climate, and informational systems to the therapeutic relationship between counselors and patients (Simpson, 2004). According to Simpson, therapeutic bonding is one of the most critical components of drug abuse treatment. Simpson's model does not include an explicit focus on social and physical environments outside treatment programs and how these environments may impact treatment effectiveness.

Babor's conceptual model expands the Simpson model to include extra-organizational factors such as resources and equity. Babor (2008) proposes a framework which identifies macro-level influences on treatment system effectiveness: treatment policies (planning, financing, monitoring), structural resources (facilities, programs), and system qualities (equity of resources, efficiency, economy). Effectiveness is moderated by patient case mix, social capital, and drinking/drug use subcultures, which, Babor proposes, have their own independent effect on population health. Babor's framework situates treatment programs within a social, economic, and political context. Without attention to the broader contexts in which treatment programs operate, including interorganizational contexts, performance measures evaluate programs as autonomous actors, and unfairly attribute responsibility to individual providers for outcomes that require the resources of multiple providers.

Contextual Analysis and Treatment Research

The majority of the research on substance abuse treatment services explains patient outcomes in relation to individual and/or program-level attributes. There is scant research examining the impact of social and physical environments on patient behavior and outcomes. In fact, the places where treatment occurs and the people who deliver treatments are commonly invisible in treatment outcome studies. This is curious, considering the association between social environments and drug use behaviors (Babor, et al., 2008; Davis & Tunks, 1990-1991;

Sherman, Hua, & Latkin, 2004). There is some research that examines potential relationships between social and physical environments and substance abuse treatment outcomes. One line of research is on organizational settings such as that pursued by Simpson and colleagues. The other line of research comes from the public health field and concerns neighborhood environments and their impacts on continuing drug use after treatment.

Broome, Flynn, Knight, and Simpson (2007), a group of researchers at TCU, studied the relationship between organizational context and client engagement in treatment in 94 outpatient drug-free units. Broome et al. (2007) conducted a multi-level analysis to determine the proportion of explained variance in client engagement attributable to organizational-level factors. The authors found a small amount (8%) of the variance was explained by the organizational level. The strongest effects at the program level were contributed by program size (negatively related to engagement), staff members' sense of community (peer collaboration, focus on outcomes, collective responsibility), and accreditation by a national body.

Several studies have looked at neighborhood contexts and cessation of drug use. Jacobson, Robinson, and Bluthenthal (2006) studied racial disparities in substance abuse treatment completion rates in publicly-funded programs in Los Angeles County. The authors used multi-level modeling to examine the effects of neighborhood context on completion rates net of individual attributes (including treatment severity, source of referral, distance to treatment, and relevant demographics). Neighborhood context was conceptualized in terms of disadvantage and comprised the following measures: percent of individuals living in poverty, male unemployment rate, percent of female-headed households, and percent of families receiving public assistance. Data were analyzed at the zip-code level. In the initial variance components analysis, the authors found a very small amount of variance in completion was explained by clustering at the home and treatment center location. However, further analysis showed a significant, negative relationship between treatment completion and disadvantage in the vicinity of the treatment programs. Neighborhood disadvantage associated with treatment sites accounted for 32.3% of the differences in treatment completion between African-Americans and whites.

In another study, Jacobson et al. (2006), Sherman, Hua, and Latkin (2004) found a relationship between cessation of injection drug use and the neighborhoods where drug users lived. Sherman et al. (2004) examined the associations between neighborhood environments and quitting heroin among a sample of long-term injection drug users in Baltimore. The study compared the following environmental features between individuals who quit and those who continued injecting: any use of drugs in shooting galleries, abandoned buildings, outside presence of drugs in one's neighborhood, e.g. streets, parks, alleys, and whether individuals travelled in the same area of town in which they lived to buy drugs. Results showed that, compared to quitters, people who continued injecting heroin had five times the odds of buying drugs near their home, five times the odds of using drugs in outside places, and two times the odds of using in shooting galleries. These neighborhood effects were independent of individuals' drug use history and prior enrollment in treatment.

Longitudinal Perspectives

Substance abuse treatment evaluations have commonly evaluated patient outcomes in terms of discrete time points (before treatment/after treatment). In light of the research that describes addiction as a chronic, relapsing disorder, there is a need to capture patterns of behavior over time (Hser, Longshore, & Anglin, 2007). Longitudinal research methods, along with current analytical tools, allow researchers to model the impacts of time, place, and social relationships on individual treatment outcomes (Hser, Shen, Chou, Messer, & Anglin, 2001).

Longitudinal research has shown that the recovery from addiction is not always a linear process. Individuals typically have multiple tours in treatment before achieving sobriety (Hser, Huang, Chou, & Anglin, 2007). Moreover, drug use trajectories can fluctuate over time as a result of significant turning points in people's lives (Hser, Longshore, et al., 2007).

Treatment evaluations have shown that patients who engage in treatment for a sustained period of time can reduce their drug use and improve functioning (Gonzales et al., 2009; Hubbard, et al., 2003; Prendergast, et al., 2006). To broaden our knowledge of how treatments can work in diverse community settings, research is needed to understand how treatments work under real-world conditions. These conditions include physical and social environments of treatment facilities and neighborhoods in which people make their daily rounds. Other conditions that need to be considered are the resources available for treatment, availability of services, public policies, and local cultures.

In sum, the reduction of substance abuse and related health risks is an important public health issue. The impacts of substance abuse on population health has drawn more types of researchers into the substance abuse treatment field, which was once limited to physicians. Greater diversity of research perspectives in the field, e.g., psychology, anthropology, community science, public policy, has heightened awareness of the need to understand substance abuse behavior in context. Douglas A. Luke, argues that more research is needed in public health that can "capture context" (Luke, 2005); he encourages the use of analytical methods such as multi-level modeling, social network analysis, and cluster analysis to inform the field of community science.

Performance Measurement

In addition to measurement of patient outcomes, there are also efforts to measure the processes and practices used by substance abuse treatment providers. Performance measurement is part of a larger process of institutionalization within the substance abuse treatment field. Researchers have criticized the treatment field because of the lack of treatment standards, professional workforce, and poor infrastructure (McLellan, Carise, & Kleber, 2003). The institutionalization of an organizational field commonly involves the standardization of procedures and the professionalization of practitioners. In the substance abuse field, university-based researchers and policymakers have been in the forefront of this process. Discourse around "quality treatment" and "effective treatment" plays a pivotal role in the institutionalization process. As McLellan, Chalk, and Bartlett explain, "We define quality care operationally as evidence-based treatments that are provided by licensed or credentialed practitioners who have demonstrated core competence in their practice areas and whose activities are monitored regularly by program- and system-level measurement of quality indicators" (2007, p. 333).

Performance indicators are tools used to assess functioning of a treatment organization or treatment system (McLellan, et al., 2007). The use of performance indicators such as use of evidence-based practices to determine allocation of funds is the idea behind performance-based contracting. One such experiment is underway in the state of Oregon. In 2004, a new state law in Oregon required behavioral health agencies to adopt evidence-based drug treatment practices. The state law specified that behavioral health agencies such as the Office of Mental Health and Addiction Services and the Department of Corrections use 25% of their funding to support evidence-based addiction programs. The law intended to increase the mandate to 50% in 2007 and 75% in 2009 (Join Together, 2004). Programs that do not comply lose funding. The use of evidence-based practices has become institutionalized in the substance abuse field; their use is a requirement for federal funding through the Substance Abuse and Mental Health Services Administration. The effectiveness of mandates by payers of substance abuse treatment to change clinical practices is undetermined at this point.

In addition to the use of evidence-based practices, a group called the Washington Circle has proposed several performance indicators to measure treatment processes (Garnick, et al., 2009). The Washington Circle group, convened by the Substance Abuse and Mental Health Services Administration, has identified three very specific performance measures: identification, treatment initiation, and treatment engagement. Identification has to do with the annual number of individuals identified as having a substance use disorder. Initiation has to do with people who are identified as having a substance use disorder and receive services within 14 days. Initiation also refers to receiving outpatient services within 14 days of discharge from an inpatient service. Engagement refers to the receipt of two treatment services within 30 days of treatment initiation. The overall goal of these measures is to increase identification of substance use disorders, access to treatment, engagement in treatment, and continuity of care over time. Engagement and retention in treatment are associated with positive treatment outcomes.

Access to treatment and provision of comprehensive services to treat addiction requires both services and systems integration. Service integration refers to the organization of treatments at the clinical level, whereas system integration refers to organizational strategies at the system-wide or macro level (Mares, Greenberg, & Rosenheck, 2008). The Washington Circle performance indicators are geared toward the services or clinical level, but they also imply integration at the systems level. The underlying assumption behind the performance measures is that treatment programs will coordinate care across levels of treatment, e.g., residential, outpatient, after-care, etc. In speaking of the goal of providing continuity of care after intensive treatment episodes, Garnick et al. (2002) explain that the "rationale is that the residential facility has made the connection with the next level of care after discharge" (p.7). The proposed performance measures capture the desired outcomes of organizational systems, but do not shed light on what types of systems need to be in place to support performance.

Lacking in the treatment discourse on performance indicators is a clear understanding of systems. Performance of organizations and systems are treated as the same concept in the treatment literature. As a result, the notion of a system is narrow because it is implies a focus on individual providers. The only paper that tackles the concept of systems directly is by Thomas Babor. Babor (2008) suggests that systems be defined as "linkages between different facilities and levels of specialized care, and by the extent of their integration with other types of services…" (p.S51). The Babor conceptual model expands the Simpson model to include extra-organizational factors such as resources and equity.

Treatment providers are embedded in social relations with other organizations and within the broader institutional environment of substance abuse treatment policies, funding, and regulations. When comparing programs on their performance, more awareness is needed with respect to broader contexts that constrain or enhance organizational functioning. Neighborhood disadvantage and other community-level factors such as financing for treatment and availability of public services are important to examine in relation to performance.

III. Evaluation of Detoxification Programs

The success of detox programs is measured in large part by whether patients enter and remain in a substance abuse treatment program after detox. Repeat admissions to detox is common (Carrier, et al., 2011; Mark, et al., 2006; McLellan, Weinstein, et al., 2005; Stein, Kogan, & Sorbero, 2009). The common explanation for this problem found in the literature in this area is that patients with a more severe illness or who lack a stable living environment are more likely to return to detox and return within a short amount of time (Callaghan & Cunningham, 2002; Carrier, et al., 2011; Mark, Vandivort-Warren, & Montejano, 2006). Because detox does not address the underlying behavioral and psychosocial issues related to addiction, one of the best ways to reduce readmissions to detox is to engage patients in treatment (McLellan, Weinstein, et al., 2005).

A few studies have identified attributes of detox programs that influence whether their patients enter treatment. For example, a study by Campbell, Tillotson, Choi et al. (2010) examined whether characteristics of residential detox programs made a difference in reported entry into outpatient treatment within 6 months of detox. The patients in this study were injection drug users. The study found that fewer beds, accreditation (e.g., Joint Commission on the Accreditation of Health Care Organizations), distance to outpatient treatment clinics that were part of the same organization as the detox program, and larger city size predicted entry into treatment.

There are also treatment practices that impact the likelihood that patients enter into treatment. McLellan, Thomas, Weinstein, et al. (2005) tested an intensive case management intervention with patients who frequently used detox services without entering into treatment ("multiple detox only" admissions). The intervention involved the use of case managers who provided a range of support services for patients. The case managers initially completed assessments of patients' drug use severity, health problems, socioeconomic circumstances, and social support. To help patients accept the idea of entering treatment, the case managers provided counseling using motivational interviewing techniques. Because many substance abuse patients have multiple and complex needs, the case managers provided referrals to help patients meet their basic needs (food, housing, clothing) and access specialty services such as medical care, mental health care, employment assistance, and legal aid. Case managers organized transportation to help patients reach the rehabilitation programs and often would accompany them to their appointments. Case managers monitored the patients' progress in treatment and provided support when needed.

The evaluation of the intensive case management package described above examined the number of "detox-only" episodes and the number of "detox plus rehabilitation" episodes in administrative records of 100 multiple detox-only patients. Treatment data during the year prior to the case management intervention were compared with data in the year following the intervention. In the follow up year, the evaluators found 37% fewer detox-only admissions and 40% more admissions to treatment among the sample (McLellan, McKay, et al., 2005).

The influence of performance-based contracting has also been examined as a possible strategy for increasing the rates of treatment initiation among detox patients. With performance contracting, a funding agency usually pays a service provider a base rate for their services and provides financial incentives if the provider meets performance targets. A study by Haley, Dugosh, and Lynch (2011) documented a performance contracting arrangement commonly referred to as the "Delaware Experiment." In 2008, the Delaware Department of Substance Abuse and Mental Health initiated a performance contract with the only state-funded inpatient detox provider. The terms of the contract were as follows. The provider could earn 90% of the base rate each month if the program was at full capacity. The other 10% would be earned if the program transitioned at least 25% of its detox patients to treatment within seven days of discharge. To reduce the number of multiple detox-only admissions, the funder gave the provider an incentive of $500 for each frequent detox patient that entered rehabilitation within seven days and remained in treatment for at least 30 days for residential and 60 days for outpatient treatment.

The evaluation found that the detox program did increase the proportion of patients that were transferred to treatment within seven days of discharge from detox. However, despite the incentives for transitioning frequent detox patients and retaining them in treatment for a minimum length of stay, the program was not able to meet the required targets. In fact, there were three times more frequent detox patients treated during the performance contract year compared with the year before. Several challenges were noted. First, the patient population in the performance contract year had more complex issues than the prior patient population. During the performance contract year, the detox program had significantly more patients who were homeless and more patients with a long-term drug use history compared with the prior year. Second, there was a lack of residential treatment slots for homeless patients. Third, residential and outpatient providers were not contracted to provide additional assistance to engage and retain the frequent detox patients in treatment. The study authors suggest that contracts for both detox programs and treatment programs need to be coordinated so that providers are working towards the same goal. This study highlights the need to consider treatment capacity and linkages between providers when evaluating the performance of detox programs.

Summary

Traditional approaches to substance abuse treatment evaluation have focused primarily at the individual patient level. Because of the need to understand what makes treatment work, researchers began to examine program-level attributes associated with positive treatment outcomes. Today there is an appreciation within the field for examining substance abuse treatment from an ecological perspective. There is a growing literature on the impact of macro-level factors such as neighborhood disadvantage and availability of drugs in one's neighborhood on treatment outcomes. A better understanding of the influences of social and environmental contexts on treatment outcomes can inform the evaluation of treatment and the development of community-level interventions.

Given the significant role that public funding plays in providing treatment services, funding agencies are emphasizing the need to evaluate the performance of treatment providers. Detox readmissions are an ongoing challenge for publicly-funded treatment systems. The Washington Circle Group developed a performance measure around the engagement of detox patients in treatment shortly after discharge from detox. Several patient- and program-level predictors of detox readmissions have been identified in the literature. For example, treatment practices such as intensive case management may facilitate the entry into treatment for frequent detox patients. It is clear that treatment programs do not function as autonomous entities, but have interdependent relationships with other treatment programs and funding agencies. The literature on continuity of service within the substance abuse treatment field highlights the importance of interorganizational linkages for improving access to care among vulnerable patients. However, the topic of interorganizational relationships among treatment providers and their impact on performance has not yet been studied.

CHAPTER 3

THEORETICAL PERSPECTIVES

The problem of detox readmissions is often understood as a failure on the part of detox programs to transfer patients to rehabilitation. Intensive case management as part of detox has been identified as one possible solution to help engage detox patients in rehabilitation (Ford & Zarate, 2010; McLellan, McKay, et al., 2005). The need for continuity of service is not only important for detox; however. Research has shown that outpatient counseling after residential treatment sustains abstinence (Godley, Godley, Dennis, Funk, & Passetti, 2006). Implicit in the continuity of service framework is the existence of interorganizational relationships among treatment programs. Godley et al. (2006) acknowledge this assumption by saying that the "rationale is that the residential facility has made the connection with the next level of care after discharge" (p.7). These connections, however, cannot be taken for granted given the reputation treatment systems have for being fragmented (McLellan, et al., 2003; Saitz, Larson, LaBelle, Richardson, & Samet, 2008). This study takes the perspective that the presence or absence of relationships between programs is an important aspect of the treatment delivery system and one that may have bearing on the problem of detox readmissions.

I. Treatment Systems as Interorganizational Networks

The inspiration for this study came from research on systems integration in the mental health field, particularly the work of Morrissey, Johnsen & Calloway (1997), Rivard and Morrissey (2003), and Provan and Milward (1995). These authors have used social network analysis to examine the processes and structural features of service systems. To quote Milward and Provan (1998): “Social network analysis is focused on the structure of relationships among networks of individuals or organizations where the network consists of a set of nodes linked by a set of social relationships” (p.388). Network analysis is a tool for identifying social structures based on patterns of relations between two or more actors. In the context of interorganizational relations, social structure is created from the exchanges between individuals and organizations. Morrissey et al. (1985) call these exchanges “resource flows” and the types of resources in the context of human services integration can include referrals, information, and services. Borrowing from Morrissey et al. (1997), I conceptualize service systems in the addiction treatment field as “networks of interacting organizations” of which client referrals, joint programs, and collaborative planning are constitutive elements (p.6).

The service integration literature has many insights that may be relevant for the problem of continuity of service in addiction treatment. Service integration is studied at two main levels: the service or clinical level and the interorganizational or system level. Mares, Greenberg, and Rosenheck (2008) clarify the distinction between these two levels. Service system research addresses the “impact of system-wide organizational strategies on the health status of individual clients,” whereas clinical services research addresses the “impact of the organization of treatments and treatment settings more proximate to the individual” (p.368). Systems research focuses on the extent and manner in which otherwise autonomous organizations coordinate efforts to achieve a common goal. System research also examines how interagency arrangements are affected by community, state, and national factors (Morrissey, et al., 1985). The patient- and system-levels are not entirely separate in practice, however. As Wright and Shuff (1995) explain, system-level integration is “an important condition of service-line coordination and cooperation” (p.321-322). For example, case management is a service delivered to patients, but the work of case managers can create linkages between programs and new strategies to coordinate care.

One way in which addiction treatment providers interact is through referrals. Referrals are intended to help patients transfer to another service that can meet their needs. Treatment programs exchange patients in order to provide them with ongoing care. For example, residential treatment programs may last 90 days because this is what a funding agency or a health insurance company allows. In order to extend services after residential treatment, program counselors may transfer a patient to an outpatient program for weekly counseling. The meaning of patient transfers is becoming codified in the treatment field as national pressures for evaluation and accountability have increased. Transfers have recently been defined by the Washington Circle Group as an admission to a treatment service within 14 days of discharge from the prior service (Garnick, et al., 2009). As such, patient transfers tell us about continuity of service within the treatment sector. Transfers can be made in-house if a program is part of a multi-service organization or to other organizations.

When aggregated to the treatment program or community level, patient transfers provide evidence of the overall patterns of care. Program evaluators may wish to determine the proportion of detoxification patients that are transferred to treatment upon completion (McLellan, Kemp, Brooks, & Carise, 2008; Urada, et al., 2010). In addition to patterns of care, a collection of patient transfers occurring within a particular locale may illuminate the types of organizational ties that exist and the options patients have for treatment. In this sense, patient transfers link programs together and provide a picture of local systems of care.

Examining patient transfers is like following a trail of crumbs that someone has left behind. Patient transfers are identified through admissions and discharge data, which are typically found in administrative records. Transfers indicate ties between two treatment programs. When a patient transfers from one program to a different program, these two programs are tied from the perspective of the patient because he or she received treatment in both places. A program may or may not be aware of this exchange because patients may go places that the program does not know about. Therefore, at a minimum, programs are tied to one another by the fact that they treated the same patient. When multiple patients are treatment at the same two programs, it is likely a more formal relationship exists between the programs. Ties based on patient transfers are not inconsequential if one considers that the care a patient received or did not receive at the first program impacts a patient's condition when they present to the second program. Coordination of care between providers is based on the idea that different providers share information about the patient and reinforce the care that each provider offers the patient.

II. Interorganizational Networks as a Form of Social Capital

The assumption underlying the present study is that treatment programs' connections to other programs form social structures and these social structures may provide useful resources for programs and patients. This assumption is grounded in network theory and social capital theory. Resources such as availability of services and systems of coordination can be seen as a form of social capital. Network theory and social capital theory are concerned with the impact of social structures on individual and group behavior. In general, network theory focuses on structural features of networks and social capital theory focuses on the resources embedded in networks (Szreter & Woolcock, 2003).

Social ties can be a source of instrumental support to individuals (Wellman & Wortley, 1990). Studies have documented the role of ties in helping individuals find jobs (Lin, Ensel, &

Vaughn, 1981) and in providing companionship, financial aid, emotional aid, and a variety of services, e.g., lending household items, help with repairs, and day care help for parents (Wellman & Wortley, 1990). Social ties are equally valuable to organizational actors in the development of financial capital (Uzzi, 1999), innovations (Burt, 2004; Liebeskind, Oliver, Zucker, & Brewer, 1996), and human service integration (Provan & Milward, 1995; Provan & Sebastian, 1998; Rosenheck et al., 2001). In sum, social capital and networks are related because social networks provide access to resources (Nahapiet & Ghoshal, 1998).

Social capital is defined through concrete actions of people whose shared interests bring them together. According to Coleman (1990), social capital is defined by its function. It is a social entity that involves social structure and that facilitates the achievement of individual and collective goals. Burt (2000) describes social capital as a metaphor for the competitive advantage individuals derive from social relations. People who do better tend to be better connected. Resources, therefore, are embedded in social relations (Granovetter, 1985). People can derive certain advantages by capturing the benefits that inhere in social relations. Burt argues that in order to move beyond the metaphorical qualities of social capital, the network mechanisms creating social capital need to be examined (2000).

A central focus of network theory is the question of how network structures create social capital (Burt, 2000). The strength of relationships or ties is one determinant of social capital. The strength of ties depends on the amount of time people interact with each other, the level of intimacy people share, and the extent to which individual provide reciprocal services (Granovetter, 1973). Multiplex ties are thought to be strong ties and a source of social capital. Multiplex ties are linked by more than one context, e.g., tennis partner and coworker. Multiplex ties are useful because one can draw upon resources from one relationship for use in another relationship (Coleman, 1988). The stronger a tie between two people, the more their social worlds overlap and the greater the chance that they have other ties in common (Borgatti & Halgin, 2011). In the context of substance abuse treatment, strong ties may allow programs to transfer patients more easily because of frequent communication between providers and knowledge of referral procedures and other forms of information useful for care coordination.

Cohesive networks consist of individuals who have close relationships or strong ties. Cohesive networks provide opportunities for collaboration, social support, and innovation (Ahuja, 2000; Coleman, 1988; Goes & Park, 1997; Kilduff & Brass, 2010). There are also strategic advantages to weak or arm's length ties. Grannovetter's weak tie theory suggests that weak ties provide access to diverse information. When a network is closed and interaction is limited within a cohesive group, information is redundant. Weak ties are good for dissemination of information because weak ties can connect networks that are not otherwise connected to each another, allowing for information to spread across networks (Granovetter, 1985; Granovetter, 1973).

In the view of Coleman and Putnam, social capital results from dense networks. Dense networks exist when everyone is connected and behavior is well regulated. When everyone knows everyone else and interacts in multiple social settings, the network is said to have closure. Dense networks are one form of social organization. Such networks can help people achieve certain goals that would be impossible to achieve in the absence of others (Coleman, 1990). Putnam and Coleman suggest that connectedness between individuals fosters trust and mutual support. Common membership in associations and clubs, interacting with one's neighbors, all tie people together.

Dense networks that are built on trust and reciprocity are associated with less crime, safety, better educational outcomes, and economic development because behavior is closely regulated through norms and sanctions (Coleman, 1988; Putnam, 1995). Coleman (1988) gives the example of the mother with six children who moved with her husband and children from suburban Detroit to Jerusalem. One main reason for the move was that the children would have the freedom to move around the town without concern for safety. For instance, in Jerusalem, the mother could let her children play unsupervised in the local park and her eight year old could take the six year old on a city bus to school. Dense networks, social attachments, and social regulation allow for the social capital in Jerusalem that protects young children. Social capital, therefore, can be seen as both an individual and a collective asset (Lin, 1999).

Network theory draws upon the concept of social capital, but seeks to explain how different types of ties provide different resources. Social capital may depend on the nature of the relations people have with people in different social contexts, e.g., neighborhood, family, friends. Wellman and Wortley (1990) found in ongoing research in a community in East York, Canada that stronger ties provided more forms of social support and more support overall than weak or arm's length ties. While strong ties did provide most of the support individuals received in Wellman and Wortley's study, strong ties did not provide individuals with financial aid or large services; these supports were provided by kin.

In another study by Uzzi (1999), strong or embedded ties within the banking sector were found to be an advantage for medium-sized firms that sought access to loans at lower cost. Embedded ties allowed partners to share private information and resources. Trust was found to be critical to the development of these ties. Weak ties, however, were also important for firms to have in their network because weak ties provided access to diverse pools of information in the market (Uzzi, 1999).

The other main focus of network theory is the question of how network structures create social capital (Burt, 2000). Cohesive networks provide opportunities for collaboration, social support, and innovation (Ahuja, 2000; Coleman, 1988; Goes & Park, 1997; Kilduff & Brass, 2010). When a network is closed and interaction is limited within a strong, cohesive group, information is redundant. There is a strategic advantage to having weak ties.

Lin, Ensel, and Vaughn (1981) studied the impact of weak ties on job attainment among a sample of working males in the Albany, New York area. In support of the "strength of weak ties" theory, Lin et al. (1981) found that weak ties helped men reach high-status contacts who had strong ties with potential employers. Weak ties are useful to people because they have information and connections that help people get closer to his/her desired destination. The authors found that the effectiveness of weak ties in helping people attain higher status jobs was a function of a person's personal resources (family background, education, prior occupational achievements). If, for example, a person occupies a higher status position in society, strong ties may be more useful for getting a job than weak ties.

Like Grannovetter, Burt's theory of structural holes (2000, 2004) offers an alternative to Coleman's closed network perspective. Structural holes are the weaker connections between groups in a social structure. As Burt (2000) explains, "structural holes create a competitive advantage for an individual whose relationships span the holes…structural holes are thus an opportunity to broker the flow of information between people, and control the projects that bring people together from opposite sides of the hole" (p.9). Networks with structural holes can lead to opportunities for non-redundant information and competitive brokerage (Burt, 2000).

Structural hole theory focuses on an individual's immediate network or ego-network. Other research has focused on "whole networks" or macro-level networks and the relationship between network structure and effectiveness. One common feature examined within networks is centralization. Centralization is the extent to which activity within the network centers on a few actors or organizations. Centralization within networks is a structural feature that has been linked to successful integration of human services at the city level. For instance, Provan and Milward (1995) compared service networks in four mid-size cities and found that a hierarchical structure involving centralization around a core agency was more important for effectiveness than overall density of ties. Integrated networks of service organizations represent a necessary but not sufficient condition for effective service delivery. Provan and Milward's theory of network effectiveness posits that network effectiveness is not only a function of centralized structure, but also conditions of resource munificence and system stability (Provan & Milward, 1995).

Cohesion within a network is another important factor for service delivery. Foster-Fishman, Salem, Allen, and Fahrbach (2001) found an association between the number of cohesive subgroups or cliques in a network and better service outcomes (see also Morrissey, et al., 1997; Wright & Shuff, 1995). On the other hand, Provan and Sebastian (1998) found that the overlap of cliques was more important than the number of cliques because benefits can accrue through bridging structural holes between diverse organizational actors. While the structural hole theory is supported by multiple empirical studies (Burt, 2004), Ahuja (2000) found in his work on innovation in the chemicals industry that the benefits of structural holes is a function of the context. Ahuja's findings suggest that in contexts involving collaboration among potential competitors from the same industry, closed networks are beneficial because they foster a sense of interdependence and prohibit opportunism (Coleman, 1990).

There is a mutually reinforcing relationship between networks and social capital. Networks are thought to provide opportunity for social capital. Putnam (1995) portrays networks as a mechanism for social capital. On the other hand, social capital may give rise to interorganizational networks because trust is an important factor for certain types of exchanges. As Rosenheck et al. explain the "levels of systems integration reflect the state of civic culture in the community at large" (2001, p. 701).

III. Readmissions to Detox as a Network Problem

The impact of interorganizational networks on patient outcomes has not yet been studied in the substance abuse treatment field. Based on the research in the mental health services field, there is no clear guidance as to which theory best predicts patient outcomes. On the one hand, there appear to be advantages to local clusters of dense multiplex networks, which would support the network closure theory. On the other hand, centralization has been found to be associated with network effectiveness. This study is focused on the immediate networks of detox programs because most of the day-to-day work of service integration takes place on a local level with a limited number of partners (Provan & Sebastian, 1998).

Initially, after conferring with fellow students of network analysis, I associated the notion of continuity of service with network closure because I thought that closure between detox, residential, and outpatient treatment programs—the three general modalities of treatment—would facilitate transitional care for detox patients. The more closure, I reasoned, the more programs may share common goals and norms, which could eventually help patients obtain treatment. This assumption of closure eventually proved to be problematic because of the nature of the networks.

Patient transfers are based on access; that is, patients get one service and then transition to another service. Patients may transfer from detox to residential treatment, from detox to another detox, or a range of many different options. Readmission to detox is only possible if access exists. Therefore, networks with many readmissions will be networks with a lot of access to and from detox programs. Given the nature of the network ties in the present study and the outcome of interest, an analysis of embeddedness (closure) within ego networks will show a positive association between embeddedness and readmission. Since access is a given with patient transfer networks—and access is generally a good thing for patients—it became important to consider alternatives to network closure because of how I defined the networks.

IV. Relevance of Structural Holes for Detox Programs

Network closure at the level of ego-networks implies a situation in which a detox program's ties are themselves tied. Information and patients can travel from one program to another in what could be considered a "tight-knit" social circle. When a program's ties are also tied with each other there is redundancy in the types of information people share and the services patients can access. Applying structural hole theory to the detox readmission problem, one could hypothesize that redundancy within a network creates constraints in terms of referral sources. Less redundancy in a network, on the other hand, may mean that patients are accessing services beyond a detox program's immediate group of contacts.

Structural hole theory emphasizes the role of brokerage for competitive advantage. If an actor "bridges" a structural hole, he or she can function as a broker for the actors on each side of the hole. Actors that connect otherwise unconnected actors have an advantage in that they can control the flow of information and resources. For example, several large treatment organizations in Los Angeles were awarded grants from the county to become community assessment centers. These assessment centers are supposed to be the community "hubs" for assessment and referral for substance abuse treatment services. The organizations that serve as the assessment centers occupy a strategic position in their networks because they can control to some degree where patients go for treatment. When assessment centers are run by treatment organizations, the centers have the advantage of referring patients into their own programs. Additionally, small treatment centers may not have many ties to other treatment centers and, therefore, rely on the assessment centers to make referrals for their patients.

How does the concept of brokerage apply to detox programs? Brokerage may be important for detox programs because if they span structural holes they may be well positioned to connect patients with diverse opportunities for services. A diverse set of contacts is important because treatment centers tend to be small non-profit organizations that serve very specific populations (Chalk, 2010). Some treatment centers serve women with children, while others may not. Some programs provide special services for co-occurring mental health disorders, but such programs are limited. The more specialized services are within a particular sector, the greater the need to develop interorganizational ties (Nahapiet & Ghoshal, 1998). In sum, weak ties may be an important structural feature of treatment provider networks. The presence of structural holes within a local network may represent a potential for providers to connect with members of other networks in order to expand the range of services for patients.

The advantage of brokerage is not having a lot of ties, but having certain ties that lead to additional resources. Too many ties are hard to manage (Morrissey, et al., 1985). This is where the concept of efficiency comes in. The most efficient contacts for detox programs, for instance, may be the programs that broker connections to weak ties beyond the core network. The idea of continuity of service is that detox programs refer to intensive treatment modalities such as residential or intensive outpatient programs. These treatment programs in turn should ideally provide a referral source for less intensive treatment. The contacts of the detox program's contacts are relevant to the extent that they can potentially meet the needs of the patient over time. In effect, the detox program benefits from the referral resources of its direct contacts because if the detox program's patients enter treatment and stay in treatment over time, the detox program enjoys fewer readmissions.

Summary

Network theory provides a foundation for defining health and human service delivery systems and understanding the influence of network ties on effectiveness. In the current literature on substance abuse treatment, service systems are often take for granted; characteristics of the broader social structures in which treatment programs work are rarely captured in substance abuse treatment research and tested as predictors of patient outcomes. In this chapter, I suggest that substance abuse treatment systems can be defined in terms of the interorganizational relationships between treatment programs.

Social networks are often thought of as channels through which resources flow (Borgatti & Halgin, 2011). Because networks provide benefits for individuals and groups, social relationships function as a source of social capital. Most research on social capital has focused on the benefits of information sharing, trust, and mutual aid that inhere in closed or tight-knit networks. Weak ties represent a different form of social capital. Networks with structural holes create opportunities for accessing new and diverse information through weak or arm's length ties. Applying network theory to the problem of detox readmissions suggests that the types of referral sources detox programs have impacts patients’ access to treatment.

CHAPTER 4

METHODOLOGY

I. Study Design

This study uses administrative data from the California Outcomes Measurement System (CalOMS) to measure addiction treatment networks and test the influence of treatment networks on patient readmissions to detox. The California Outcomes Measurement System (CalOMS) is a state data collection and reporting system for alcohol and other drug treatment services that reports to the federal Treatment Episode Data System (TEDS). The main purpose of CalOMS is to evaluate treatment services that are in large part funded through public funds. Treatment systems are accountable to the federal government, who provides block grant funds for treatment, but also to local governments and citizens. The intent of CalOMS was also to allow for continuous quality improvement of treatment programs (California Department of Alcohol and Drug Programs, 2012).

CalOMS requires all publicly funded treatment providers to provide admissions and discharge data on all patients regardless of funding source; that is, programs are required to send data on private-pay patients in addition to patients treated under county contracts. Treatment providers send patient treatment data electronically to the California Department of Alcohol and Drug Programs each month. Information on funding source is not collected in CalOMS. Therefore, one cannot determine from CalOMS the proportion of patients that pay for treatment out of pocket or through private insurance. Research suggests, however, that private funding represents approximately one-quarter of treatment expenditures (Mark et al., 2007).

CalOMS includes information on alcohol and drug use, criminal justice involvement, employment and education, family and social ties, and physical and psychological health. CalOMS includes measures that correspond to the National Outcome Measures developed by the Substance Abuse and Mental Health Services Administration. The outcome measures contain single items and do not include diagnostic information. This study uses data for the fiscal year 2008-2009.

In this study, provider networks are inferred from patient transfers. Transfers are defined as admissions to services within 14 days of discharge from a prior service (Garnick, et al., 2002). Patient transfers from one service to another define the dispersion of care received by detox patients. For example, patients may enter a detox service then transfer to a residential service. Other patients may enter two detox services in a row and then transfer to a residential or outpatient treatment program. Transfers from detox to treatment are a recommended performance measure because research shows that patients are at high risk of relapse after detox (Center for Substance Abuse Treatment, 2006). Treatment initiation is critical for patients' health and rehabilitation from alcohol or drug dependence.

CalOMS provides a good platform for the study. First, administrative data provide an opportunity to observe large numbers of patient transfers between treatment providers. Second, administrative data have the advantage over survey data in that provider ties are observed from the patient perspective. Self-reports of organizational ties are subject to a variety of respondent biases including recall bias, reporting bias, and social desirability bias. Lastly, there is interest in the substance abuse treatment research field in using administrative data to monitor treatment processes for performance measurement (Evans, Grella, Murphy, & Hser, 2010; McCarty, McGuire, Harwood, & Field, 1998). The use of administrative data for program evaluation and monitoring avoids the costs associated with primary data collection as well as the delay in receiving results.

II. Sample

This study uses administrative data that includes all patients admitted to publicly-funded treatment services between 7/1/2008 and 6/30/2009 in 32 California counties. These counties were selected out of a total of 56 counties because they had admissions data for detox services. Data on the entire patient population in the 32 counties were used to construct provider networks. From the patient populations in the 32 counties, patients admitted to a detox unit between 7/1/2008 and 6/30/2009 were sampled to study predictors of readmission to detox. To measure readmission to detox within one year of the initial detox service in 2008-2009, admissions data was observed one year after the first admission during 2008-2009.

The 32 counties range in size from large (more than 800,000 people), medium (250,000-800,000 people), and small (90,000-250,000 people) (County Alcohol and Drug Program Administrators' Association of California, 2006). In the sample, there are 13 large counties, 10 medium counties, and 9 small counties. The number of detox units per county ranges from 1 to 39. The majority of detox admissions in the state were in Los Angeles, San Francisco, Alameda, and San Diego counties.

The administrative data from the 32 counties includes 150,955 patients who had a total of 440,496 admissions to treatment over the course of one year. The patients were treated by 1,600 service units. To create a sample of detox patients, I selected all patients in the administrative record who were admitted to a detoxification service during the 2008-2009 timeframe. The sample was defined by having an admission record because discharge records do not include complete demographic and drug use information. Patients admitted to their initial detox service in the records on July 1, 2009 or after were excluded from the sample. Patients with only a discharge record were also excluded from the sample. The final analytical sample included 25,423 detox patients. The number of detox units is 156 (99 narcotic treatment programs and 57 residential detox programs). The mean number of unique patients per detox unit was 172 (range=1-1,915). Patients can have more than one admission to the same service provider. The mean number of detox admissions across all patients was 284 per detox unit (range=1-4,824). The number of admissions is an indication of provider size (Urada, Fan, & Rawson, 2010).

III. Study Procedures

Social network analysis

Network analysis is useful for studying systems integration because there are a range of measures that quantify the structure of service provider networks. Network analysis tools describe systems in concrete terms, as networks of organizations that interact to share information and resources and pursue common goals. As Morrissey, Johnsen, and Calloway explain (1997), the level of integration within a system can be inferred from patterns of interagency exchanges related to clients, resources, or information. Network studies observe actual ties between pairs of actors and groups of actors. Actors can be individuals, organizations, cities, or some other entity. Ego-network analysis focuses on individual actors and their local circumstances. Ego is an individual actor or "focal" node in network terms (Hanneman & Riddle, 2005). Ego-network analysis examines the extent to which actors are embedded in a web of social relationships or social structures. These social structures surrounding individual actors are referred to in network analysis terms as "neighborhoods." A neighborhood is the set of ties to whom an actor is directly tied to by a path of one-step (Hanneman & Riddle, 2005). Neighborhoods also include the ties that exist between ego's contacts.

The building blocks of networks are the dyadic relations between actors. Many network studies have used dyads as the unit of analysis (Mares, et al., 2008; Provan, Milward, & Isett, 2002; Rivard & Morrissey, 2003). A focus on dyads is useful to the extent that one can examine the factors leading to the formation and evolution of organizational ties. Studies of dyads are concerned with the relational aspects of networks. For example, trust between organizations has been found to be predictive of current and future partnerships (Provan, et al., 2002). The limitation of a focus on dyads is that it does not inform knowledge of how overall networks function. Part of the limitation has to do with perception of what a network is. With dyad-level research, as Provan, Fish, and Sydow (2007) explain, a network "is primarily seen as a collection of 2-party relationships rather than as a unique, multi-organizational social structure or even a social system in its own right" (p.483). Whole network studies, on the other hand, use aggregated actor-to-actor data to measure aspects of networks at large. Provan defines whole networks as a "group of three or more organizations connected in ways that facilitate achievement of a common goal" (p. 482).

Defining Provider Networks

The unit of analysis for the network analysis is the service delivery unit. Service delivery unit is a specific treatment program or modality such as a residential program or a methadone maintenance program. The service delivery unit has been recommended by researchers in the addiction treatment field as the appropriate level for purposes of evaluation (Carise, McLellan, & Gifford, 2000). Service delivery units are programs within an organization. An organization may have multiple service delivery units and facilities. For instance, one organization may provide detox, residential, and outpatient services. Each service is a service delivery unit with its own staff and possibly its own service contracts. Intra-organizational transfers occur as patients are transferred from one service to another within the same organization. In order to capture linkages between distinct programs that may or may not be a part of the same organization, each service delivery unit was given a unique code corresponding to the type of service: outpatient (including drug-free counseling and narcotic replacement therapy/methadone maintenance programs), day treatment in outpatient settings, outpatient detox, residential detox, short-term residential, and long-term residential.

Network Boundaries

The first step of a network analysis involves identifying the boundaries of a network under study. Boundaries can be based on geography, such as a city or a neighborhood, or they can be based on individuals' affiliation with a particular social group. CalOMS data could logically be bounded by county, as social services are funded by county agencies. However, preliminary analyses showed patient transfers across county lines.

Given the lack of prior network analysis research on substance abuse treatment providers, I decided to allow network boundaries to emerge based on the data. Intra- and inter-county transfers were identifiable because each service unit has a unique identification code that includes a provider and county code. To identify within county transfers, county codes were listed for all pairs of service units, e.g., sending unit and receiving units, in two columns. I created a new variable that coded whether for each pair the county codes were the same (code=1) or different (code=0). I ran a frequency on the variable and calculated the proportion of transfers that were within the same county.

After coding patient transfers, I found a total of 25,090 transfers within the 32 counties. A total of 96.6% of patient transfers were within county. Given this result, I decided to bound networks by county. In the network analysis, I dropped the 3.4% of transfers that crossed county lines and ran network measures for each county separately. This approach allowed for nesting providers within counties and construction of network measures that were based on within-county transfers. If I had incorporated transfers that providers in county 1 shared with county 2, for example, providers from county 2 would be members of more than 1 county network. While membership in multiple networks reflects the realities of geographic proximity between providers in neighboring counties and resource exchanges between counties, network measures were run for providers using only ties with other providers in their county network.[4]

Patient Transfers

Ties are defined by patient transfers. To construct the networks, I used treatment admissions and discharge data for all patients admitted to treatment during 2008-2009. A total of 137,982 unduplicated patients were included in the dataset. The majority of patients (73.1%) received only one service (range=1-16). A total of 18.8% of patients received two services and 8.1% received three of more services. Seven patients received 16 services; however, these patients received the same service multiple times from the same set of providers. The patterns for the seven patients who received a total of 16 services are captured within the observation window of 15 services because the patterns were repeated multiple times. Allowing for 15 service exchanges provides sufficient coverage of patient transfers.

[4] A total of 847 transfers (3.4%) crossed county lines. The inter-county transfers consisted of 556 ties between programs. Approximately 85% of the inter-county ties were based on one transfer between programs.

The proposed study assumes that transfers between providers within 14 days constitute ties between two providers based on patient exchanges—one provider "sends" the patient and the other provider "receives" the patient. Fourteen days has been validated as a meaningful window for effective continuity of services in the addiction field (Garnick, et al., 2009). Patients can have multiple transitions within a year and can receive care from more than one service provider. Prior research on transfers in CalOMS found that the mean number of days between services during a transfer was 6.8 and the median was 3 days (Urada, et al., 2010). Fourteen days was chosen as the cut-off in this study primarily because of its relevance to the addiction health services field. Additionally, most of the transfers are captured within 14 days in CalOMS. Thirty days is considered the maximum number of days to elapse between services to justify continuity of service (McLellan, Weinstein, et al., 2005).

The original CalOMS dataset is in long format, which means that patients' admissions and discharge records are stacked. To code transfers, I first ordered the admissions records by date. Then I created a separate wide file to code the transfers. The wide file organized all records horizontally and by date (one row per patient). Admission and discharge data were contained in separate columns. To code transfers, I identified sets of two consecutive services, e.g., service 1 to service 2, service 2 to service 3, etc. To calculate the number of days between each set of services, I subtracted the admission date for the second service from the discharge date for the first service. If the number of days between discharge and admission was less than 14 days, I coded this as a transfer. This process was repeated for 15 possible services. In 5% of cases, the number of days between a discharge date and a subsequent an admission date was negative. The reason for a negative number is that the recorded discharge date occurred after the subsequent admission date. It is not uncommon for program staff members to delay discharging patients until they are sure the patients will not return. As such, I decided to code these cases as transfers.

Transitions were coded in Stata v.11 and the data were then imported into UCINET version 6.374, a network analysis software program (Borgatti, Everett, & Freeman, 2002). UCINET organizes network data into matrices from which calculations are made. Within the 32 counties, there were a total of 1,600 service delivery units in the dataset. Only 1,370 programs were included in the network analysis because 230 providers were not involved in transfers. In the regression analysis, programs without network data receive a zero on the network measures. Network diagrams were produced in the NetDraw software program (Borgatti, 2002).

Coding Care Patterns

I evaluated continuity of service after patients' first detox service in the administrative record. All index detox services were captured within the first eight services in the record. For most patients, the detox service is the initial service in their record. This is not the case for all patients, however. For example, patients who had a detox admission in the first record (or column in the database) have a discharge entry in the second record (admissions and discharges are in separate rows). Other patients may have nothing in the first record, a detox admission in the second record, and a discharge in the third record.

Based on each of the eight initial records, I created a new variable that indicated whether each detox service was the patient' first detox in the 2008-2009 record. Then, for each of the eight records, I created a string variable to combine the code for the initial detox service with code for the next service the patients received, provided that the transition to the second service was a transfer. There were a total of 14 possible patterns: NTP detox and no other admission within 14 days (1); residential detox and no other admission (1); NTP detox to either a second

NTP detox, residential detox, short-term residential treatment, long-term residential treatment, outpatient treatment, or day treatment detox (6); residential detox to either a second residential detox, NTP detox, long-term residential treatment, short-term residential treatment, outpatient treatment, or day treatment (6). Appendix A provides an overview of how I coded the transfers and care patterns in a wide file.

Based on the service patterns, I created an additional dichotomous measure to indicate whether detox patients transferred to either residential or outpatient treatment after their initial detox. The purpose of creating this measure was to examine the association between linkage to treatment and readmission to detox. This association is a critical first step for the subsequent analysis on the influence of provider networks on detoxification readmissions.

IV. Patient Transfers as a Measure of Interorganizational Ties

Patient transfers indicate interorganizational ties from the patient perspective. An attempt was made to determine the agreement between the transfers and reports of referrals by treatment staff. I used two methods to examine agreement: 1) running a frequency on the discharge status question in CalOMS for all transfers made after the first service in the record, and 2) conducting qualitative interviews with staff members at substance abuse treatment programs. The discharge question consists of eight categories, three of which document referrals for additional services: 1) patient completed treatment and referred, 2) patient left before completion with satisfactory progress and referred, and 3) patient left before completion with unsatisfactory progress and referred. Unfortunately, CalOMS does not require providers to indicate which treatment programs they refer to. Such information would allow for a comparison between reported referrals and actual transfers. Given the complexity of the dataset with multiple admissions and discharges per patient, discharge status was only examined for patients that had an admission record in the first field of the dataset, a discharge record in the second field, and a new admission in the third field. A total of 16,322 patients transferred to a second service after their index service.

There are two additional questions in CalOMS that refer to referrals, but that were not used because of concerns about their reliability. The first is called "admission transaction type". The two codes for "admission transaction type" are initial admission and transfer/change in service. An initial admission is a service that begins a new treatment episode, i.e., there was not another service before the admission that occurred within the prior 30 days. A transfer or change of service is when a patient receives an additional service within 30 days that is part of the same treatment episode. A recent evaluation of CalOMS data found that this question has limited utility because providers do not routinely answer the question (Urada, et al., 2010). A frequency of "admission transaction type" for patients that were transferred to a second service after their initial service in the record showed that 30.8% of patients were coded as having a transfer (n=16,322).

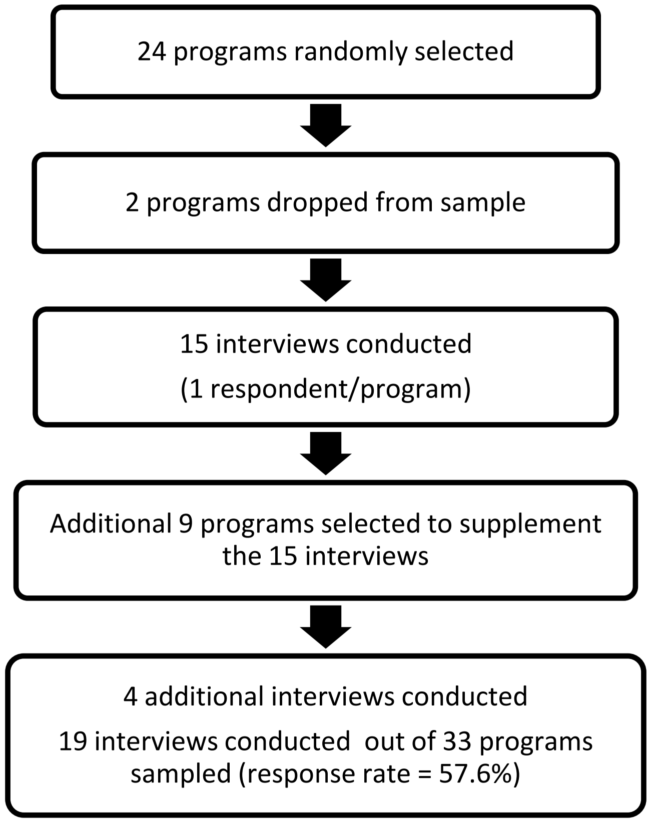
The second question asks the treatment counselor to document the referral source for each admission. I ran a frequency on the referral source for the second admission for patients that transferred to a second service after their initial service in the record. I found that 65.3% of patients were referred by an outside service agency or self-help program. More than one-third of patients, 34.7%, were coded as not having a referral. Among those patients that were coded as having a referral, 12.4% of patients had a referral from another alcohol or drug abuse program. It is possible that referrals from alcohol and drug programs are underestimated because referrals coded as coming from a criminal justice agency often involve the assistance of alcohol and drug treatment counselors in the selection of the treatment program.

As an additional source of information, I conducted qualitative interviews with staff members at substance abuse treatment programs to examine whether transfers in CalOMS represent referral relationships and to elicit information on the referral process, including data reporting in CalOMS. The sampling strategy for the interviews was a combination of random and self-selected volunteer sampling. First, the number of direct ties with other service units was counted for each service unit. Next, I created a separate database with a listing of programs with the most ties and the least ties to other programs, i.e., the top and bottom 20%. I chose to examine programs with the fewest and greatest number of ties to determine if transfers observed in the admissions data reflected referral ties and whether programs on each end of the spectrum differed in terms of their services and referral procedures. I randomly shuffled the list in STATA.

Starting from the top of the randomly shuffled list, I selected 12 programs from the top 20% and 12 units from the bottom 20%. I chose to sample 12 programs from each quintile because I wanted to have two programs from each of the six treatment modalities: outpatient programs (drug-free and narcotic treatment programs), outpatient day treatment, outpatient detox, residential (non-hospital) detox, short-term residential, and long-term residential. I matched program codes with a master list of programs from 2008. The list was obtained from the California Alcohol and Drug Program Administration back in 2008 by researchers at the Integrated Substance Abuse Programs at UCLA. Once program names were found on the master list, I searched for updated contact information on the online Treatment Facility Locator search engine operated by the Substance Abuse and Mental Health Services Administration.

After programs were randomly selected, letters were sent to program directors explaining the purpose of the study, including my intent to interview staff members that were familiar with referral sources and discharge procedures of their program. Within two weeks of mailing the letters, I made follow-up calls to the program managers. A maximum of three attempts were made to reach people by phone. Out of the 24 selected programs, two units were dropped from the list. One program could not be found on the Treatment Facility Locator web site. The second program was dropped because it was a program based at the same agency in the same city as a previously selected program. Of the 22 programs, 15 interviews were conducted. To increase my sample size closer to 24 programs, I selected another 9 programs by modality type. Of the additional 9 programs selected, 4 interviews were conducted. A total of 19 interviews were conducted: 4 from NTP detox programs, 3 from residential detox programs, 1 from a day treatment program, 5 from outpatient drug-free programs, 2 from short-term residential programs, and 4 from long-term residential programs. Eight participants were interviewed from programs in the 1st quintile (lowest number of ties) and 11 participants were interviewed from the 5th quintile (greatest number of ties). Based on the 31 programs selected in two rounds, 19 interviews represent a response rate of 57.6%. See a recruitment diagram in Figure 3.1.

Figure 3.1 Recruitment Process for Qualitative Interviews



The interviews were semi-structured. Participants included 16 individuals in management or supervisorial positions (e.g., program director, program managers, and clinical supervisors), one program coordinator and two counselors. Participants were asked to describe the services provided by their unit as well as the services provided within their organization as a whole. Participants were asked to name up to five programs that their program referred to recently, to describe procedures for making a referral, and to discuss other ways in which staff from their program interacted with the programs they refer to. The purpose of the last question was to assess to what extent referral sources constituted other types of relationships based on information exchange or joint activities. After completing the interview, participants were mailed a thank you letter and a gift card for $10. The qualitative interviews, along with the secondary analysis, were approved by the UCLA Institutional Review Board.

I compared the nominations from the program staff with the observed ties from the network analysis. To compare the results, I first used the master provider list to identify the provider IDs of the nominated providers. Next, I located the nominated provider in the network data and noted whether a transfer existed or not and the number of transfers between the two providers. Complete agreement between the nominations of referral sources and the administrative records was not expected. The transfers were observed from the patient perspective and my respondents may be unaware of all the places they are tied to through patient transfers. Linkages between providers, therefore, may represent “hidden” assets as providers may not fully identify the linkages they have based on the service patterns of their patients.

Some network studies may use only confirmed or reciprocated links, e.g., agency A reports sending patients to agency B and agency B reports receiving patients from agency A. While confirmed links may be important for some types of relationships, there is the possibility of underestimating service linkages (Foster-Fishman, et al., 2001). With confirmed links, the assumption is that the people responding to the network inventory have sufficient awareness of their organizations’ ties. While confirmed ties may be too conservative for ties that may be ephemeral or ad-hoc, confirmed ties may be important for documenting formalized activities, e.g., joint programs, which require a greater level of awareness and management by agency staff. In the present study, self reports of program staff cannot fully confirm that the patient transfers represent actual relationships between programs. To do that, one would need to interview staff from agencies on both the sending and receiving ends of the transfer. In the context of the present study, it is impossible to know for sure which programs were coordinated by programs and patients. As a result, all ties are assumed to be potentially meaningful and were included in the network analysis.

V. Measures

Dependent Variable

The dependent variable is readmission to detox, which is a binary variable. Readmission to detox is measured at the patient level and is defined as having two or more detox services within one year of the first detox service. The one-year observation period is common in substance abuse treatment outcomes research and has been used to evaluate detox readmissions in prior research (Mark, et al., 2006). I also chose the one year time-frame to allow for the fact that some patients receive treatment after their first detox. I wanted to be able to capture a higher proportion of readmissions. For each patient, a cut-off date was created, which was equal to 365 days after the date of the index detoxification. If the date of the second detox admission fell before the cut-off date, the patient was coded as having a readmission. No distinction was made between which detox providers patients went to after the index detoxification. Patients were grouped by their index detoxification provider; therefore, patients' readmissions were attributed to their index detoxification providers.

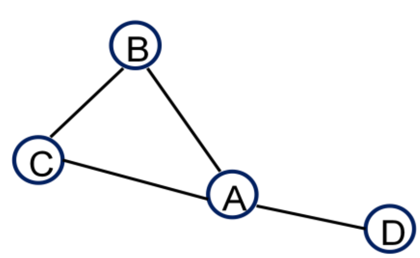
Independent Variable

The substantive theory driving the present study is that service networks with structural holes can allow for greater reach to other services and, as a result, fewer readmissions to detox. Structural holes may create opportunities to reach diverse treatment programs to meet a diversity of patient needs and circumstances. Rosenheck (2002) argues that linkages created at the local level by service providers are the building blocks for system-level integration. Based on this perspective, the present study examines program ties at the ego-network or neighborhood level. Ego-network measures determine the structural position of actors within their neighborhood and the benefits or constraints that may arise from occupying certain positions within a network. The network measures, efficiency and degree, were both based on out-going transfers to other programs.

Network Efficiency

The concept of network efficiency is that non-redundant contacts lead to certain advantages for an actor because these contacts may provide an actor with new information or access to resources not available within an actor's local network. Efficiency is the proportion of an actor's direct ties that are non-redundant (Hanneman & Riddle, 2005). Redundancy occurs when an actor's contacts are also tied to each other. For example, suppose detox program A has three contacts (program B, C, and D). The ties between these programs are illustrated in figure 4.1. If program B and C are connected to each other, then program A's tie to B is redundant because program A can access program B through program C. Program A's tie to B does not provide any new referral sources for program A because program A is already tied to program C.

Figure 4.1 Ego-Network of Program A



Efficiency is calculated by first determining the effective size of a network. The effective size is the number of ties an actor has minus the average number of ties an actor's contacts have with each other, not including their ties to the main actor (Hanneman & Riddle, 2005). For example, program A has 3 ties. Program B has 1 tie. Program C has 1 tie. Program D has 0 ties. The average number of ties of Programs B, C, and D (not counting their ties to A) is 2 divided by 3 or .67. The effective size of Program A's network is 3 - .67 or 2.33. Efficiency is the effective size relative to the actual size of the network. Program A's efficiency is 2.33 (amount of non-redundant ties) divided by 3 or .78. Efficiency was calculated for each detox program that had ties to other programs through transfers. If detox programs had no network data, they were given a zero on the efficiency measure.

Program-Level Covariates

Out-Degree

Out-degree is the number of out-going ties a program has based on patient transfers (note: degree is simply the number of direct ties an actor has). Out-degree is strongly correlated with the number of admissions a program had during the 2008-2009 year. Out-degree and admissions are indicators of program size. Size is an important for several reasons. First, larger detox programs will have more patient transfers and, as a result, more ties to other providers. Second, program size has ramifications for patient transfers to treatment. In research on detoxification and treatment engagement, smaller detox program size was associated with higher transfer rates to treatment (Campbell, et al., 2010). At the same time, detox programs with at least 35 beds have been found to be associated with longer length of stay in detox (Campbell, et al., 2010), which is a predictor of successful transfers to residential treatment (McCusker, Bigelow, Luippold, Zorn, & Lewis, 1995). If detox programs had no network data, they had a degree of zero.

<u>Detox Type</u>

Outpatient detox units are often a part of larger narcotic treatment agencies, which means that most of the outpatient detox units are connected to outpatient methadone maintenance programs, often in the same facility. In fact, the majority of outpatient detox programs in the sample have a methadone maintenance program within their agency (93.5%). By comparison, 72.2% of residential detox programs had residential or outpatient treatment programs within the same organization. Location within an organization that houses addiction treatment programs in addition to detox may facilitate the initiation of treatment for detox patients (Campbell, et al., 2010; Ross & Turner, 1994). In addition, the conventional wisdom of treatment providers themselves suggests that integration of services within organizations may be the optimal arrangement for ensuring patient transfers to treatment. There are two main types of detox programs, outpatient narcotic treatment programs and residential detox programs. As a result, the detox type variable is defined as a binary variable.

Patient-Level Covariates

Predictors of readmission to detox fall within a couple of domains: socio-demographics, patient severity, physical health status, and amount of treatment services received. Patient-level factors associated with readmissions to detoxification include alcohol as the primary drug problem, drug use severity, residential instability, older age, unemployment, single marital status, Hispanic ethnicity, and lack of follow up rehabilitation care (Callaghan & Cunningham, 2002; Campbell, et al., 2010; Mark, et al., 2006). Having health coverage through a fee-for-service Medicaid plan has also been identified as a predictor of detox readmissions (Carrier, et al., 2011).

Because of the link between follow up rehabilitation care and reduced detox readmissions, it is important to consider predictors of treatment entry following detoxification. Patient-level factors that have been identified as predictors of treatment entry include criminal justice involvement (Kleinman, Millery, Scimeca, & Polissar, 2002), Medicaid eligibility (Mark, et al., 2006), and a longer length of stay in detoxification (Campbell, et al., 2010). In the case of criminal justice, Kleinman et al. (2002) found that heroin and cocaine users that were on parole were more likely to enter treatment after detoxification. There are a couple of explanations for the high rate of treatment access among offenders. First, parolees may face legal consequences for not following through with a treatment plan mandated by a judge. The second reason has to do with availability. In the case of diversion programs that offer non-violent offenders treatment in lieu of incarceration, treatment providers may receive special funding to treat offenders and, as a result, reserve treatment beds or outpatient slots for offenders.

Socio-Demographics

Gender

Gender is a dichotomous variable with 0 for women and 1 for men. Women are the reference group in the present analysis.

Age

Age is based on patients' age at admission to the index detoxification. In CalOMS, age is a continuous variable and ranges from 14 to 89 years. Because of the wide age range, I recoded age into 4 categories based on quartiles for ease of interpretation: 0 = under 30, 1 = 31-41, 2 =

42-48, and 3 = 49 and older). The “under 30” group is the reference group in the present analysis.

Race

Race consists of three categories: white, black, and other. Approximately 76.5% of the sample is either white or black. The “other” category consists of American Indians, Alaska Natives, Asian Indian, Cambodian, Chinese, Filipino, Japanese, Korean, Laotian, Samoan, Vietnamese, Hawaiian and Guamanian peoples, who together comprise approximately 3.5% of the sample. The “other” category also includes individuals who self-identify with being multi-racial or from a racial background (“other race”). Approximately 20% of the patients are included in “other race” category. Three categories were selected to simplify the number of groups for the analyses.

Hispanic Ethnicity

Hispanic ethnicity is a dichotomous variable that is coded 1 for individuals that self-identified as Mexican, Mexican American, Cuban, Puerto Rican, or other Hispanic/Latino. CalOMS does not distinguish between Hispanic whites and non-Hispanic whites. Individuals who do not identify with Hispanic or Latino ethnicity are the reference group in the present analysis.

Current Employment

Currently employed is a dichotomous variable that distinguishes those individuals who are unemployed, coded as 0, versus working part- or full-time, coded as 1. A status of unemployed includes unemployed but looking for work and unemployed and not seeking employment. Current employment status was assessed at admission to the index detoxification. Not employed is the reference group for the present analysis.

Living Situation

Current living situation includes 3 categories: homeless, dependent living, independent living. Homeless is defined as having no permanent residence. A dependent living situation is defined as living in a supervised setting such as a residential institution, jail, halfway house, or living with one's parents or relatives. Independent living is defined as owning a home, renting an apartment, or having some other situation in which one pays rent and is not under supervision. Current living situation was assessed at admission to the index detoxification. Individuals who are homeless are the reference group for the present analysis.

Criminal Justice Status

Criminal justice status is a categorical variable in CalOMS. The question in CalOMS includes seven response categories. The original variable was recoded into four categories: 0) no criminal justice involvement, 1) on parole, 2) on probation, and 3) other, e.g., in a jail diversion program, incarcerated, or awaiting trial. Criminal justice status was assessed at admission to the index detoxification. Individuals who are not currently involved with the criminal justice system serve as the reference group for the present analysis.

Medi-Cal Beneficiary

Patients are asked as admission if they are a Medi-Cal beneficiary. In California, the federal Medicaid program is called the California Medi-Cal Assistance Program (Medi-Cal). Medi-Cal provides health care services to low-income families with children, elderly, and blind or disabled individuals. The Department of Alcohol and Drug Programs administers Drug Medi-Cal, which covers residential and outpatient treatment services. Medi-Cal beneficiary is a dichotomous measure and was assessed at admission to the index detoxification. Individuals without MediCare coverage are the reference group for the present analysis.[5]

Addiction Severity

Primary Drug

Patients addicted to alcohol and heroin face the challenges of a physical addiction, but these patients may receive different forms of detoxification. One of the main differences is the standard use of methadone or other opiate replacement therapies to detox heroin-dependent patients. Many fewer patients with alcohol dependence receive medications during detoxification. Alcohol as the primary drug has been found to be associated with more detoxification readmissions (Mark, et al., 2006).

The primary drug measure in CalOMS consists of seven drug categories: heroin, alcohol, methamphetamine, cocaine, cannabis, other opiates, and other drugs. For this study, the measure was reduced to reflect the four drugs most frequently encountered in detoxification: heroin, alcohol, methamphetamine, and cocaine. Heroin and alcohol are the most common drug problems treated in detoxification because withdrawal from these drugs is particularly acute. A fifth category, "other drug," was created to organize other drug categories such as cannabis, other opioids, and psychedelic drugs. Primary drug was assessed at admission to the index detoxification. For the present analysis, heroin users are the reference group.

Frequency of Primary Drug Use

Frequency of primary drug use is defined in CalOMS as the number of days in the past 30 days that a patient used the primary drug. Frequency of use is commonly used as a proxy for

[5] Low-income patients that do not qualify for Medi-Cal receive treatment from other public sources such as federal block grant funds.

addiction severity (McLellan, Weinstein, et al., 2005). Frequency of primary drug use is a continuous measure and was assessed at admission to the index detoxification.

Age of Onset of Primary Drug

Age of onset is an indicator of drug use severity because research has shown that the younger individuals begin using substances, the higher their risk of future substance use disorders (Grant, Stinson, & Harford, 2001; King & Chassin, 2007). Age at first use of the primary drug is a continuous measure and was assessed at admission to the index detoxification.

Lifetime Mental Illness Diagnosis

Being diagnosed with a mental illness at any point in one's lifetime is self-reported by patients. This is a dichotomous measure and was assessed at admission to the index detoxification. Individuals with no lifetime mental illness diagnosis are the reference group for the present analysis.

Any Medical Problems

Physical health is defined in CalOMS as the number of days in the past 30 days that a person has experienced physical health problems. CalOMS does not provide a listing of potential health problems. Physical health is a self-reported by patients. In the present study, a new dichotomous variable was created "any medical problems." Approximately 75% of patients reported zero days of having medical problems in the past 30 days (range= 0-30). As a result, I dichotomized the variable. A code of 0 means no days of physical health problems and 1 means at least 1 day of physical health problems. Physical health assessed at admission to the index detoxification. Individuals with no medical problems are the reference group for the present analysis.

Prior Treatment for Addiction

CalOMS includes a variable that measures the number of treatment episodes a patient had prior to the index detoxification. Number of prior treatment episodes is considered an indicator of an ongoing substance use disorder because multiple treatment episodes are common among patients with substance dependence. While multiple treatment episodes may signal a chronic disorder, there may be cumulative effect in which multiple exposures to rehabilitation lead to abstinence (Hser, Anglin, Grella, Longshore, & Prendergast, 1997). Mark et al. (2006) found that having two or more treatment services prior to the detoxification service was associated with a lower risk of readmission within one year. Approximately 62% of patients reported one or no prior treatment episodes. The number of prior episodes measure was dichotomized at the median of 1. A code of 0 means no prior treatment and 1 means at 1 or more prior treatments. Number of prior episodes was assessed at admission to the index detoxification. Individuals with no prior treatment comprise the reference group for the analysis.

Transfer from Detox to Treatment ("Detox-to-Treatment")

Receipt of treatment after detox has been found to be associated with lower readmission to detox (McLellan, Weinstein, et al., 2005). To code whether a patient transferred to treatment after their initial detox, I tracked patient transfers from patients' index detox service to one additional services received within 14 days. All index detox services were captured within the first eight services in the record. To define a set of two possible services, e.g., detox plus another service, I concatenated the codes from the index detox and subsequent services. This means that if a patient was transferred from service 1 to service 2 within 14 days, the two services were combined. If patients went just to detox they would only have one service recorded in the variable. After the service sets were defined, I created a new variable that documented whether patients received residential or outpatient treatment after detox.

Still In Treatment after Detox

Patients that were transferred to treatment directly after detox and remained in treatment for a year of more post detox do not have the opportunity to readmit to detox. Patients in NTP programs, e.g., methadone maintenance, can remain in treatment for years because methadone maintenance is an ongoing form of treatment. Therefore, I created a variable to measure whether a patient had been transferred from detox to treatment and remained in treatment one year after the index detox. This measure was included as a control variable in the NTP detox analyses.

To code this variable, I started with patients who received a detox service as their first service in the record. For the patients who transferred to a second service, I created a new variable that took the difference between the date of discharge from the second service and the date of discharge from the initial detox service. If the difference was 365 days or more, the patient was coded as 1 for being in treatment during the observation period for the study (one year after the initial detox service). Patients that did not have a second discharge date, but who transferred to treatment were also coded as being in treatment.

Patients that did not transfer to treatment directly after treatment or who went to treatment after detox but stayed less than 365 days serve as the reference group for the present analysis.

Hypotheses and Statistical Tests

Patient-Level Hypotheses

1. Patients who are transferred from detox to residential or outpatient treatment have lower odds of readmission to detox than those without a transfer to treatment.
2. Men have higher odds of readmission to detox compared with women.
3. Patients who report higher frequency of drug use in the 30 days prior to entering detox have higher odds of readmission to detox.
4. Patients who have health coverage through Medi-Cal have lower odds of readmission to detox.

Provider-Level Hypotheses

1. Patients served in detox programs that have networks with high efficiency have lower odds of readmission.
2. Patients served in detox programs that have intra-organizational ties to treatment programs have lower odds of readmission compared to patients treated in stand-alone detox programs.

Analysis

<u>Descriptive Analyses</u>

The first step in the analysis of provider linkages involved testing the association between readmission to detoxification and the detox-to-treatment service pattern. Because provider networks are inferred from service patterns, a significant association would provide support for my hypothesis that provider networks have an impact on a patient's odds of readmission. Both readmission and detox-to-treatment variables are dichotomous. To test the association between the two variables, I ran a chi-square test. Given the large sample size, I set the significance level for all descriptive analyses at an alpha level of .001. Stata version 11 was used to run all statistical tests (StataCorp, 2009).

Bivariate analyses were run to examine associations between readmission and patient socio-demographics, addiction severity, physical condition, and prior treatment episodes. Chi-square tests were used for dichotomous patient-level variables and t-tests for continuous patient-level variables.

Testing the Influence of Provider Networks on Readmission to Detoxification

Modeling the differences in interorganizational networks of detox providers is at the heart of the present analysis. Multi-level models take into account variation in patient outcomes across groups. The assumption with multi-level analysis is that structure may influence individual outcomes. If outcomes are similar within groups, the residual errors across individuals will not be independent, which violates an assumption of ordinary least squares regression. Ignoring the hierarchical structure of the data may underestimate the standard errors of the estimates, creating confidence intervals that are too narrow and p values that are too small (Seltzer, 1994).

The data in CalOMS have a hierarchical nature: patients within providers and providers within counties. To test the hypothesis that network structure impacts patient outcomes, a binary mixed model was conducted. The analysis has two levels. The first level is the patient and the second level is the detox provider. Patients were attributed to detox providers based on their index detox service. Level one predictors include all patient-level variables. Level two predictors include variables that describe the detox providers and their ego-networks. Counties were not added as a third level because the number of counties was too small to accommodate the number of predictors in the model.

Model Specification

To test the assumption that some of the variance in the log odds of readmission is at the detox program level, an intercept-only logit model with all detox programs included was run without any predictors. The "xtmelogit" program in STATA was used. The "xtmelogit" program calculates a likelihood ratio that tests for differences in the outcome across level two units. A significant difference between a standard logistic regression and a mixed model suggests that there is variation at the program level. The likelihood ratio test was significant, which supports the use of a mixed model (χ^2=1589.32, p<0.001).

Another indicator of between group variation is the intra-class correlation coefficient. The intra-class correlation measures the extent to which values of the outcome variable are similar for individuals within the same groups. An intra-class correlation (ICC) is the proportion of between group variation relative to the total variation. In a multi-level model, the ICC is calculated using the estimate for the random intercept as the between-group variance and $\pi^2/3$ as the within-group variance. The estimate for the random intercept is taken from an intercept only model without predictors. For NTP detox patients, an intra-class correlation of .136 was found. For residential detox patients, an ICC of .126 was found. These ICCs were deemed to be strong because the design effects, i.e., the corrections that need to be made to account for clustering, significantly reduce the effective sample sizes (Killip, Mahfoud, & Pearce, 2004). The design effects for NTP and residential detox are 10.7 and 41.6, respectively (design effect = 1 + (average cluster size - 1)* ICC). These two sources of information, the likelihood ratio test and the ICC point to the need to account for clustering by program.

The mixed model includes a random intercept and a random slope. The random effect on the intercept was added at the detox program level or level two. All predictors were fixed with the exception of the "detox-to-treatment" predictor at the patient level. A random effect was added to the coefficient for "detox-to-treatment" to allow the slope to vary within program. In mixed models, the residual errors are assumed to be normally distributed with mean zero and variance to be estimated (Kreft & de Leeuw, 1998). The transition from detox to treatment is assumed here to vary within program based on circumstances of the program and patient. Finally, the parameters for the fixed effects are estimated directly and the random effects are summarized in terms of the variance that exists between programs. An unstructured variance-covariance structure was specified; the unstructured approach allows for all covariances to be estimated. For the random slope, "detox-to-treatment," the variance captured by the random effect is the variance in the slopes across programs.

The fit of the full mixed model was assessed by the Wald chi-square test. The "xtmelogit" program in Stata calculates a Wald chi-square test with degrees of freedom equal to the number of predictors in the model. To assess model fit, the chi-square for the mixed model with only the dependent variable and the random effects was subtracted from the chi-square for the full model with the predictors and random effects. A large difference implies an improved fit. The difference in the test statistics can be compared against a chi-square table with degrees of freedom equal to the difference in the number of predictors between the two models.

Selection of Patient-Level Predictors

The selection of patient-level predictors for the mixed models took place as follows. First, salient patient-level variables from those available in the dataset were identified from the literature on detox readmissions and engagement in addiction treatment. Engagement in treatment refers to individual characteristics associated with treatment entry. Second, the patient-level variables were entered simultaneously into a logistic regression predicting readmission to detox. Predictors significant at the .001 level were candidates for inclusion in the multi-level model.

Assessing Readmission Outcomes by County Networks: Exploratory Approach

In California, counties receive public funds to provide addiction treatment to low income individuals in need of treatment. From the point of state policy makers with the Department of Alcohol and Drug Programs, there is an interest in evaluating patient outcomes by county. Efforts are underway in California to identify performance measures to evaluate continuity of service from detox to treatment at the county level. One question is whether a high rate of detox-to-treatment transfers is associated with certain network structures. In other words, is it possible to identify network structures at the county level that are associated with a high level of continuity of service?

In an exploratory analysis, I calculated network measures that have been associated with network effectiveness in prior research: centralization and clustering. Because this part of the study is exploratory, the intent here is to examine both types of network structures to see what patterns, if any, emerge. Centralization and clustering imply different network structures. These two concepts are described below.

Centrality has to do with the dispersion or spread of providers within a network. Providers that receive the most nominations from other providers occupy a central and potentially powerful position in the network. Centralization is a group level measure of centrality. Centralization measures the extent to which relationships are organized around particular focal points (Friedman et al., 2007; Heflinger, 1996; Provan & Milward, 1995). It is an aggregate measure of individual actor centralities and quantifies the heterogeneity of actor centralities. The type of centralization examined in this study is out-degree centralization, which is the extent to which the out-going transfers are sent by few highly central providers.

Centralization of organizational exchanges is an indicator of service coordination and governance. In a landmark study by Milward & Provan (1995) of four mental health service delivery networks (based in four mid-size cities in the U.S.), the most effective networks, as perceived by patients, families, and case managers, were not the networks with the highest density or number of linkages, but rather the ones with high levels of centralization around a core mental health agency.

In contrast to centralization, clustering within a network implies a decentralized structure in which local clusters of programs organize service delivery amongst themselves. Clustering is a network construct that describes the extent to which networks are defined by dense groups of providers or local clusters of providers that are connected to each other. At the ego-network level, clustering is the density of the ego-network or the extent to which one's ties are connected to each other. There is a global clustering measure called the clustering coefficient, which is defined as the average of each actor's personal network density (Valente, 2010).

The global clustering coefficient is a measure of transitivity or the proportion of transitive triads within the network. Transitive triads involve a combination of links between three actors such that if actor A has a tie to actor B and B has a tie to actor C, A and C are also tied. Transitivity is a measure of network cohesion. Cohesion of service providers in clusters may facilitate coordination of care (Morrissey, et al., 1997; Provan & Sebastian, 1998).

Counties were summarized in terms of their population size, total number of programs, number of programs involved in patient transfer networks, number of detox programs specifically, and number of detox patients. With the exception of population sizes, all information is from the CalOMS 2008-2009 administrative record. The information on population sizes came from a summary document produced by the County Alcohol and Drug Program Administrators' Association of California that groups counties into four categories: large (over 800,000), medium (250-800,000), small (90-250,000), and small/rural (under 90,000) (County Alcohol and Drug Program Administrators' Association of California, 2006). In the exploratory analysis, I compared network characteristics of counties of similar size.

CHAPTER 5

PATIENTS, PROVIDERS, AND THE TRANSFERS THAT LINK THEM

This chapter has two parts. The first part describes detoxification (detox) patients in publicly funded clinics in California from 2008 to 2009. I describe their pathways through services, starting with their first detox service during the 2008-2009 year and tracking them over the course of multiple transfers to additional services. I address the question of whether some patients are more likely to transfer to rehabilitation after detox, whether in residential or outpatient programs. The second part of the chapter introduces the detox providers. I provide an overview of the differences between residential detox programs and outpatient detox programs, which are based in narcotic treatment centers. Detox programs can differ greatly in terms of their size and patient populations.

I. Patient Characteristics

Table 5.1 summarizes patient socio-demographics and treatment history. A total of 25,423 patients received at least one detox service in 2008-2009. Overall, 41,835 unduplicated detox admissions were found in CalOMS, representing 18.8% of all admissions in the 32 selected counties. There were 7,145 patients in narcotic treatment programs (NTP), which use methadone for detox and for ongoing treatment. There were 18,278 patients in residential detox programs.

Seventy-percent of detox patients are men. The population is highly diverse in terms of age; the mean age is 40 years, but patients range in age from 16 to 80 years. The largest racial/ethnic groups are white, black/African American, and Hispanic. Hispanic ethnicity includes Mexican, Puerto Rican, Cuban, and other Hispanic/Latino. Groups with too few respondents for separate analysis (Pacific Islanders, Native Hawaiians, Asian-Indians, and American-Indians/Alaska Natives) were combined into one composite group along with those who declined or for whom no response was recorded.

In terms of drug use, the majority of patients in detox services are either alcohol or heroin users. Other common drugs patients report at detox admission as primary drug problems are methamphetamine, cocaine, and other opiates (e.g., prescription pain killers). Patients, on the whole, appear to have multiple challenges. The rate of employment at either a full-time or part-time level is under 20%. More than a quarter of patients are affiliated with the criminal justice system. Furthermore, more than a quarter of patients report having had a mental illness diagnosis during their lifetime.

Age of first use of one's primary drug is another indicator of severity of drug use; that is, patients with long histories of drug abuse and addiction have a more severe substance use disorder. The mean age of first use is 20 years (s.d. =8.5). Patients who are 40 years old and older have engaged in substance use behaviors for a mean of 21.2 years (range = 5-87).

Detox patients report a mean of 2.7 prior treatment episodes; however, the median number of prior episodes is 1. With respect to detox readmissions, 23.9% of patients readmitted to detox within one year of the index detox service. Residential detox programs have a slightly higher rate of readmissions compared with NTP detox programs (24.5% vs. 22.4%, respectively).

II. Overview of Service Patterns

This section describes service patterns for patients leaving their first detox service. Service patterns are paths travelled by patients and reflect the types of ties that link patients to providers and providers to each other. Approximately 48% of detox patients did not receive a second service within 14 days of discharge. Slightly more patients in residential detox received only a detox service compared with patients in outpatient narcotic treatment (NTP) detox programs (49.5% vs. 44.6%, respectively). Overall, 27.9% of all detox patients transferred to residential or outpatient treatment within 14 days of discharge from the initial detox service. Approximately 24% of patients transferred to a second detox service. NTP detox programs have a higher rate of detox-to-treatment transfers compared to residential detox programs. Among those patients in NTP detox, 32.1% were transferred to treatment. In comparison, 26.2% of patients in residential detox were transferred to treatment directly after their detox service. Figure 5.1 illustrates service patterns by type of detox program.

Compared to prior research by Garnick et al. (2009), the overall rate of detox-to-treatment transfers in CalOMS is low. Testing the 14-day detox-to-treatment transfer measure in Connecticut, Maryland, New York, North Carolina, Oklahoma, and Washington, Garnick et al. found that the rate of patient transfers from detox to treatment ranged from 19% to 59%. In addition, a detox-to-treatment transfer rate of 18.7% was found in Delaware in 2006 and increased to 25% after a period of performance contracting by the state (Haley, et al., 2011). Chapter 7 explores the consequence for detox readmission when patients do not receive treatment directly following detox.

Table 5.1 Patient Characteristics of Detox Sample, California Outcomes Monitoring System, 2008 – 2009 (N=25,423)*

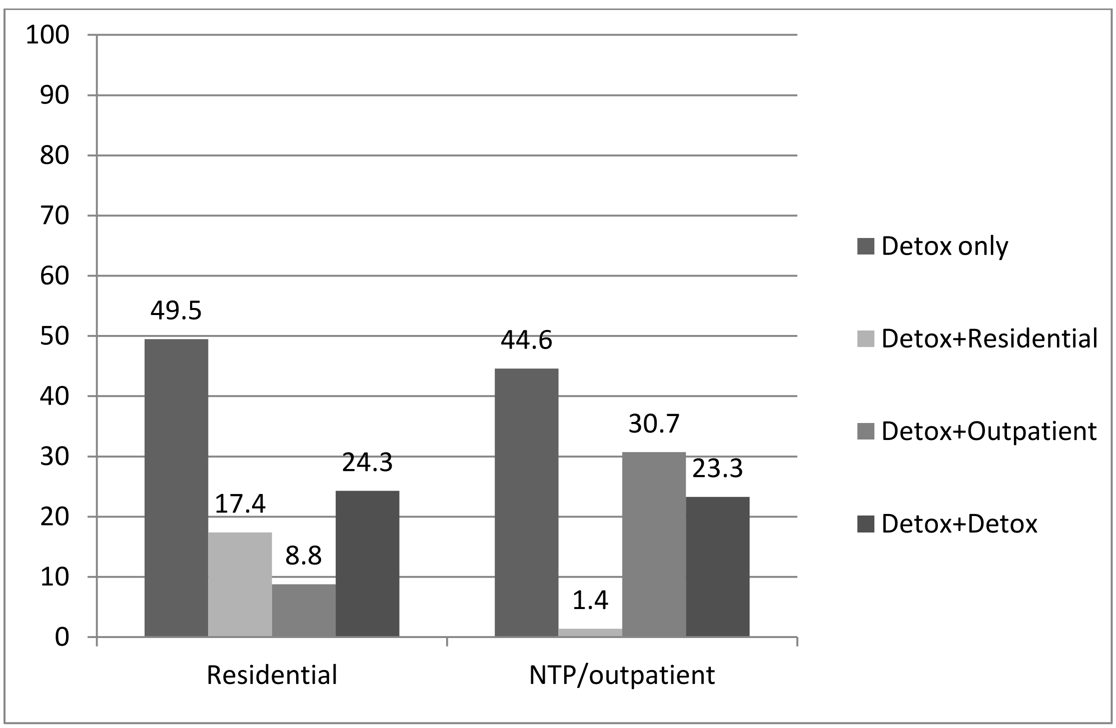
Variables	
Age at admission, mean (s.d.)	39.6 (11.5)
14-30 years, %	26.6
31-41 years, %	26.3
42-48 years, %	22.8
49-89 years, %	24.4
Male, %	70.3
Race/ethnicity, %	
White	60.8
Black/African American	15.8
Hispanic ethnicity (can be of any race)	24.3
Other race	23.4
High school education or higher, %	71.0
Employed full or part-time, %	15.4
Homeless, %	35.9
Dependent living, %	28.7
Independent living, %	35.4
Criminal justice involvement, %	
None	74.9
Is on probation	8.5
Is on parole	15.8
Other, e.g., jail, drug diversion program	.9
Treatment-related characteristics, %	
Primary drug at first admission	
Alcohol	30.7
Heroin	34.3
Cocaine/Crack	9.4
Methamphetamine	12.8
Other drugs	12.7
Medi-Cal coverage, %	18.7
Number of days of primary drug use, past 30 days	23.2 (10.4)
Any medical problems, past 30 days, %	24.1
Ever diagnosed with mental illness, %	24.4
Number of prior treatment episodes, mean (s.d.)	2.7 (7)†
Age at first use of primary drug, mean (s.d.)	20 (8.5)
Readmitted to detox within one year of index service, %	23.9

*The amount of missing data ranged from 2-190: male (n=2), Medi-Cal coverage (n=44), criminal justice involvement (n=46), ever diagnosed with mental illness (n=60), years of education (n=68), any Medi-Cal problems (n=128), and number of prior treatment episodes (n=190).

†Note: Mean number of prior treatment episodes is negatively skewed as evidenced by the standard deviation; 42% of patients indicated no prior treatment.

For patients receiving 2 to 4 services in the post-detox treatment episode, there were 100 different combinations of services that patients received; that is, combinations of residential detox, NTP detox, outpatient treatment, day treatment, short-term residential and long-term residential treatment. The most common patterns observed involved a set of 2 services, e.g., residential detox to long-term residential treatment (31.1%), NTP detox to outpatient treatment (25.2%), residential detox to residential detox (11.4%), residential detox to outpatient treatment (7.9%), and NTP detox to NTP detox (5.4%). Figure 5.1 illustrates post-detox service outcomes by type of detox.

Figure 5.1 Services Received After Discharge from Index Detox Service, by Type of Detox Program (n=24,920)*



* Data not available for 503 patients. Included here are 17,896 residential detox patients and 7,024 NTP detox patients.

Residential detox has a slightly higher rate of "detox only" admissions compared to NTP detox (49.5% vs. 44.6%, respectively). A higher proportion of NTP patients transferred to some form of treatment (residential or outpatient) than patients in residential detox (32.1% vs. 26.2%, respectively, for residential and outpatient combined). As mentioned earlier in the chapter, NTP detox programs are almost always located within NTP/methadone maintenance clinics. The co-location of detox and treatment programs facilitates transfers to treatment for many patients. While the proportion of NTP detox patients that transfer to treatment is higher than that of the residential detox patients, a slightly higher proportion of patients in NTP detox "recycle" back to detox within 14 days compared with patients in residential detox.

III. Characteristics of Patients Transferred from Detox to Residential or Outpatient Treatment

The receipt of rehabilitation care, whether in a residential or an outpatient facility, has been found to reduce readmissions to detox within a year (Mark, et al., 2006; McLellan, Weinstein, et al., 2005). Table 5.2 compares characteristics of patients transferred from detox to residential or outpatient treatment when detox was the first service documented in the administrative record. Receipt of treatment directly following detox is associated with fewer detox readmissions. The rate of readmission among patients that transferred to treatment after detox is 12.9% compared with 26% for patients that did not transfer to treatment directly after detox. It is, therefore, of interest from a policy and clinical standpoint to explore potential disparities in continuity of care after detox. This section reviews the characteristics of patients that transferred to treatment after detox.

A few socio-demographic characteristics are associated with transferring to treatment from detox. Patient characteristics associated with fewer transfers to treatment include male gender, older age, being homeless, and lack of Medi-Cal insurance. Patients that are on parole or probation at admission to detox are more likely to transfer to treatment compared with patients with no criminal justice involvement. Overall, differences in transfer rates across socio-demographic characteristics are small. The largest differences were found by primary drug. Alcohol and cocaine users are less likely to transfer to treatment, while methamphetamine and other drug users are more likely to transfer to treatment.

Table 5.2. Proportion of Patients Transferred from Detox to Residential or Outpatient Treatment within 14 days of Discharge from Detoxification, by Patient Characteristics (N=24,920)*

Characteristic, %	Transferred (n=6,944)	Not Transferred (17,976)
Gender		
Male**	25.4	74.7
Female	33.8	66.2
Age (based on quartiles)**		
14-30 years	30.8	69.3
31-41 years	30.3	69.7
42-48 years	26.1	73.9
49-89 years	23.8	76.2
Race**		
White	27.2	72.8
Black	26.1	73.9
Other	30.8	69.2
Latino**	30.9	69.1
Other ethnicity	26.9	73.1
Employed**	25.0	75.0
Unemployed	28.4	71.6
High school education or more	27.9	72.1
Less than high school	27.8	72.2
Homeless**	24.8	75.2
Independent living	28.2	71.8
Medi-Cal beneficiary**	31.2	68.8
No Medi-Cal	27.1	72.9
Primary Drug**		
Heroin	29.6	70.4
Alcohol	21.3	78.7
Methamphetamine	38.5	61.5
Cocaine	23.2	76.8
Other	31.7	68.3
Criminal justice**		
None	24.8	75.2
Is on parole	34.6	65.5
Is on probation	38.4	61.7
Readmission to detox**	12.9	28.3
No readmission	87.2	71.7
Served in NTP detox**	32.1	67.9
Served in residential detox	26.2	73.8

*Missing data on some variables ranged from 2-503: male (n=2), Medi-Cal coverage (n=44), criminal justice involvement (n=46), ever diagnosed with mental illness (n=60), years of education (n=68), any Medi-Cal problems (n=128), number of prior treatment episodes (n=190), and detox-to-treatment transfers (n=503).
** p<.001

IV. Detox Providers

Residential detox programs and NTP detox programs differ greatly by patient characteristics and type of care. First, residential detox programs collectively have more than four times the number of patients as NTP detox programs. Second, residential detox accommodates a broader range of drug use problems. NTP detox program serve almost all heroin and other opiate users because NTP detox uses methadone to detox patients. In NTP detox programs, 76.5% of patients are in detox for heroin and another 23% of patients are in detox for use of other opiates such as Vicodin and OxyContin. In contrast, residential detox programs serve patients with diverse drug use problems. Residential detox programs treat mainly alcohol users (42.5%) and methamphetamine users (34%). Table 5.3 summarizes the basic characteristics of residential and NTP detox providers.

NTP and residential detox programs have some differences with respect to the racial/ethnic backgrounds of their patients. The majority of patients in NTP and residential detox programs are white. However, blacks/African Americans are more likely to be served by residential detox programs. Latino patients, on the other hand, are more likely to be served in NTP detox programs. These differences are due to the types of drugs patients use. Among blacks/African Americans, 27.37% are in detox for alcohol and 41.15% are in detox for cocaine use. Residential detox accommodates alcohol and stimulant users. Latinos are prevalent in NTP detox because 50.85% of Latinos report heroin use as their primary drug problem.

Residential detox programs appear to serve a more severe patient population. Patients in residential detox programs are more likely to be unemployed. Unemployment is common for all detox patients, but residential detox programs have approximately 17% more patients that are unemployed. Additionally, the rate of homelessness is nearly 38% higher in residential detox programs. Residential instability is one of the determinants of patient placement in treatment (Mee-Lee, 2007). Finally, the rates of having Medi-Cal problems in the past 30 days and having a mental illness diagnosis in one's lifetime are nearly double that which is found in NTP detox programs. See table 5.3 for a comparison of residential and NTP detox settings.

Proximity to treatment programs can facilitate the transitions from detox to treatment services (Campbell, et al., 2010). The vast majority of NTP detox programs are located within organizations that have an outpatient methadone maintenance clinic (93.5%). In contrast, 72.2% of residential detox programs are located within organizations that have residential or outpatient programs or both.

Table 5.3 Characteristics of NTP/Outpatient and Residential Detox Programs (N=25,423)

Characteristics	**Outpatient/ NTP (n=7,145)**	**Residential (n=18,278)**
Patient Characteristics, %		
Male	69.5	70.6
Primary drug problem**		
Heroin	76.5	18.0
Alcohol	.3	42.5
Methamphetamine and cocaine	.2	30.8
Other (e.g., other opiates)	23.0	8.7
White	61.7	60.4
Black/African American**	8.0	18.8
Latino**	30.5	21.8
Unemployed**	72.5	89.4
High school education**	64.2	73.6
Any medical problems, past 30 days**	16.6	27.0
Lifetime mental illness**	16.0	27.7
Homeless**	8.9	46.5
Is on parole**	6.7	9.2
Is on probation**	7.5	19.0
Patient Transfers		
Detox to any treatment* **	32.1	26.2
Readmitted to detox within one year**	22.4	24.5
Organizational Characteristics (N=154)		
Part of multi-service organizations, e.g., methadone maintenance, outpatient drug-free, and/or residential**	93.5	72.2
Mean number of admissions (size of program)**	107.5 (s.d.=126)	526.0 (s.d.=863)

*The number of patients used to calculate detox-to-treatment was 24,920 because admissions data were missing for 503 patients.

** p< .001. Differences tested using chi-square tests and t-test for mean admissions.

Summary

Publicly-funded detox programs in California are diverse in terms of the type of care provided, the numbers of patients served, and the patient characteristics. NTP and residential detox programs are very different. NTP detox clinics provide medication-based detoxification for heroin and other opiate users. Residential detox programs, the majority of which are not medication based, accommodate a variety of substance use disorders. Alcohol and stimulant users are commonly found in residential detox programs.

NTP detox programs are smaller, on average, and are almost always co-located with outpatient methadone maintenance clinics. A majority of residential detox programs are located within organizations that house short- and long-term residential programs and/or outpatient drug-free programs. The next chapter examines the networks created through patient transfers between all types of treatment programs.

CHAPTER 6

PATIENT TRANSFER NETWORKS

I. Patient Transfers as Networks

The publicly funded treatment system in the United States is characterized as a collection of mostly small non-profit organizations that operate independently of each other (Chalk, 2010). Treatment providers, policy makers, and researchers rarely use the term "network" to describe a treatment system. Linkages between programs, however, are becoming increasingly important, as evidenced by the literature on continuity of care and performance measurement (Garner, Godley, Funk, Lee, & Garnick, 2010; Garnick, et al., 2009; McKay, 2009). This chapter explores the use of patient transfers to infer referral networks among treatment programs. I describe patient transfers as a social process. My perspective is informed by my conversations with treatment professionals, program evaluators, and the literature on addiction health services research.

Patient transfers result from actions taken by patients and providers. Because the present study is based on patients' movements through a system, it makes sense to consider the actions of the patients. The role of patients in coordinating transfers is obvious. Patients choose whether they want to enter a detox or treatment program and make their choices known by enrolling in a program. Patients make decisions about where to go based on their circumstances, where they live, their knowledge of what different programs have to offer, their personal preferences, and, in some cases, their ties to the criminal justice or child welfare systems. For example, one detox program administrator told me that the average wait for a residential treatment bed was 3-6 weeks. He also mentioned that most of his referrals are to outpatient programs because outpatient treatment is more convenient. Patients can maintain a normal routine while attending outpatient treatment. Patients in residential treatment programs must be fully immersed in the activities of their programs and have little freedom to work or engage in other activities outside of their programs.

Transferring to rehabilitation after detox may require patients to organize financial resources. Transportation to and from the treatment program requires coordination on a daily basis. Some patients prefer to go to detox programs on a regular basis as opposed to entering a rehabilitation program (McLellan, McKay, et al., 2005). As one of the treatment staff members I interviewed related, the patients that regularly return to her detox center are looking for "three hots and a cot," which means three hot meals and a place to sleep. As described in the previous chapter, a high proportion of patients in residential detox centers in California is homeless or has an unstable living environment.

Treatment providers, particularly counselors and case managers, also play an important role in developing patient transfer networks. Providers organize options for patients to pursue after completing their treatment program. Options after detox often involve outpatient or residential treatment programs. For example, programs may have case managers or "patient navigators" that help patients access treatment and social support services (Godley, et al., 2007; McLellan, McKay, et al., 2005). Case managers often help patients transition to additional treatment programs by obtaining the initial appointments for them and providing transportation. In some cases, providers may have no role in coordinating where patients go for additional treatment. It is worth mentioning that treatment programs are not mandated by the state or accreditation boards to transfer patients from one service to another. Rather, transfer activity on the part of providers is largely voluntary.

The extent to which providers play a role in organizing patient transfers is not discernible from the administrative record. The discharge record may show that a patient was referred, but, because the program receiving the referral is not identified in the record, one cannot confirm that the patient transfer took place as planned by the provider. In sum, evidence suggests that patient transfers from one service to the next are the result of a combination of both patient and provider factors.

Patients may only visit one or two providers over the course of a year, but when patient transfers are aggregated, these transfers reflect an image of the treatment system. The more patients engage in transfers, the more ties programs have with each other. Through the lens of patient transfers, one can study the size and structure of treatment networks. One can determine how many providers are tied through patient transfers. If transfers are common among providers, networks will be dense with multiple ties between providers.

II. Description of Networks

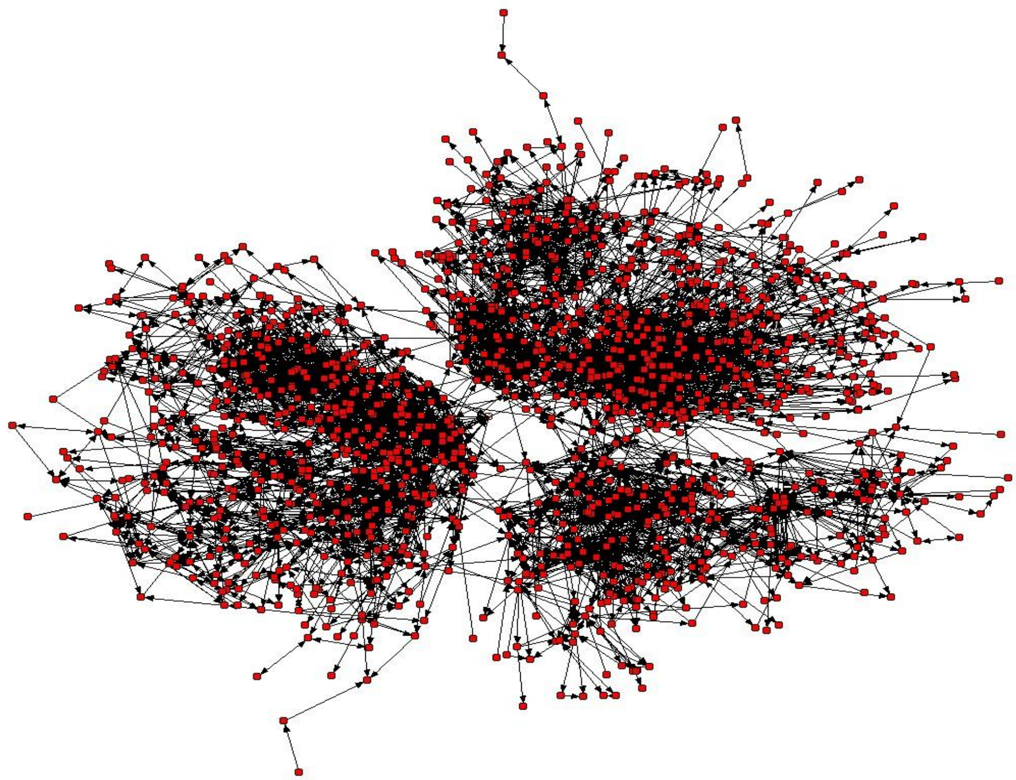
A total of 25,090 transfers were observed in the 32-county dataset. The total number of treatment programs, i.e., service delivery units, in the 32 counties is 1,600. Of the total, 1,370 programs or 85.6% have at least one patient transfer. Nineteen of these programs are isolated, meaning their patients did not transfer out to another program, but instead came back to the same program. The proportion of programs with network ties after subtracting the nineteen isolates is 84.4%.

The majority of the programs located in the patient transfer networks are outpatient programs (53.0%) and long-term residential programs (23.0%). These programs are the most common in the treatment system in general (Rawson et al. 2008). Detox programs comprise 11.2% of all programs in the patient transfer dataset.

Network Bounding

The first decision of a network analysis involves identifying the network boundaries. This process is called "network bounding." Given that treatment services are organized by county, it is natural to question whether counties represent boundaries for patient transfer networks. Counties are certainly important from an administrative and policy standpoint. The California Department of Alcohol and Drug Programs disperses federal and state funds to each county for alcohol and drug treatment and prevention services. Program evaluations are often conducted at the county level. If networks are contained in counties, then comparative analyses could be conducted just as Provan and Milward (1995) compared the structural properties of service provider networks from four cities. In order to answer this question, I first mapped the entire set of patient transfer data from the 32 counties to explore the presence of sub-networks.

Figure 6.1. Patient Transfers Networks across 32 Counties (n=1,329)*



* 1,329 programs (97% of total) are in the largest weak component.

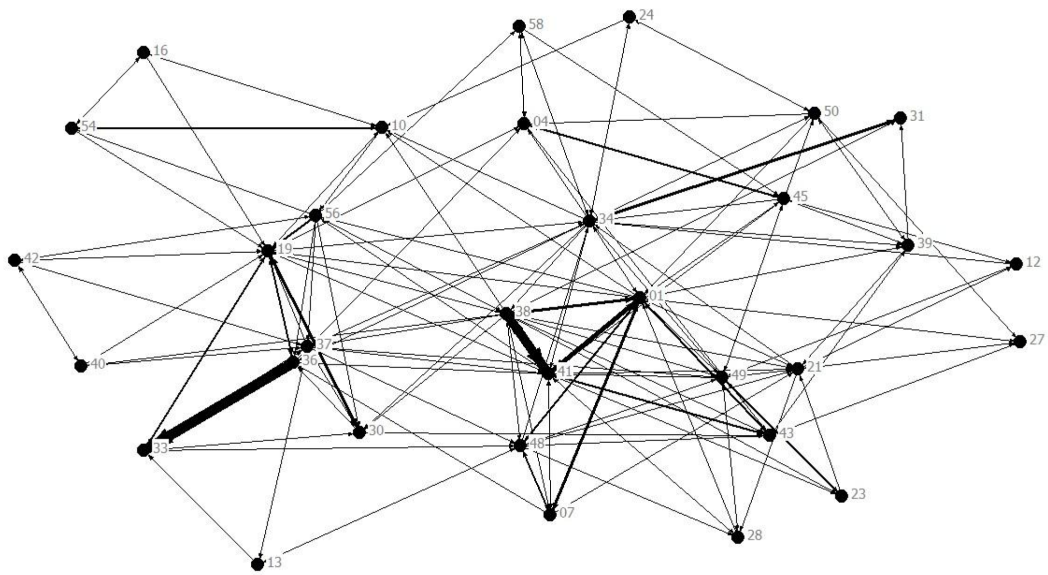
A components analysis identifies the number and size of sub-regions within the entire network. A sub-region or component contains a set of actors that are connected to each other; that is, there is a path between all actors in the component and no path between actors in the component and actors not in the component (Wasserman & Faust, 1994). Figure 6.1 shows what is called a "weak" component, meaning that every actor is connected, but the directions of the paths are ignored. There are a total of 1,329 or 97% of all programs in the entire transfer dataset that are contained in one large weak component. There are a total of 31 weak components in the dataset. Thirty weak components consist of only 1-2 programs. Components with one program are basically "self-loops," which occur when patients transfer back to the same program. Based on the finding for weak components, one can see that networks can expand well beyond counties lines. How connected the programs are to one another is unclear from the analysis of weak components.

Components that contain actual paths between programs based on the direction of the ties are called "strong" components. With strong components, direction of ties is taken into account. That is, if program A and program B are in a strong component together, patients in program A can transfer to program B and then transfer back to program A because there is a path between the two programs. One main strong component in the dataset was found containing 1,028 or 75% of the programs or 75% of the programs. All 32 counties are represented in the main strong component, which again raises the question of how to bound the networks.

All 32 counties are connected by at least a few patient transfers. Figure 6.2 illustrates the inter-county networks. See Appendix A for a list of counties by name and county code. The thickness of the lines represents the volume of patient transfers. There are some counties that exchange a lot of patients, e.g., #33 and #36 are Riverside and San Bernardino counties; #38 and #41 are San Francisco and San Mateo counties. Inter-county transfers are based on geographic proximity and availability of services (see Ford & Zarate (2010) as an example of a joint endeavor between services in Ventura and Los Angeles counties).

While there is evidence of inter-county transfers within the substance abuse treatment sector, it is important to examine the extent of the inter-county transfer activity. If the bulk of the patient transfers are within counties, there may be support for bounding networks by county. An analysis of within county and outside county transfers was conducted. The result was that the vast majority or 96.6% of transfers occur within counties. This finding suggests that counties may be meaningful network boundaries.

Figure 6.2. Inter-County Network in California (n=32), CalOMS 2008-2009



*Note: Line widths represent the strength of ties. The minimum number of transfers is 5 and the maximum is 25.

III. Moving from Macro to Micro: Ego-Networks as Local "Neighborhoods"

Patient transfers were bounded by county. However, coordination of care between programs was assumed to take place at the local level based on the analysis of service provider networks by Provan and Sebastian (1998) and Morrissey, Johnsen, and Calloway (1997). County networks were used to measure the size and structure of programs' ego networks. An ego network is the immediate "neighborhood" of a program based on the program's direct ties. Direct ties are one's "neighbors" because they are close by or reachable within one step.

Table 6.1 lists the number of undirected and out-going ties by program type. Undirected ties are ties between two programs without regard for which program sent or received the transfer. An out-going tie signals the direction in which the patient is travelling, e.g., the patient leaves one program and is admitted to another program. Also included in the table are the densities of undirected and out-going ties, again by program type. Density is the proportion of actual ties that exist, e.g., transfers, relative to the total possible ties. For example, if a detox program is tied to 4 other programs in its ego network, the number of possible ties among the detox program's neighbors is 12 or 4(4-1). The density of the detox program's network is 4/12 or 33.3%. Ties and density of ties correspond to the programs' ego-networks and are averages of all of the program's values for each type of program, e.g., residential, outpatient, and residential detox.

Residential detox programs have the highest number of undirected ties, more than twice the amount of every other group. On average, patients transfer in and out of residential detox more than any other type of program. Residential detox programs are not as numerous as other types of programs in the treatment system; however, residential detox programs can be considered "hubs" in the overall network. As seen in the previous chapter, residential detox programs have an average size of 526 admissions. The number of ties a program has to other programs is strongly associated with its number of admissions ($r=.86$, $p<.001$, $N=154$).

Table 6.1 Provider Ties Based on Programs Involved with Patient Transfers, CalOMS 2008-2009 (n=1,370)

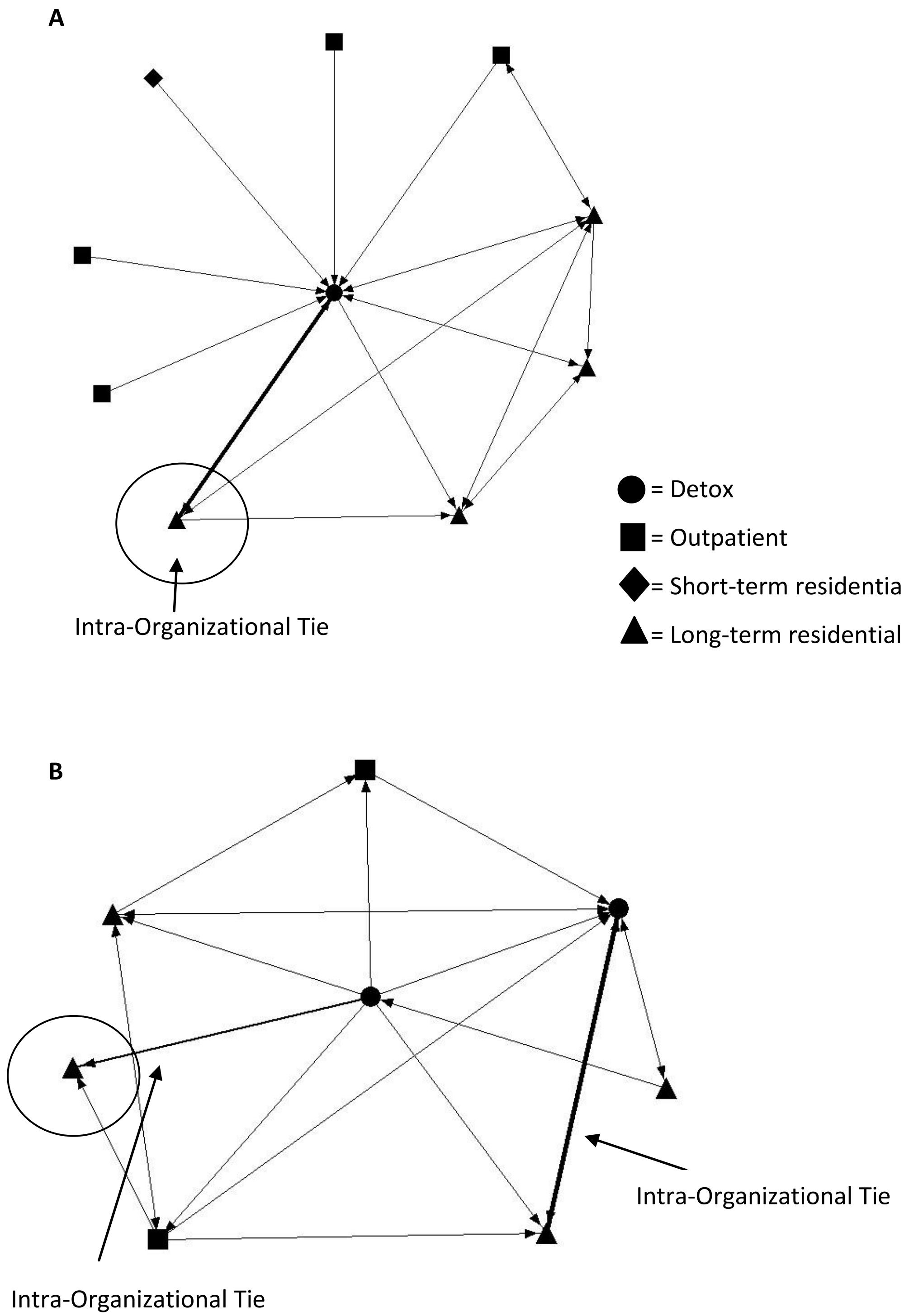
		Undirected		Out-Neighborhood	
Program Type	**# Programs**	**Ties Mean (s.d.)**	**Density Mean (s.d.)**	**Ties Mean (s.d.)**	**Density Mean (s.d.)**
Outpatient Treatment	726	6.64 (5.53)	20.36 (22.53)	4.08 (3.92)	23.29 (25.38)
Day Treatment	149	3.95 (3.26)	23.77 (28.92)	2.64 (2.41)	29.22 (31.02)
NTP Detox	99	4.77 (4.24)	21.93 (21.04)	3.42 (3.15)	30.26 (27.29)
Residential Detox	55	18.55 (18.36)	21.70 (19.32)	12.35 (11.98)	25.42 (21.51)
Short-Term Residential	26	5.23 (4.9)	30.25 (32.80)	2.88 (2.94)	24.32 (31.88)
Long-Term Residential	315	8.44 (6.67)	24.27 (22.28)	4.94 (4.65)	27.65 (27.10)
Total	**1,370**	**7.08 (7.06)**	**21.9 (23.31)**	**4.38 (4.83)**	**25.50 (26.56)**

The program group with the lowest number of undirected ties is short-term residential, which also has the highest density based on ego-networks. Based on a density of 30.25, we can say that, on average, 30.25% of programs connected to short-term residential through in-going or out-going ties are connected to each other. Density is often negatively associated with number of ties because as the number of actors increases in a network, the harder it becomes for each actor to have ties with all of the other actors.

In the context of patient transfers, the treatment professionals I spoke with reported referring patients to an average of 4.3 treatment programs. When detox programs are situated within organizations that also have outpatient or residential programs, these ties are stronger because many detox patients can transfer to these services within the organization. In the two ego-networks shown in Figure 6.3, we can see that while the detox programs in the center of the graphs have multiple ties to other programs, the thicker lines are between programs within the same organization.

Figure 6.3 illustrates the concept of density. Both detox programs have a similar number of admissions, but a different numbers of out-going ties. Program A has 147 admissions and Program B has 143 admissions. Following the arrows, we can see that Program A has 4 out-going ties or an “out-degree” of 4. Program A’s network of out-going ties has a density of 66.7 (8 out-going ties out of 12 possible out-going ties). Program B has 6 out-going ties and a density of 36.7% (11 out-going ties out of 30 possible ties).

Figure 6.2. Ego-Networks of Two Detox Programs of Similar Size, CalOMS 2008-2009



IV. Inferring Inter-Organizational Ties from Patient Transfer Networks

Patient transfers represent information about the actual services received by patients. Do these transfers represent referral relationships between providers? The question of whether patient transfers represent interorganizational ties is explored in this section. Several methods were used to address this question. First, I interviewed a sample of 19 treatment professionals by phone to identify their main referral sources and document their procedures for making referrals. Eight of the programs had a low number of patient transfers (bottom 20th percentile) and eleven programs were in the top 20th percentile. Second, I attempted to corroborate patient transfers using a question in the discharge record that measures whether the patient was referred at the time of discharge.

At the outset of this chapter, I expressed my view that patient transfers result from a combination of patient and provider actions. The aim here is not to use the self reports of treatment professionals or discharge records to validate referral ties. Rather, the triangulation of patient transfers, self-reports, and discharge records is useful for understanding the coordination of services as well as the utility of administrative data for evaluating continuity of service.

Combining results from codes 1, 3, and 5, 67.8% of transfers were coded as a referral at discharge. See table 6.2 for a list of discharge status categories and frequencies for each. Fourteen patients had discharge statuses of death and 161 were recorded as being incarcerated. In these cases, it is very likely that the patients dropped out of the programs prematurely. If patients drop out of a program, treatment counselors commonly keep the patients' files open for 30 days or more in case the patients return. Counselors may make follow up calls to the patients to determine the patients' status before closing out the files. In these cases, the counselors complete a discharge record after 30 days or more since the last contact with the patient. For about 5% of cases in the administrative record, discharge dates come after the admission to the next service.

Table 6.2. Discharge Status for Patient Transfers (n=16,322)*

Discharge Status	% (n)
1. Completed treatment and referred	37.9 (6,181)
2. Completed treatment/not referred	6.2 (1,009)
3. Left before completion with satisfactory progress and referred	19.5 (3,188)
4. Left before completion with satisfactory progress /not referred	7.1 (1,157)
5. Left before completion with unsatisfactory progress and referred	10.4 (1,703)
6. Left before completion with unsatisfactory progress /not referred	17.8 (2,908)
7. Death	.1 (14)
8. Incarceration	1.0 (162)
Total	100.0

* This frequency includes patients that were transferred after their first service in the record.

While the majority of patient transfers were coded as receiving a referral at the time of discharge, it is difficult to determine whether the patients actually went to the places they were referred to. In the interviews, I asked staff members to nominate up to five addiction treatment programs that they referred patients to recently. Several respondents told me about other types of places they referred patients to such as mental health providers and halfway houses. While I recorded this information, I was only able to confirm ties to publicly funded addiction treatment programs because only those programs funded by alcohol and drug treatment agencies are included in the dataset. For each program nominated, I found its identification code in the master list and then scanned the ego network graphs to see if the program was present. I made note of the number of transfers shared by each pair of programs.

I found that 53.6% of the programs nominated by my respondents were confirmed as ties in the programs' ego networks. Programs with the most ties, or those programs in the top 20th percentile for patient transfers, had a higher percentage of confirmed ties compared with programs in the bottom 20th percentile (65.8% vs. 36.9%, respectively). In reaction to this finding, I questioned whether there were any differences in referral procedures that may explain the differences in number of confirmed ties.

First it is necessary to explore the why some programs have few ties and others have many ties. A few potential patterns emerged from the interviews. First, the programs in the bottom 20% are much smaller than those programs in the top 20%. The average number of patients served by programs in the bottom 20% is 64.9 (range = 3 - 259), compared to an average of 441.2 patients in programs in the top 20% (range = 32 - 1,666). The median number of ties to other programs for the programs in the bottom 20% is 2, while the median number of ties for the programs in the upper 20% is 13. With more patients, a program has more potential to transfer patients to a variety of places. Patients often have unique circumstances that dictate the type of place and location where they can go for services, e.g., homeless, co-occurring substance abuse and mental health disorders, or mothers with children.

If NTP detox programs have in-house methadone treatment and have less of a need for ties to other treatment programs, residential detox programs tend to have a high number of outgoing ties. Three of the programs in the top 20% sample are residential detox programs. Two of the three have a very high volume of admissions, e.g., 1,539 and 1,666 admissions. There is one NTP detox program in the top 20% sample, but this facility is larger, with 292 admissions.

Program size and treatment modality are two program characteristics that may determine number of referral ties. Available resources for referrals may be another important factor. While some patients in NTP detox or maintenance could benefit from outpatient counseling, one provider told me that Medi-Cal—the Medicaid program in California—will not pay for outpatient counseling in addition to methadone maintenance.

Another example of limited resources came from a supervisor in a residential treatment program funded by the Veterans Administration. The clinical supervisor at this program told me that, while outpatient treatment may benefit the men who complete residential treatment, he does not know of any affordable outpatient services in his area. The veterans in this particular residential program are not insured for additional treatment on an outpatient basis. Moreover, these patients do not have the financial resources to pay for care themselves. Most of the veterans served in this program are homeless and the residential program has to refer them to shelters or halfway houses at discharge if the patient does have access to subsidized housing through a Section 8 housing program.

As I mentioned earlier in the chapter, patients have a role in coordinating where they go for care. Programs may have many ties based on outgoing transfers, but do programs have relationships with all of the places they are tied to? What I found is that programs tend to have strong ties to a few places, with strong ties defined as the exchange of multiple transfers. The average number of strong ties among programs in the bottom 20% is 1.1. Programs in the top 20% have an average of 3.2 strong ties.

Programs within an organization tend to be strong ties, which is to be expected because close proximity can facilitate transitions. Stronger referral ties between programs, however, are facilitated through social interaction. Linkages between programs can be facilitated by frequent contact between staff members and cooperation. Nine of the eleven programs in the top 20% have procedures in place to help patients make it to the next service or, as two staff members told me, to help patients “stay plugged in” and “transition without a break.”

Referral procedures in the nine programs involve assessment of the patient’s needs, identifying programs with availability, and communication with the referral source. A staff member from a residential detox program in San Mateo County described having a strong relationship with a residential treatment facility in their area. In fact, the administrative record shows over 100 transfers between the two programs. Every two days, staff from this detox program transports clients to the residential facility for an intake assessment. Patients are then put on a waiting list for residential treatment, but detox patients are given top priority. Because of the relationship the detox facility has built and the frequent interaction at the residential facility, many of the detox program’s patients receive continuity of service at the residential facility.

Evidence of active coordination of care was also found at a residential detox program in Sacramento. This detox program is also in the top 20%. At the detox program in Sacramento, the staff member told me that during the discharge process, counselors call their referral sources and talk to a program manager to identify availability. If the program manager confirms availability, the treatment counselors ask the program manager to hold the patient’s slot and subsequently coordinate transportation to help the patient get to the program. My respondent from the Sacramento detox program told me that counselors are “constantly coordinating with other programs.”

Unconfirmed Ties

It is unrealistic to expect that treatment professionals are aware of all their ties to other programs. Patients can access other treatment services without a referral; therefore, it is possible for patient transfers to occur between programs that do not have a relationship. Moreover, patients may be referred to a particular program, but choose to go elsewhere.

The difference between actual ties as represented by patient transfers and perceived ties reported by program staff members represents the number of programs beyond the staff members' "horizon of observability." Friedkin defines "horizon of observability" as "a distance in a communication network beyond which persons are unlikely to be aware of the role performance of other persons" (Friedkin, 1983).[6] If the difference is negative, programs may have fewer actual ties than they think based on transfers. If the difference is positive, programs have more actual ties than they realize. Programs in the bottom 20% had slightly more perceived ties to substance abuse treatment programs than actual ties. The average difference for the bottom 20% was -1 (range = -5, 4). In contrast, programs in the top 20% had on average difference of 26 ties (range = 3, 183). If direct ties can lie beyond one's horizon of observability, indirect ties most certainly do. Despite the fact that treatment professionals are unaware of some of the places where their patients receive care, network ties, whether present or absent, may exert an influence on a program's performance.

[6] Friedkin examines this concept in relation to social control within networks, i.e., how close do actors need to be to one another for those ties to function as a source of informal social control. I borrow the term "horizon of observability" here, but use it to suggest the limits of staff members' awareness of other treatment programs as referral sources.

Summary

Transfers are the result of social interaction among treatment professionals and among treatment professionals and their patients. Based on the interviews with program staff members, frequent interaction between programs and coordination of patient transfers may explain why some programs have more transfers than others. There are several other factors that can influence the number of patient transfers from one program to another: treatment modality or type, program size, availability of services, and patient resources.

Residential programs tend to have a higher number of transfers, particularly if they have access to other treatment programs within the same organization. Residential detox programs can serve a high number of patients because of the short duration of these detox services. Higher turnover leads to higher transfers to residential or outpatient rehabilitation programs.

Provider networks with more confirmed ties suggest a high level of coordination on the part of programs and patients. Moreover, programs that have many patient transfers and a small number of strong ties may enjoy a certain level of efficiency in terms of linking with treatment programs. It is possible that strong ties broker a variety of indirect ties that may be critical for organizing continuity of service. The influence of network size and structure on readmissions to detox is explored in the next chapter.

CHAPTER 7

A MULTI-LEVEL MODEL OF DETOX READMISSIONS

This chapter addresses the question of whether the structure of treatment program networks influences readmissions to detox. The analysis was guided by the hypothesis that greater efficiency in detox programs' networks, or fewer redundant ties, is associated with lower odds of readmission to detox within one year. To build a multi-level model that includes salient predictors of readmission at the patient level, I first conducted separate logistic regression analyses for narcotic treatment programs (NTP detox) and residential detox programs. I ran separate models for NTP detox and residential detox because these two contexts are qualitatively different in terms of patient population, service modality, program size, and patient transfer networks. Tables 7.1 and 7.2 list the results from the patient-level models. Next, I specified binary mixed models for NTP and residential detox programs with patient and program-level predictors. The results from the mixed or multi-level models show the impact of network structure on readmission, controlling for patient-level characteristics.

I. Patient-Level Predictors of Readmission to Detox within One Year

<u>NTP Detox Programs</u>

In the NTP detox patient-level model, several demographic variables were significantly associated with readmission to detox. I summarize the socio-demographic predictors first. Males have 25% higher odds of readmission than females. No differences by race/ethnicity were present. Patients aged 42-48 have a higher odds of readmission compared with patients under 30 years old. No other differences were found by age. Being employed at admission to detox is associated with a lower odds of readmission. Educational attainment is not associated with readmission. Last, a stable living environment, even on a short-term basis, reduces one's odds of readmission to detox. Patients living in an institutional setting or in a halfway house, i.e., "dependent living," have lower odds of readmission compared with patients that are homeless. Similarly, independent living, e.g., having one's own apartment, is associated with lower odds of readmission compared with patients that are homeless.

Patient severity is predictive of readmission to detox. Patients with a history of drug addiction tend to be more severe (Dennis, Scott, Funk, & Foss, 2005). Prior treatment in one's lifetime is a measure of addiction history and it reflects the chronic nature of drug use disorders. Patients reporting prior treatment in their lifetime have almost 25% higher odds of readmission. Another proxy for severity of drug addiction commonly used in outcome evaluations is the frequency of primary drug use or the number of days used the 30 days prior to admission. The results show that with each additional day of drug use, a patient's odds of readmission increase by 31%. Co-occurring mental health or Medi-Cal problems compound problems of addiction; however, neither of these co-occurring conditions is associated with readmission for NTP patients.

In addition to individual-level factors that may predispose patients to readmission, one's access to methadone maintenance at an NTP program—the most common form of treatment for patients with opiate dependence—appears to impact one's odds of readmission to detox. For example, having Medi-Cal coverage is associated with lower odds of readmission. Medi-Cal coverage facilitates access to methadone maintenance treatment. In addition, transferring from detox to treatment within 14 days of discharge is strongly associated with much lower odds of readmission compared with detox patients that did not transfer to treatment directly following detox. Results from the NTP detox model are summarized in table 7.1.

Residential Detox Programs

The patient population in residential detox programs differs from the patients in NTP detox programs. As a result, predictors of detox readmission vary by program type. For instance, residential detox programs have more patients who are black than NTP detox programs. A disparity by race emerged in the patient-level model for residential detox. Patients who are black have more than 50% higher odds of readmission than whites (OR=1.59, 95% CI: 1.43, 1.76). Being a member of a Hispanic ethnic group, e.g., Mexican or Mexican-American, was not associated with readmission.

Several predictors in the residential detox model are similar to the NTP detox model. First, men have 1.4 times the odds of readmission for women. Second, employment is protective of readmission. If employed full or part time, the odds of readmitting to detox are .75 times the odds of residential detox patients that are unemployed. Homelessness is associated with higher odds of readmission. Prior treatment and having a lifetime mental illness are both associated with readmission. In contrast to the NTP model, being on probation is association with lower odds of readmission among residential detox patients. Patients on probation have lower odds of readmission compared with patients that have no involvement with the criminal justice system. Another difference between residential detox and NTP detox models is that Medi-Cal coverage is not a significant predictor of readmission for residential detox patients.

The residential detox programs treat a variety of drug use disorders. Primary drug problem was included as a predictor in the residential detox model. The results suggest that heroin users appear to be at a disadvantage in residential detox programs. Patients in detox for alcohol, methamphetamine, or other opiates had lower odds of readmission. The odds of readmission were no different for cocaine than for heroin. Receipt of an opiate replacement medication in residential did not impact one's odds of readmission. On the other hand, taking medications other than opiate replacement therapies, e.g., antabuse for alcohol dependence, was associated with lower odds of readmission. As with the NTP model, being transferred from residential detox to some form of rehabilitation reduces one's odds of readmission. The effect is stronger for NTP than for residential as evidenced by the lower odds ratio (OR=.24 vs. OR=.6, respectively).

In sum, the hypotheses related to male gender and higher frequency of drug use in the 30 days prior to admission were supported in both the NTP and residential detox models. Support for the criminal justice hypothesis was found in residential detox programs only and only for patients on probation. Medi-Cal coverage was associated with lower odds in NTP detox, but not in residential detox. Finally, with respect to continuity of service after detox, a strong association was found between transferring to rehabilitation from detox and lower odds of readmission. Results from the residential detox model are summarized in table 7.2.

Table 7.1. Results from Logistic Regression Predicting Readmission for NTP Detox Programs, Patient Characteristics at Admission, CalOMS 2008-2009 (n=7,145)[*]

				95% CI for OR[**]	
	Coefficient	**SE**	**OR**	**Lower**	**Upper**
Male vs. female	.23	.07	1.3	1.1	1.4
Race/ethnicity					
Black vs. white	-.01	.12	.99	.78	1.26
Other race vs. white	.10	.10	1.10	.90	1.33
Latino ethnicity vs. not	.003	.10	.99	.82	1.20
Age group					
Age 31-41 vs. under 30	.04	.09	1.04	.88	1.24
Age 42-48 vs. under 30	.28	.09	1.32	1.10	1.58
Age 49+ vs. under 30	-.03	.09	.97	.81	1.16
Currently employed vs. unemployed	-.19	.07	.82	.71	.95
High school education or higher vs. less than high school	.01	.07	1.01	.89	1.15
Current criminal justice involvement (c.j.)					
Is on parole vs. no c.j. involvement	.26	.12	1.29	1.03	1.62
Is on probation vs. no c.j.	-.001	.12	1.00	.79	1.26
Incarcerated vs. no criminal justice	-.22	.33	.80	.42	1.54
Living situation					
Dependent living vs. homeless	-.59	.12	.55	.44	.69
Independent living vs. homeless	-.41	.11	.66	.54	.82
Medi-Cal beneficiary vs. not	-.22	.09	.80	.68	.95
Addiction severity					
Any prior treatment in lifetime vs. none	.24	.07	1.28	1.12	1.45
Days of primary drug use, past 30 days	.01	.00	1.30	1.11	1.55
Age of onset, primary drug	-.01	.004	.99	1.10	1.54
Lifetime mental illness vs. none	-.06	.09	.94	.79	1.13
Any medical problems, past 30 days	-.13	.09	.88	.74	1.04
Treatment					
Transferred from initial detox to treatment vs. not	-1.62	.17	.24	.19	.29

[*] Sample was reduced by 286 cases to 6,857 due to missing data.

** OR=odds ratio, SE=standard error, CI=confidence interval

Table 7.2. Results from Logistic Regression Predicting Readmission to Detox for Residential Detox Programs, Patient Characteristics at Admission, CalOMS 2008-2009 (n=18,278)*

				95% CI for OR**	
	Coefficient	**SE**	**OR**	**Lower**	**Upper**
Male vs. female	.35	.04	1.42	1.30	1.54
Race/ethnicity					
Black vs. white	.46	.05	1.59	1.43	1.76
Other race vs. white	.03	.06	1.03	.91	1.16
Latino ethnicity vs. not	-.08	.05	.92	.82	1.03
Age group					
Age 31-41 vs. under 30	.15	.05	1.16	1.04	1.29
Age 42-48 vs. under 30	.17	.06	1.19	1.06	1.33
Age 49+ vs. under 30	.12	.06	1.13	1.002	1.27
Currently employed vs. unemployed	-.29	.07	.75	.65	.85
High school education or higher vs. less than high school	.06	.04	1.06	.98	1.15
Current criminal justice involvement (c.j.)					
Is on parole vs. no c.j. involvement	-.13	.07	.88	.77	1.0
Is on probation vs. no c.j.	-.21	.05	.81	.73	.89
Incarcerated vs. no criminal justice	-.15	.24	.86	.54	1.36
Living situation					
Dependent living vs. homeless	-.37	.05	.69	.63	.75
Independent living vs. homeless	-.40	.05	.67	.61	.74
Medi-Cal beneficiary vs. not	.16	.05	1.17	1.07	1.29
Primary drug problem					
Alcohol vs. heroin	-.22	.06	.80	.72	.90
Methamphetamine vs. heroin	-.48	.07	.62	.54	.71
Cocaine vs. heroin	.03	.07	1.03	.89	1.19
Other opiates/drugs vs. heroin	-.52	.09	.59	.50	.70
Addiction severity					
Any prior treatment in lifetime vs. none	.42	.04	1.53	1.42	1.65
Days of primary drug use, past 30	.01	<.01	1.01	1.00	1.01
Age of onset, primary drug	-.01	<.01	.99	.99	1.0
Lifetime mental illness vs. none	.15	.04	1.16	1.07	1.26
Any medical problems, past 30 days	.11	.04	1.11	1.02	1.21
Current treatment					
Transferred from initial detox to treatment vs. not	-.69	.05	.50	.46	.55
Taking opiate replacement medication for treatment vs. no medication	.21	.12	1.23	.98	1.55
Taking other medication for treatment, e.g., antabuse, vs. no medication	-.30	.05	.74	.66	.82

*Sample was reduced by 683 cases to 17,589 due to missing data.

** OR=odds ratio, SE=standard error, CI=confidence interval

II. Estimating the Impact of Network Structure on Readmission to Detox

Significant variation in detox readmissions was found between detox programs as evidenced by the intra-class correlation and the likelihood ratio test. The multi-level models described in this section take into account the nested structure of the data. Not only are patients nested within detox programs, but also within interorganizational networks. In what follows is a summary of results for NTP detox first and residential detox second.

<u>NTP Detox Programs</u>

Results from the NTP detox model are summarized in table 7.3 At the program level, network efficiency is negatively associated with readmission. Patients that receive detox services in NTP programs with fewer redundant ties have .34 times the odds of readmission than patients in programs that are more constrained by redundant ties (95% CI: .14, .82). Contrary to my expectations, out-degree or the number of out-going ties to other programs, is associated with higher odds of readmission (OR=1.14, 95% CI: 1.09, 1.19).

Several patient-level predictors remain associated with readmission to detox in the mixed model. Men have higher odds of readmission compared with women (OR=1.25, 95% CI: 1.09, 1.44). Patients who are 42-48 years old have higher odds of readmission compared with patients under 30 years (OR=1.26, 95% CI: 1.04, 1.52). Increasing educational attainment still has a small influence on readmission. Homelessness and employment are no longer significant predictors.

Medi-Cal coverage remains one of the stronger patient-level predictors of readmission to detox among NTP patients. Patients with Medi-Cal have substantially lower odds of readmission compared with patients without coverage (OR=.82, 95% CI: .68, .99). All of the patient severity measures, as measured by the number of days of primary drug use in the past 30 days, age at first use of primary drug, and prior treatment are no longer significant in the mixed model. Transferring from detox to rehabilitation remains significant, but the magnitude of the effect is slightly diminished compared with the patient-level model. Patients that transfer to rehabilitation have one fourth the odds of readmission compared with patient that do not transfer (OR=.25, 95% CI: .19, .32).

<u>Residential Detox Programs</u>

The results of the residential detox model are shown in table 7.4. The influence of network efficiency is also negatively associated with readmission for residential detox patients. Patients that receive detox services in programs with fewer redundant ties have .25 times the odds of patients in programs that are more constrained by their network (95% CI: .08, .83). In contrast to the NTP model, out-degree or the number of out-going ties, are not associated with the odds of readmission.

In contrast to NTP detox programs, which almost always have an outpatient methadone maintenance treatment program within the same organization, 72% of residential detox programs have treatment programs within the same organization. These ties to treatment programs within the organization are referred to in the model as intra-organizational ties. The presence of intra-organizational ties to treatment services, therefore, was added to the residential detox multi-level model. Contrary to expectations, however, having ties to treatment services within the same organization as the detox programs was associated with readmission, after controlling for other predictors in the model.

Many of the patient-level predictors that were significant in the level one model remain significant in the multi-level model; however, the effects are slightly diminished in the multi-level model. Patients that have their own place to live, either an apartment or a house, have .78

times the odds of readmission compared with individuals that are homeless (95% CI: .71, .87). Patients in a dependent living situation also have lower odds of readmission compared with homeless patients, but the effect is smaller than that for independent living. The odds of readmission among blacks are approximately 15% higher than the odds for whites (95% CI: 1.03, 1.29). As a group, patients of Asian, American Indian/Alaska Native, and other racial/ethnic backgrounds have lower odds of readmission compared with whites. Transferring from detox to rehabilitation remains a significant predictor of readmission for patients in residential detox programs (OR=.58, 95% CI: .47, .71).

As with the patient-level model, heroin users appear to be at a disadvantage in residential detox programs. Patients with alcohol, methamphetamine, cocaine, and other opiate drug use disorders have significantly lower odds of readmission compared with heroin users. The odds ratios for non-heroin users range from .54 to .73. In addition, the use of opiate replacement therapy such as methadone in residential detox does not appear effective in preventing readmission. Patients that are prescribed opiate replacement therapies in residential detox have more than 50% higher odds of readmission on average compared with patients not taking opiate replacement medications (OR=1.56, 95% CI: 1.19, 2.03). This relationship between opiate replacement therapies and readmission is not present in the standard logistic regression.

A shift also occurred with non-opiate medication as well. In the standard logistic regression, medication use for non-opiate disorders was associated with lower odds of readmission. In the multi-level model, however, the direction of the association changes and use of medications for non-opiate disorders is associated with higher odds of readmission (OR=1.21, 95% CI: 1.01, 1.46).

Several patient severity predictors were significantly associated with readmission in residential detox programs. Prior treatment in one's lifetime, more frequent use of the primary drug in the 30 days prior to detox, and having a lifetime mental illness all increase a patient's odds of readmission. The transfer from detox to rehabilitation care, however, is associated with lower odds of readmission, even after patient severity is accounted for.

Table 7.3. Results from the Binary Mixed Model Predicting Readmission for NTP Detox Programs, CalOMS 2008-2009 (n=7,145)*

NTP Detox Programs, Model fit: χ^2 = 109.4 (DF=15), p<.001				
FIXED EFFECTS	**β**	**S.E.**	**OR**	**95% CI****
Ego-networks (n=99)				
Efficiency	-1.10	.46	.34	.14, .82
Degree	.13	.02	1.14	1.09, 1.19
Gender				
Male vs. female	.24	.07	1.25	1.09, 1.44
Age group				
Age 31-41 vs. under 30	-.01	.09	.99	.82, 1.18
Age 42-48 vs. under 30	.23	.10	1.26	1.04, 1.52
Age 49+ vs. under 30	-.08	.09	.92	.77, 1.11
Employed vs. unemployed	-.07	.08	.93	.80, 1.09
High school education or higher vs. less than high school	.13	.07	1.14	.99, 1.32
Living situation				
Dependent living vs. homeless	-.18	.14	.83	.63, 1.10
Independent living vs. homeless	-.04	.13	.96	.74, 1.25
Medi-Cal beneficiary vs. no	-.20	.10	.82	.68, .99
Addiction Severity				
Any prior treatment in lifetime vs. none	.10	.07	1.1	.96, 1.28
Days of primary drug use, past 30 days	.14	.09	1.15	.96, 1.39
Age of onset, primary drug	-.003	.004	1.0	.99, 1.01
Treatment				
Detox-to-Treatment vs. not	-1.40	.12	.25	.19, .32
Still in treatment vs. not	-.95	.22	.38	.25, .60
Constant (intercept)	-1.42	.35		
RANDOM EFFECTS	**Variance estimate**	**Se**		**95% CI**
Detox-to-Treatment	.18	.12		.04, .69
Constant	.33	.08		.21, .52
Covariance (Detox-to-Treatment, constant)	-.06	.09		-.23, .11

* Sample size was reduced to 6,878 due to missing data. Only significant predictors from initial logistic regression are included in this model.
** OR=odds ratio, SE=standard error, CI=confidence interval

Table 7.4. Results from the Binary Mixed Model Predicting Readmission for Residential Detox Programs, CalOMS 2008-2009 (n=18,278)*

Residential Detox Programs, Model fit: χ^2 = 414.2 (DF=24), p<.001				
FIXED EFFECTS	**B**	**S.E.**	**OR**	**95% CI****
Ego-networks (n=57)				
Efficiency	-1.37	.60	.25	.08, .83
Degree	.02	.01	1.02	1.0, 1.05
Intra-organizational tie(s) to treatment services	-.33	.20	.72	.48, 1.07
Gender				
Male vs. female	.22	.05	1.25	1.14, 1.37
Age group				
Age 31-41 vs. under 30	.09	.06	1.10	.99, 1.23
Age 42-48 vs. under 30	.09	.06	1.10	.98, 1.23
Age 49+ vs. under 30	.02	.06	1.02	.90, 1.14
Race/ethnicity				
Black vs. white	.15	.06	1.16	1.04, 1.30
Other race vs. white	-.17	.05	.84	.76, .93
Employed	-.26	.07	.77	.67, .88
Living situation				
Dependent living vs. homeless	-.08	.05	.92	.84, 1.02
Independent living vs. homeless	-.23	.05	.79	.71, .88
Current criminal justice involvement (c.j.)				
Is on parole vs. no c.j. involvement	-.03	.07	.97	.85, 1.11
Is on probation vs. no c.j.	-.08	.05	.92	.83, 1.03
Incarcerated vs. no criminal justice	.02	.23	1.02	.65, 1.60
Primary drug problem				
Alcohol vs. heroin	-.39	.06	.67	.60, .76
Methamphetamine vs. heroin	-.57	.07	.57	.49, .65
Cocaine vs. heroin	-.35	.08	.70	.60, .82
Other opiates/drugs vs. heroin	-.65	.09	.52	.44, .62
Addiction severity				
Any prior treatment in lifetime vs. none	.53	.05	1.70	1.55, 1.87
Days of primary drug use, past 30 days	.005	.002	1.00	1.00, 1.01
Lifetime mental illness vs. none	.10	.04	1.10	1.00, 1.20
Treatment				
Taking opiate replacement medication for treatment vs. no medication	.44	.14	1.56	1.19, 2.03

Taking other medication for treatment, e.g., antabuse vs. no medication	.19	.09	1.21	1.01, 1.45
Detox-to-Treatment vs. not	-.74	.09	.48	.40, .57
Constant (intercept)	-.72	.43		
RANDOM EFFECTS	**Variance estimate**	**S.E.**		**95% CI**
Detox-to-Treatment	.13	.06		.05, .32
Constant	.34	.09		.20, .57
Covariance (Detox-to-Treatment, constant)	-.07	.06		-.19, .04

*Sample size was reduced to 17,589 due to missing data. Only significant predictors from initial logistic regression are included in this model.

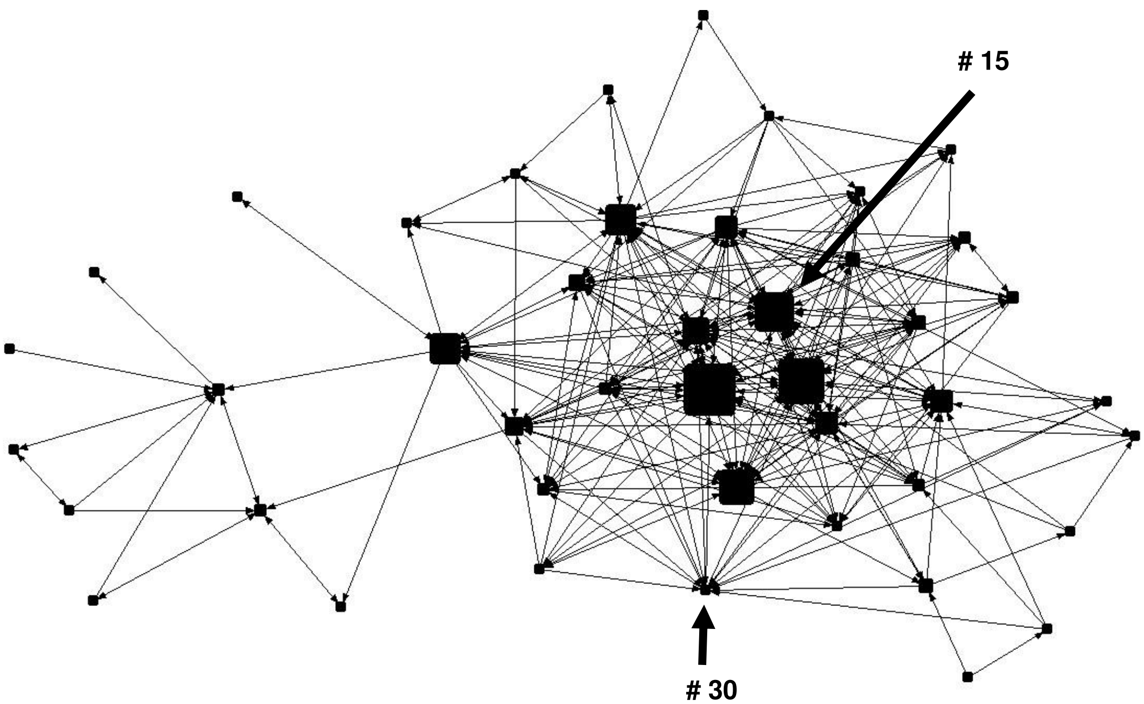
** OR=odds ratio, SE=standard error, CI=confidence interval

III. Efficiency in Ego-Networks

A qualitative comparison of two residential detox programs within the same county can render the concept of efficiency less abstract. A close look at two programs can shed some light on the potential role of efficiency for readmissions, but also that of additional factors at the program-level. The two programs are #15 and #30. The programs differ in size. Program 15 is larger with 441 admissions in 2008-2009 compared with 232 admissions for program 30. Program 30 has a lower readmission rate than program 15. Given the difference in readmission rates, it is interesting to explore differences in network characteristics. Because the two programs are located in the same county, we can assume that, for most part, they access similar resources and function within a similar environment.

The county-wide network is presented in figure 7.1. The squares represent individual programs or service delivery units. To illustrate central positions within the network, the size of the squares is based on programs' betweenness scores. Betweenness measures the extent to which an actor serves as an intermediary for other actors. Technically, betweenness is the proportion of times an actor sits on the shortest path between all pairs of actors (Hanneman & Riddle, 2005). Betweenness is a centrality measure. Actors with high centrality are in a position to broker relationships between actors who are disconnected and play an influential role in the network. Betweenness tends to correlate positively with efficiency.

Figure 7.1County Network Showing Distributions of Betweenness Scores, CalOMS 2008-2009



Program 15 is more centrally located as indicated by its size. Program 15 has more out-going ties in its ego network than does program 30 (16 and 7, respectively). The contacts of a program's direct contacts are programs that are reachable within two steps. Both programs have twenty ties reachable in two steps. For example, if Program 30 refers to its direct contacts, these contacts have 20 different places they can refer patients to. Because Program 30 has fewer direct ties and the same number of indirect ties as Program 15, Program 30 gets more "bang for the buck" with its direct ties. Program 30 has a slightly lower efficiency score than does Program 15, which suggests that it has a few more redundant ties in its ego network. Table 7.5 compares the network characteristics for Programs 15 and 30.

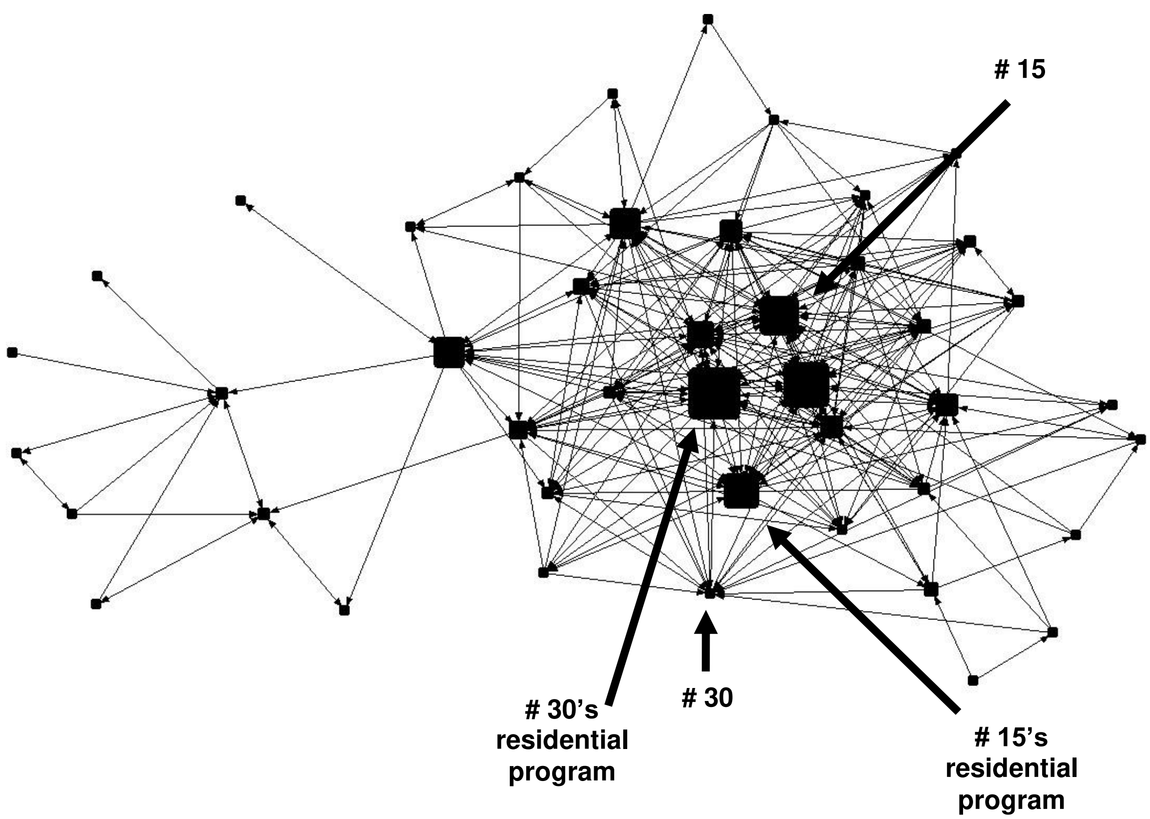
Table 7.5 Comparison of Two Residential Detox Programs within the Same County CalOMS 2008-2009

Network Attributes	Detox Program 15	Detox Program 30
Number of out-going ties (size of ego network)	16	7
Number of ties 2 steps removed*	20	20
Efficiency	56.3	47.9
Betweenness score	40.9	.6
Betweenness score of in-house residential program	34.4	58.7
% transfers to own residential program	41.4	83.6
% transfers to any residential program	69.1	85.5
% patients transferred to residential that did not readmit to detox	66.4	87.3
Overall readmission rate	29.7	16.2

* By 2 steps removed, I mean the ties of the programs' direct contacts.

Programs 15 and 30 both have residential treatment programs within their organizations. Program 30's residential program is one of the most central programs in the county network; the residential program has the highest betweenness score as shown by the size of its symbol (see Figure 7.2). Residential detox programs commonly transfer patients to residential treatment facilities because residential is a more intensive form of rehabilitation, which patients with severe conditions need. If a detox program is tied to a residential program that brokers many different services, this relationship can be very useful for the detox program.

Figure 7.2 County Network Showing Distributions of Betweenness Scores and Location of Residential Programs for Programs 15 and 30, CalOMS 2008-2009



Patients in Program 30 appear to access residential treatment more than their counterparts in Program 15. In Program 30, 85.5% of the transfers out went to a residential program compared with 69.1% in Program 15. Program 30's residential program is its primary tie; 83.6% of its transfers went to the residential program. In contrast, Program 15 transferred 41.4% of its patients to its own residential program. Finally, patients in Program 15 that transferred to residential treatment after detox were less likely to readmit to detox within one year. Of the patients that transferred to residential treatment in Program 30, 82.3% did not readmit to detox. In Program 15, 61.4% of patients that transferred to residential treatment after detox did not readmit.

Summary

This chapter explored the patient-level predictors of readmission to NTP detox and residential detox programs. The two settings are quite different, with different populations, different treatments, and different treatment philosophies. NTP detox programs treat opiate users with opiate replacement therapies such as methadone. Residential detox programs treat a more diverse population, a population with very limited financial and housing resources. Most residential detox programs do not use medications for detox and have a much shorter stay of six days on average. The predictors of readmission are different for the two settings. Entry into treatment within 14 days of discharge from detox was associated with lower odds of readmission.

This chapter also documented the impact of network structure on readmissions to detox. Patients who pass through detox programs that have fewer redundant ties to other programs, i.e., high efficiency, have lower odds of readmission to detox. Network size also has an effect in that detox programs with larger networks have slightly higher odds of readmission. The impact of county environments on local network structures was not measured in this study. The next section, however, explores the size of county networks in terms of the number of programs and detox patients. A few structural features of county-wide networks are examined in relation to detox-to-treatment transfers.

CHAPTER 8

NETWORK CHARACTERISTICS OF DETOX-TO-TREATMENT TRANSFERS AT THE COUNTY LEVEL

I. Description of County Networks

County networks vary greatly in terms of population size, number of treatment programs, number of detox programs, and number of detox patients. None of the 32 counties in this study were classified as very small or rural by the County Alcohol and Drug Program Administrators' Association's listing (County Alcohol and Drug Program Administrators' Association of California, 2006). Table 8.1 shows the total number of treatment programs in each county, the total number of programs within the patient transfer networks, and the number of detox programs by county size. The number of treatment programs in the counties ranges between 6 and 391.

The number of programs within the county networks tends to increase as population size increases. There are several exceptions, however. For example, county 31 is in the small category for population size, but has 21 treatment programs in its network, more than four medium-size counties. County 40 is a large county in terms of its population, but only has 11 programs in its network. With the small sized counties, the number of detox patients ranges from 31 to 396. Counties also vary greatly in terms of the number of detox patients they serve.

Table 8.1 County Characteristics: Number of Programs, Detox Patients, and Detox-to-Transfer Rates in 2008-2009, CalOMS (N=32)*

County	Total # programs	# programs in network	# detox programs	# detox patients	Detox-Treatment transfer rate
Small size counties (pop 90,000 – 250,000)					
Placer	28	21	2	143	7.0
Mendocino	6	6	1	87	8.1
Humboldt	16	14	1	396	9.6
Imperial	9	9	2	135	16.3
Napa	6	4	1	258	17.4
Shasta	14	12	1	353	19.0
Merced	10	8	1	47	21.3
Butte	23	19	1	49	53.1
Yuba	14	12	3	31	54.8
Kings	8	8	2	57	73.7
Medium size counties (pop 250,000 – 800,000)					
Marin	14	13	2	815	3.4
San Luis Obispo	12	11	3	74	5.4
Santa Barbara	29	27	5	554	7.4
Sonoma	31	27	5	664	8.4
Solano	32	29	3	506	18.8
Tulare	27	27	6	330	22.4
San Joaquin	19	19	2	330	26.7
Stanislaus	25	24	3	87	34.5
Santa Clara	48	44	6	617	49.5
Monterey	11	10	3	178	56.2
Large size counties (pop >800,000)					
San Francisco	67	60	8	2,529	12.3
Orange	59	54	6	1,549	12.8
Alameda	60	54	5	1,519	14.2
San Mateo	43	42	2	702	14.4
San Diego	130	122	14	2,216	14.8
Los Angeles	592	391†	38	5,207	16.0
Santa Barbara	62	57	3	407	17.0
Fresno	68	55	10	1,286	17.8
Sacramento	50	46	8	947	18.9

County	Total # programs	# programs in network	# detox programs	# detox patients	Detox-Treatment transfer rate
Ventura	24	22	4	290	21.7
Riverside	76	64	10	576	25.4
Contra Costa	37	29	2	351	26.8

* Network measures are based on out-going transfers between providers of the same county.
† A total of 415 programs experienced transfers, but analysis is based on the 319 programs located in the main component of the network. The 24 programs not in the main component are isolates or programs involved in dyads that are not connected with any other programs.

II. Network Structures

Tables 8.2-8.4 summarize network characteristics for small, medium, and large counties. The types of county characteristics examined include mean number of treatment programs of all types, mean out-degree (number of out-going transfers), mean density, mean centralization (based on out-degree), and mean transitivity (clustering within triads). The tables also present correlation coefficients between the network measures and between the network measures and detox-to-treatment transfer rates ("transfer rate"). Because this analysis is exploratory and the number of counties within each category is small, I set the significance level at .1.

Smaller counties have fewer treatment programs than medium size counties. The mean number of out-going ties ("out-degree") increases with county size; however, the difference in mean out-degree between medium and large counties is slight (3.9 vs. 4.5, respectively). As size and out-degree within counties increases, density decreases. Density is highest in smaller counties; .3 or 30% of programs are tied to each other through transfers. Interorganizational networks in medium counties are, on average, more centralized than small and large networks. Centralization, in this case, is the degree to which out-going transfers are sent from a few providers. Smaller counties have a higher transfer rate (28%) compared with medium (23.3%)

and large counties (17.7%). Because ties are based on transfers, the more transfers within a network, the greater the density within a network.

The number of programs within counties is associated with out-degree for small and medium counties; the more programs in a county, the higher the number of out-going ties programs have. Several associations were found between network measures. In all three groups, network density is positively associated with transitivity. In the large counties, transitivity is positively associated with centralization; that is, clustering within triads increases with increasing levels of centralization. The only network measure associated with transfer rates at the county level is transitivity, and this was only the case in medium-sized counties ($r=.65$, $p<.1$). The scatterplot of transfer rates and transitivity for medium-size counties shows that as the level of transitivity increases, transfer rates also increase (see Figure 8.1).

Table 8.2 Means, Standard Deviations, and Correlations for Small-Size Counties (n=10) CalOMS 2008-2009

	Mean	S.D.	1.	2.	3.	4.	5.
1. Number of programs	11.3	5.5					
2. Out-degree	2.2	.8	.56*				
3. Density	.3	.1	-.66*	.05			
4. Centralization, out-degree	33.5	23.0	.09	.35	-.12		
5. Transitivity	.3	.1	-.48	.23	.89*	.05	
6. Detox-to-treatment transfer rate	28.0	23.5	.03	-.31	-.40	-.39	-.51

* p<.1

Table 8.3 Means, Standard Deviations, and Correlations for Medium-Size Counties (n=10) CalOMS 2008-2009

	Mean	S.D.	1.	2.	3.	4.	5.
1. Number of programs	23.1	10.3					
2. Out-degree	3.9	1.7	.74*				
3. Density	.2	.1	-.46	.21			
4. Centralization, out-degree	38.5	12.7	.54	-.61*	.00		
5. Transitivity	.3	.1	.20	.63*	.68*	-.55	
6. Detox-to-treatment transfer rate	23.3	18.6	.22	.52	.54	-.15	.65*

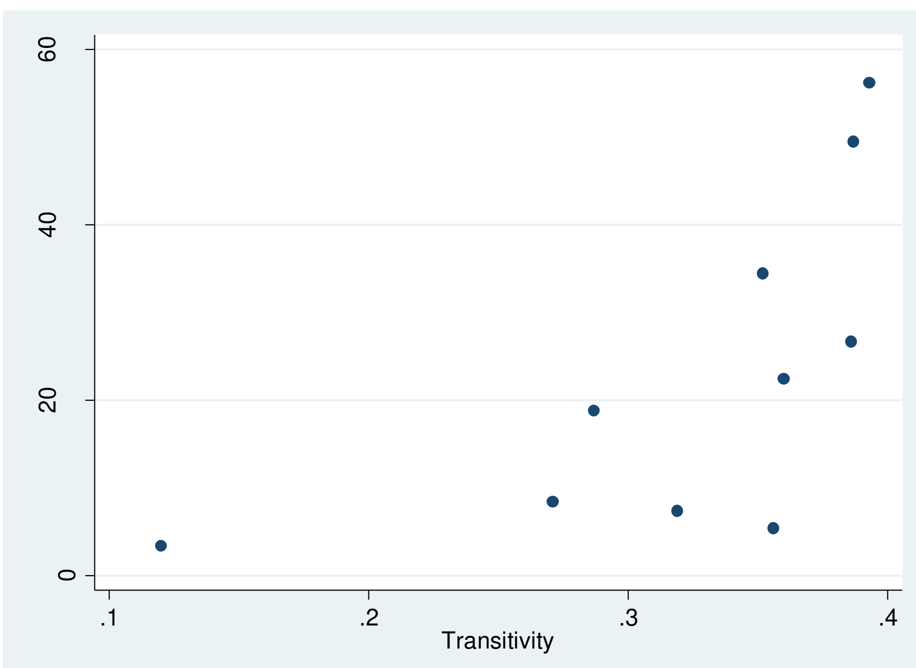
* p<.1

Table 8.4 Means, Standard Deviations, and Correlations for Large-Size Counties (n=12) CalOMS 2008-2009

	Mean	S.D.	1.	2.	3.	4.	5.
1. Number of programs	83	100					
2. Out-degree	4.5	1.3	-.26				
3. Density	.1	.1	-.64*	.56*			
4. Centralization, out-degree	27.9	12.2	-.57*	.32	.59*		
5. Transitivity	.2	.1	-.69*	.72*	.89*	.62*	
6. Detox-to-treatment transfer rate	17.7	4.7	-.20	-.28	.36	-.20	.16

* p<.1

Figure 8.1 Scatterplot Showing Detox-to-Treatment Transfer Rates by Transitivity in 10 Medium-Sized Counties, CalOMS 2008-2009



CHAPTER 9

DISCUSSION AND CONCLUSIONS

This discussion reviews the findings from each of my four aims. The first aim of my study was to determine the extent to which detox patients transfer to some form of rehabilitation within 14 days of discharge from a detox service. The rate of patient transfers from detox to rehabilitation is a recommended performance measure and one that California Department of Alcohol and Drug Programs is considering as part of its outcomes monitoring efforts (Garnick, et al., 2009; Urada, et al., 2010). The second aim of my study was to map the linkages between all types of treatment programs within 32 counties. The goal of this aim was to define treatment systems in terms of the interorganizational networks that exist within counties. I used patient transfers to infer referral relationships between programs. The third aim of my study was to test the impact of detox programs' network ties on their patients' odds of readmission to a detox service within one year. The network measure is "efficiency" or the extent of non-redundant ties within the of detox programs. My fourth aim was to evaluate the utility of patient transfer rates as a county-level performance measure for detox. The last part of the discussion is a review of the study limitations and strengths, as well as my conclusions and future directions.

I. Care Patterns among Detox Patients

The rate of transfers to any form of treatment after detox was 32.1% for NTP detox and 26.2% for residential detox. Nearly half of patients in residential and NTP detox received no additional services within 14 days of discharge. It is clear from these findings that transitional care from detox to rehabilitation is a significant challenge in California.

At the point of discharge from detox, patients are at risk of relapse and overdose due to their reduced tolerance for alcohol and drugs. Entry into a treatment program after detox helps patients prevent relapse and lowers their odds of readmitting to detox. Patients in NTP and residential detox who transferred to treatment within 14 days of discharge had significantly lower odds of readmission compared with patients that did not receive treatment directly after detox. Given the significance of transitioning to treatment from detox, it is necessary to examine characteristics of patients that benefit from coordination of care after detox and to identify any potential disparities among patients.

There appear to be certain types of patients that have a better chance of transferring to treatment than others. Across both types of detox programs, women, individuals under 30, individuals who have a stable living environment, and individuals with Medi-Cal coverage are more likely to transfer to treatment. Having Medi-Cal is a necessity for entering methadone maintenance for patients without the financial means to pay out of pocket. The Affordable Care Act of 2010 includes several provisions that will result in expanded coverage for all types of substance abuse treatment. First, the law mandates coverage for substance abuse and mental health treatment. Moreover, coverage for substance abuse and mental health treatment must resemble that which is currently offered in a typical employer plan. Another provision of the Affordable Care Act is that substance abuse and mental health treatment cannot be subject to co-payments and treatment limitations that are greater than those placed on normal medical benefits (Buck, 2011). Lastly, Affordable Care Act of 2010 may also result in greater integration of behavioral health treatment and primary care (Buck, 2011).

In terms of primary drug group, individuals receiving detox for methamphetamine or other drugs, i.e., other opiates, have higher rates of transfers to treatment. Primary alcohol and cocaine users have the lowest rates of transfers to treatment. Involvement with the criminal justice system, e.g., being on parole or probation, is associated with higher rates of transfers. Lastly, patients in NTP detox programs are more likely to transfer to treatment than patients in residential detox programs. It is common for NTP detox patients to continue receiving methadone at the same facility as part of a long-term maintenance program, the transition from detox to treatment is much easier than for patients that need to seek care from a different facility. Coordination of care across facilities is a challenge for service providers.

II. Interorganizational Networks and Substance Abuse Treatment Programs

The majority of substance abuse treatment programs are housed within small non-profit organizations. Treatment organizations tend to be highly specialized in that they provide a specific type of service such as methadone, residential, or outpatient drug-free counseling. Residential programs can be further divided into programs that exclusively serve men or women. Conventional wisdom in the substance abuse treatment field is that treatment systems are fragmented and continuity of service over time is uncommon (McLellan, Weinstein, et al., 2005). Patient transfers or transitions from one level of care to another within 14 days of discharge are mechanisms for linking patients with needed services. Patient transfers are thought to represent efficiency and quality of care (Garnick, et al., 2009). The assumption is that such transfers represent coordination on the part of program staff and patients. In this study, I framed patient transfers in terms of linkages between programs. To what extent then can we use patient transfers to create a picture of substance abuse treatment systems?

Among all patients who were treated in the 32 counties in 2008-2009, 26.9% transferred at least once to a second service within 14 days of discharge at some point during the observation period. Patients may receive multiple services within a year, but if these episodes are spread out over a month or more, it becomes hard to infer coordinated efforts by programs. The networks are based on a total of 25,090 transfers. It is worth noting that transfers across services are not mandated by funding agencies at this time in California.

While most patients do not transfer to another service within the 14 day window, I would argue that the transfers that we can observe illuminate the types of relationships that exist or do not exist between programs. Moreover, interorganizational networks based on transfers identify the possibilities that exist at a particular point in time for coordinating care for patients. In this study, I found that substance abuse treatment programs do make use of their network ties to engage patients in treatment services over time. Over 84% of all treatment programs in the 32 counties in California had at least one link to another treatment program by way of transfers.

Patient transfers represent patients' interactions with treatment programs; therefore, transfers represent interorganizational ties from the patient perspective. The extent to which patient transfers reflect referral relationships from the perspective of programs was explored in this study. Assuming providers play an active role in coordinating a transfer, the referring provider must have some awareness of the other program, e.g., types of services, eligibility requirements, location, and availability. General awareness of other programs is not too difficult. Most counties hold monthly provider meetings that convene representatives from all treatment programs. Based on my interviews, I learned that, at a minimum, counselors call the receiving program and make an appointment for the patient. Referral relationships, however, may range in terms of strength.

In general, the referral ties reported by program staff tend to be the programs they have a more intense relationship with based on frequent patient transfers. Programs within the same organization have a high volume of transfers. The intra-organizational transfers were matched by the self-reported ties. Sometimes staff members have personal connections with people at other programs. Because turnover in treatment programs is common (McLellan, et al., 2003), program staff members sometimes know someone personally at another program because they used to work together. Personal ties may help foster organizational ties. In addition to patient referrals, program staff members interact at training events and countywide provider meetings. The processes behind the formation of ties were not explored in this study, but could be a fruitful topic for future research.

Patient transfer networks and referral networks based on interviews with program staff members may be different. What is clear is that patient transfer networks are networks that link programs together based on the passage of patients coming through their doors for help. Patient transfers are what we observe in administrative records. The ties that program staff report members are what they perceive. On average, 53.6% of ties from patient transfers were reported by the program representatives that I interviewed. The concordance between the two sources was higher, 65.8%, among the programs with a high number of ties.

Lack of concordance does not necessarily represent the absence of a referral relationship. Respondents may not be able to recall all of the places they have referred to recently. In addition, it may be easier for programs to identify the programs with whom they interact regularly. Perhaps a more reliable approach would have been to present respondents with a listing of all programs in their county and allow them to select the five programs they referred to recently. In addition to the potential for recall bias, another limitation to this study is that I only interviewed one representative from each program. Had I interviewed more people from each program, I may have been able to make a more thorough comparison with the patient transfers. Each respondent may have a different perspective depending on his or her specific position within the program and experiences with patient referrals. While the nature of the referral relationships between programs remains undefined in this study, patient transfer ties in and of themselves are evidence of social structure because they collectively represent the range of possible treatment options for patients in a particular place and time.

When transfers and self-reports align, this suggests that the two programs involved in the transfer have a referral relationship and work to coordinate care. Transfers result from coordination on the part of program counselors and patients. In my interviews, the programs with more ties to other programs also appear to have well established procedures in place to coordinate referrals. Relationships between staff members in programs appear to facilitate the transfers. Based on my interviews, having personal ties to people at other programs allows for frequent updates on availability of beds, shorter wait lists, and smoother transitions because patients can start the next phase of their treatment without a break in service.

III. Predictors of Detox Readmissions

Patient-level predictors

Many of the patient-level predictors of detox readmissions that I found are consistent with prior research on inpatient detox programs. In both NTP and residential detox settings, men had higher odds of readmission compared with women. Patient severity was associated with higher odds of readmission in residential detox programs but not in NTP detox programs. In residential detox, being homeless, unemployed, having had prior treatment, and increasing frequency of primary drug use in the past 30 days were associated with higher odds of readmission. Homelessness and severity have been identified in previous research as predictors of detox readmission (Callaghan & Cunningham, 2002; Carrier, et al., 2011; Mark, et al., 2006). Homeless adults have more severe medical issues; they are more likely to have chronic diseases and have high rates of hospitalizations and emergency room visits (Sadowski, Kee, VanderWeele, & Buchanan, 2009). My interviews with detox providers also suggested that readmissions are common among patients with unstable living conditions. Several respondents mentioned referring patients to homeless shelters and halfway houses.

Age was predictive of readmission in the NTP detox model, but the only significant difference found was with adults in the 42-48 age range, who had higher odds of readmission compared with adults under 30. Being over 37 years old was predictive of detox readmission in an inpatient hospital setting studied by Callaghan et al. (2002). In the Callaghan et al. (2002) study, older age was seen as a proxy for chronic drug use problem. Higher odds of readmission among older adults could be related to chronic conditions or greater challenges in obtaining health coverage such as Medi-Cal.

The use of medications as part of treatment was associated with higher odds of readmission in residential detox programs. This result may seem counter-intuitive. Residential detox programs may administer medications to help patients detox from opiates, but in the absence of ongoing medication management such as methadone maintenance, it is unlikely that short-term medication will prove effective. Residential detox programs are typically 4-5 days. Opiate replacement therapy is most commonly provided in the context of an outpatient NTP program.

The use of medications other than opiate replacement therapies for treatment purposes was also associated with higher odds of readmission. While the question in CalOMS asks about medications for drug treatment specifically, e.g. Naltrexone for alcohol dependence, it is possible that treatment counselors code this question as positive if patients are taking any type of medication as part of their treatment such as psychotropic medications or medications for other chronic disorders (Crevecoeur-MacPhail, 2012). If program staff members answer positively to the question if patients report any use of medications, this question could possibly function as another proxy for severity.

Differences by race were found among patients in residential detox programs. Compared with whites, blacks had significantly higher odds of readmission. On the other hand, patients in the “other race” category had lower odds of readmission compared with whites. This contrasts with the study of inpatient detox programs by Mark et al. (2006) where whites had higher rates of detox readmissions and shorter time to readmission compared with blacks. The higher odds of readmission among blacks found in the present study may be due to their lower rates of transfers to treatment after detox. The study by Mark et al. (2006) indicates that fewer patients who transitioned to treatment after detox were readmitted to detox, but the authors do not report whether blacks were less likely to transition to treatment following detox. My finding does corroborate research by Stein et al. (Stein, et al., 2009) on rates of follow up care among Medicaid-enrolled adults who received detox or residential treatment services during 2004-2006. Stein et al. found that blacks had lower odds of having follow-up care compared with whites.

Heroin patients in residential appear to have poor outcomes in residential detox. Heroin users in residential detox have higher odds of readmission compared with all other types of drug users. Higher rates of readmission for heroin users were also found in a study by Carrier et al. (2011). Residential detox programs do not commonly administer methadone, despite the proven efficacy of methadone for treating heroin addiction (National Institute on Drug Abuse, 2009). Given the short duration of residential detox and the lack of medication management common in “social model” residential detox programs, it is possible that residential detox is not the best setting for individuals with heroin dependence. One analysis of national treatment episode data found that opiate users were more likely to leave residential detox programs against medical advice (Office of Applied Studies, 2004). Further investigation of detox services for heroin patients in residential (non-medical) programs is warranted.

Other factors such as Medi-Cal coverage can explain the higher rates of readmissions among heroin users. Medi-Cal coverage was found in this study to be positively associated with transfers to treatment among detox patients. Given greater access to treatment services as a result of Medi-Cal coverage, patients with Medi-Cal coverage had lower odds of readmissions, but only for patients in NTP detox[7]. While patients in residential detox are just as likely as patients in NTP detox to have Medi-Cal coverage, the finding that Medi-Cal coverage was not associated with readmissions in residential detox could be due to the higher level of severity found among patients in residential detox programs. Severity of drug use and psychosocial conditions are predictive of readmissions to detox.

Program-level predictors

Prior research has identified program-level factors associated with detox readmissions. For example, Campbell et al. (2010) found that proximity to outpatient treatment was predictive of treatment entry after detox (Campbell, et al., 2010). At the clinical level, certain interventions such as intensive case management are other program-level features that impact detox readmissions (McLellan et al., 2005). Despite some work on interorganizational ties in the drug abuse treatment sector (Wells, Lemak, & D'Aunno, 2005), no studies have explored the influence of drug abuse treatment networks on patient outcomes. The literature on substance abuse treatment outcomes provides an under-socialized account of the relationship between treatment

[7] Carrier et al. (2011) found an interesting structural issue with respect to Medicaid coverage and detox readmissions in New York State administrative data. The authors report that having coverage through a fee-for-service plan was predictive of repeat detox admissions, but managed care plans were not.

programs and treatment performance. For instance, prior research on detox readmissions presupposes the existence of strong ties between detox and treatment programs. But if the lessons from the "Delaware Experiment" taught us anything, it is that context should not be ignored. The "Delaware Experiment" was an initiative organized by the state Department of Substance Abuse and Mental Health. The initiative involved a performance-based contract that offered the sole detox facility in the state financial incentives for transferring patients into rehabilitation after detox. The evaluation study found that the incentives did not reduce multiple detox admissions and did not work to engage frequent detox users in long-term treatment (McLellan, et al., 2008). The explanations for the poor results were that there were insufficient resources for residential treatment in the state and a lack of coordinated linkages between detox and residential treatment programs.

I used an interorganizational network approach to identify program-level predictors of detox readmissions. I hypothesized that the structure of detox programs' networks would influence patients' odds of readmission. In other words, network structures can provide resources for patients but also for programs because their performance is tied to patient outcomes. The relationship between network structure and social capital is one that has consumed social scientists for quite some time (Burt, 2000; Coleman, 1988, 1990; Gulati, 1999; Lin, 1999). Network closure and structural holes are two types of network structures that provide advantages for organizations depending on the context and nature of the relationship being studied (Ahuja, 2000).

Research in the field of health and human services integration has focused on the advantages of cohesion within sub-groups of service providers or network closure (Foster-Fishman, et al., 2001; Morrissey, et al., 1997; Provan & Sebastian, 1998). Provan & Sebastian

(1998) and Foster-Fishman et al. (2001) focus on multiplex ties which occur when actors are tied together in more ways than one such as through information sharing, referral exchanges, and agenda setting. The idea is that frequency of interaction can breed relationships based on trust, an important foundation for joint endeavors (Van de Ven & Walker, 1984). The more people's social circles overlap, the more cohesion and closure within a network (Coleman, 1990), which can function as a source of social capital. Network closure has been associated with innovation output among businesses in the international chemicals industry because trust and cooperation among diverse partners are needed to launch new products (Ahuja, 2000). In the mental health services field, Provan and Sebastian (1998) found that networks that contain small clusters of health and human service agencies that interact frequently around multiple tasks have better outcomes in terms of client mental health status and quality of life.

Structural hole theory has not yet been applied to the problem of services integration in mental health or substance abuse. Networks rich in structural holes are known to provide access to new and diverse information for their members. When a person is a member of a network that has structural holes or non-redundant ties, Burt would say they are "at risk for good ideas" because new information can flow to them through their access to contacts and groups outside their immediate network (Burt, 2004). For a detox program, structural holes expand the program's referral resources. A direct tie to a treatment program that has connections to other programs provides a set of indirect contacts for the detox program.

This study tested structural hole theory by incorporating a measure of non-redundant ties (efficiency) in a multi-level analysis of readmission to detox. The efficiency measure captures the extent of non-redundant ties within ego-networks or "neighborhoods." Redundancy occurs when many programs within a network are linked to each other; in other words, a very dense network. In the context of detox services, redundancy means that patients transfer between programs in the ego-networks of the detox programs. In some cases, detox patients transfer back to the same detox program two or more times in a row. In other cases, detox patients transfer to treatment programs, but then transfer back to detox either at the first detox program or another one. Redundancy is created through reciprocal ties between programs that transfer patients to each other. It is important to recall that redundancy is not just based on detox transfers. The network ties represent all types of transfers between all possible treatment modalities: short-term residential programs, long-term residential program, outpatient drug-free counseling programs, outpatient methadone maintenance programs, day treatment programs, residential detox programs, and NTP detox programs.

The more redundant paths between programs, the easier it may be for patients to cycle back to detox. I think of these paths as the ones well-travelled by patients and well-known by programs. A network with a good deal of redundancy is a dense or cohesive network. Depending on the situation, however, too much density may be difficult to manage. In the study by Provan and Milward (1995), density was not associated with effectiveness of service delivery systems; rather, centralization of services through core agencies was the structural feature associated with better service outcomes.

I found significant variation between detox programs in terms of patients' odds of readmission. Part of that variation is explained by the structural features of the networks in which detox programs are embedded. The hypothesis that greater network efficiency is associated with lower odds of readmission was supported. After controlling for multiple patient-level characteristics found to be associated with readmission, there is an independent effect of network structure on readmission. This study found advantages to operating within networks with non-redundant ties. The advantages of structural holes for detox programs are additional and potentially more varied referral sources. Good referral sources can improve detox programs' performance should detox readmissions become a performance measure monitored by funding agencies. Most of the research on structural holes has focused on their impact on innovation at the organizational level or personal gains such as high performance ratings in one's job or income. My study contributes to the network literature because I applied structural hole theory to the mostly non-profit health and human services sector.

Less redundancy implies access to a broader set of programs because non-redundant ties may help detox patients access additional services beyond what is available in the neighborhood of the detox program. One of my hypotheses was that patients of detox programs that have internal ties to outpatient or residential treatment within their organization would have lower odds of readmission because proximity facilitates access to treatment (Callaghan & Cunningham, 2002; Friedmann, D'Aunno, Jin, & Alexander, 2000). In the analysis of residential detox programs, however, having internal ties to treatment was not a significant predictor of detox readmissions. This does not mean that proximity to treatment does not matter. The literature suggests that it does. It is possible that my measure of intra-organizational ties was not sufficient to capture proximity to treatment programs within the same organization.

In the context of drug abuse treatment, having fewer redundant ties represents a certain capacity within programs to respond to patients' diverse needs and preferences. The placement of patients into treatment after a detox service can be complicated as I learned from my interviews. In addition to a patient's preference for what the next step will be, there is the issue of limited availability of treatment slots, particularly in the case of residential treatment. Additional complexity arises when a patient lacks stable housing, has a co-occurring mental health disorder, or does not have coverage through Medi-Care. Greater access to diverse programs through non-redundant ties, therefore, can facilitate the transfer of detox patients to treatment.

Controlling for network size is important as network efficiency—like many network measures—is sensitive to network size. The size of a program's ego-network was determined by the number of out-going ties it has to other programs or its "out-degree." Number of admissions is an indicator of program size that is easily abstracted from administrative data. I found that program size was very highly correlated with network size. The more admissions a program has the more ties it can potentially have to other programs. Program size has an independent effect on the odds of readmission. As program size increases, so do the odds of readmission. Larger programs were also found to be associated with detox readmission in previous research (Callaghan & Cunningham, 2002; Campbell, et al., 2010). In addition, literature in the systems integration field suggests that larger networks may be harder to coordinate (Provan & Milward, 1995). More research into the topic of program size is needed to understand its association with readmissions.

The problem of continuity of service in drug abuse treatment and the context in which continuity of service happens is different from the contexts studied in systems integration research in the mental health field. In situations in which agencies from diverse service sectors need to collaborate to provide comprehensive services, e.g., substance abuse treatment, mental health, and housing, cliques or groups in which all actors are tied to each other through frequent interaction may be more effective in achieving those goals. Intensity of interaction is a defining feature of interorganizational collaboration (Van de Ven & Walker, 1984). Coordination of services across multiple sectors may require a higher level of integration than do referrals within one sector such as drug abuse treatment. In the situation of drug abuse treatment, continuity of service from one treatment modality to another entails complexity from a logistical point of view, i.e., assessing eligibility requirements, transportation, and waiting lists, but systems are already in place to refer patients. Moreover, the places treatment counselors refer to are the places counselors have experience with and trust. Referrals are based on existing relationships, which, of course, may limit the range of referral opportunities for patients.

Other factors may explain why structural hole theory provides an explanation for detox readmissions. Drug abuse treatment programs are highly specialized and patient populations are heterogeneous. The more complex the patient's needs, the more programs may have to look around to find services to meet those needs. For example, for many patients in residential detox, residential treatment may be the most appropriate level of care, particularly patients with unstable living environments and more severe illnesses. If a detox program is situated within a network with few residential resources, the level of cohesion between programs will not resolve the problem of limited resources. In the substance abuse treatment context, it is not just that services are coordinated, but that patients get the most appropriate service from a clinical point of view. Continuity of service within the substance abuse treatment context has highly specific parameters due to the heterogeneity of patients and their needs, the specialization of treatment services, eligibility criteria, and funding constraints.

The types of programs contained within local networks may be an important determinant of patients' ability to access appropriate care. For instance, if a local network does not include a methadone maintenance clinic to treat heroin addiction, detox programs within this network have limited referral resources for their patients. Detox prepares patients for treatment and refers to treatment, but if the treatment programs that detox programs refer to are not effective—meaning they do not engage patients in treatment and retain them for a sufficient amount of time for patients to benefit—the value of detox is diminished and patients may go back to their normal patterns of substance abuse. For example, the literature on continuity of service in the substance abuse treatment field has identified important patient-level interventions that help patients transition to rehabilitation care such as intensive case management, discharge planning, and help with transportation (Carroll, Triplett, & Mondimore, 2009; McLellan, Weinstein, et al., 2005). In sum, ties may not all have the same value. Similar to the work by Ajuha (2000), this study extends structural hole theory because it highlights the role of direct and indirect ties in addition to network structure.

IV. Detox-to-Treatment Transfers as a Performance Measure

Current addiction treatment standards conceptualize addiction as a chronic condition that requires engagement in rehabilitative care as well as ongoing monitoring and sustain the benefits of treatment (McCorry, Garnick, Bartlett, Cotter, & Chalk, 2000; McKay, 2009). Given the need for comprehensive and ongoing care for individuals with alcohol and drug dependence, interest in examining linkages between programs has grown. Patient transfers across services are the subject of new performance measures. This study responds to recommendations by Garnick et al. (2009) to expand knowledge about system-level measures of continuity of service within the addiction treatment field. System-level performance measures are garnering interest nationally. Because of the high cost of detox services and health risks associated with continued substance abuse, readmission to detox is an important performance measure for substance abuse treatment systems (McLellan, Weinstein, et al., 2005).

The findings from this study support the use of detox-to-treatment transfer rates as a performance measure for detox programs. When patients enter into treatment programs within fourteen days of discharge from detox, the odds of readmission to detox within a year are substantially less than the odds of readmission among patients who do not transition to treatment. The methods for evaluating performance, however, are in need of development. Nuanced methods of evaluation are needed because some programs may have patients with more severe substance use disorders or other psychosocial conditions than other programs. Finally, examination of network ties can shed light upon the types of structures that best enable patients to enter treatment. In addition to monitoring performance, policy makers should also investigate methods for helping detox programs explore the composition of their networks and foster the development of indirect ties to treatment programs beyond their immediate network.

V. County Network Patterns

The vast majority of patient transfers occur within counties. Treatment organizations receive funds through a central county agency and are expected to work together by sharing information at monthly provider meetings, communicating with each other around patient referrals, and sometimes collaborating to offer more services to patients. As a public payer of substance abuse treatment, administrators in the Department of Alcohol and Drug Programs are interested in assessing treatment outcomes at the county level. Because all publicly funded treatment organizations in the state collect CalOMS data, information is often aggregated to the county level and cross-county comparisons are made as part of evaluation studies. As an exploratory aim, this study examined whether county-level rates of detox-to-treatment transfers were associated with cohesion in county programs. Aggregating patient transfers to the whole county allows for a big picture view of services integration within networks at large.

The counties vary greatly by population size and network size. An analysis of network structure has to take into account these differences. Striking differences in number of treatment programs, number of detox programs, and number of detox patients were found among counties and within the like-size categories developed by the California Association of Alcohol and Drug Program Administrators (County Alcohol and Drug Program Administrators' Association of California, 2006). For example, some counties have more detox programs than other counties, but fewer detox patients than other counties. The largest portion of substance abuse treatment costs is covered by state and local governments. State and local governments provide 40% of all expenditures for substance abuse treatment and 52% of all public expenditures (Mark, et al., 2007; Mark, et al., 2006). Private insurance comprises 10% of the total substance abuse treatment spending (Mark, et al., 2007). As a result, treatment resources in counties will differ depending on the public revenues they can generate through taxes and other sources of revenue.

No obvious patterns emerged from the correlation analyses of detox-to-transfer rates and out-degree (number of ties) or out-degree centralization. A moderately strong association was found, however, between transitivity and detox-to-treatment transfer rates in medium-sized counties. This suggests that cohesion, as evidenced by a high proportion of transitive triads (sets of 3 programs with strong ties), is a possible network signature of counties with high rates of detox-to-treatment transfers. Networks marked by transitivity and density may not always be favorable, however, if the resources embedded within programs’ network are not well coordinated or not sufficient to meet patients’ needs. At the ego-network level, transitivity and density were associated with higher readmission rates.

According to Provan and Milward (1995), medium-sized networks are well-suited to analyses of services integration because small networks may not have enough service providers and other resources to organize multi-sector initiatives and large networks may have too many providers, making integration difficult. The broader county network may have an impact on local network structures surrounding detox programs. Similar to studies that have documented an association between neighborhood disadvantage and recovery from drug addiction (Jacobson, Robinson, & Bluthenthal, 2007; Sherman, et al., 2004), future contextual analyses of detox programs should include county-wide characteristics as potential predictors of local network structures and treatment outcomes. For example, Burt theorized that network closure among direct ties helps individuals and groups benefit from the resources available by bridging structural holes. One question for future research is whether transitivity at the whole network level is associated with efficiency within ego-networks.

VI. Contribution to Theory

This study contributes to current explanatory models of substance abuse treatment effectiveness. The most widely recognized conceptual model explaining treatment processes and outcomes is the one developed by Simpson and colleagues (2004). Simpson's model includes the role of organizational or program "inputs" in the process of treatment engagement. Simpson's model, however, does not include an explicit focus on the social and physical environments external to the treatment program and how these broader environments impact treatment effectiveness. It is clear, however, from the present study as well as prior research on continuing care that treatment programs do not function as autonomous entities, but have interdependent relationships with other treatment programs and funding agencies. Simpson's model could be expanded to include linkages to other treatment programs as an organizational attribute important to transitional care. Relationships to other treatment programs facilitate referrals, but also serve as a source of information about effective therapies for treating addiction.

Treatment programs often have to venture beyond their day-to-day contexts to obtain new information or learn new strategies for treating addiction. In addition to the present findings related to network structure, another example of the interdependence of treatment providers can be found in the literature on the adoption of evidence-based practices in substance abuse treatment. For example, the concept of “environmental scanning” has been used to describe the process of seeking out new information to inform treatment practice (Herbeck, Hser, & Teruya, 2008). Environmental scanning in the context of substance abuse treatment can be defined as the extent to which professionals obtain information about new treatment techniques from various sources such as journals, conferences, membership in professional provider associations, conversations with members of other treatment organizations, and conversations with county or state representatives (Herbeck, et al., 2008). In a study by Herbeck et al. (2008), the use of information sources was positively and significantly associated with self-reported use of several evidence-based therapies including motivational enhancement therapy, Matrix model for stimulants, methadone for the treatment of opiate dependence, and Disulfiram for treatment of alcohol dependence. Herbeck et al. (2008) relate that the “extent that psychosocial and pharmacologic interventions were used was associated with treatment providers' capacity to obtain treatment information from sources outside of their organizations, including journals, other treatment organizations, and county, state and research entities.” From a structural holes perspective, treatment programs with more outside contacts have the advantage of accessing information and other resources that can enhance their performance and reputation as innovators.

Extra-organizational factors such as contacts in other treatment programs, economic resources for treatment, and availability of treatment services have been identified as important for treatment effectiveness (Babor, et al., 2008). The present study contributes a new perspective to current conceptual models of substance abuse treatment and demonstrates the utility of social network analysis for capturing the day-to-day context of treatment systems. Conceptually, linkages between treatment programs are important for continuity of service from detox to rehabilitation. This study is the first to provide empirical evidence of interorganizational networks and their role in detox readmissions.

VI. Limitations

The study findings must be understood within the context of several limitations. First, the patient transfer networks only capture exchanges between programs within the publicly funded substance abuse treatment sector. To gain a complete picture of referral networks would require the inclusion of healthcare services, mental health services, housing services, as well as self-help groups, sober living homes, and other recovery support services. It is possible that many of the patients that did not receive treatment after detox received supportive services through informal channels such as self-help groups, e.g., Alcoholics Anonymous. Because CalOMS does not capture referrals to services outside the formal treatment sector, future research may need to include surveys to collect network data.

Another limitation related to capturing referral relationships between programs is that in my individual interviews, I limited respondents to five referral sources within the substance abuse treatment sector. Based on this information, I assessed the agreement between ties based on patient transfers and self-reported ties. Overall, I found a match between the two data sources about 54% of the time. Among programs with the highest number of ties based on patient transfers, the agreement between patient transfers and self-reported ties was approximately 66% of the time. Limiting respondents to five referral sources may have had the effect of underestimating the actual agreement between the two sources. Had I allowed respondents to nominate more referral sources, I may have found a higher level of agreement, particularly among the programs with the highest number of patient transfers.

The other factor that may reduce the agreement between referral sources and patient transfers is availability of treatment beds. Referrals to residential treatment programs may not be captured within the 14-day window for patient transfers because wait lists as long as three weeks are common within the publicly-funded treatment sector. In future research, it would be informative to examine the types of treatment services provided by the programs that were nominated as referral sources but not identified as interorganizational ties through patient transfers.

The second main limitation has to do with the reliability of administrative data. Administrative data may not be collected in a uniform, systematic way across counties. Differences in the reporting of detox admissions have been uncovered in recent evaluations of CalOMS (Urada, et al., 2010). In addition, the data from the referral-type questions asked at admission and discharge may be of limited value because treatment programs may not answer them in the same way. Based on this study, it appears that discharge status may be a useful indicator of referral ties between programs, particularly when patients are flagged as receiving a referral and an actual transfer can be observed between a discharge and a subsequent admission. While the quality of administrative data is a concern, hopefully reporting errors are offset by the large number of patients included in CalOMS.

Third, CalOMS data may have limited value for estimating the impact of patient severity on detox readmissions or other performance outcomes. CalOMS does not include diagnostic data on substance abuse and mental health, which would provide direct measures of patient severity. The current questions related to having any medical problems and having a lifetime mental illness diagnosis are imprecise and may not capture varying levels of severity among patients.

The ability to estimate the effects of patient case-mix on treatment performance is a critical issue for evaluation of treatment programs (Federman, Moos, & Finney, 2000).

VII. Study Strengths

Interorganizational networks have enjoyed very little attention in the addiction health services research field. The research helps to fill this gap and bring a broader ecological perspective to the substance abuse treatment field. This is the first study to use patient transfers to construct interorganizational networks in the substance abuse treatment sector. In particular, the study challenges the assumption of most evaluation studies in the field that performance should be measured at the level of individual programs or even organizations. It is clear from the network analysis that treatment programs are embedded in interorganizational networks. Programs may or may not be aware of their organizational ties or exploit these ties to enhance their capacity, but these ties create social structures that impact their performance.

While administrative data have many limitations, there are also advantages. Administrative data can be used to examine interactions between patients and service delivery systems. Because these data are collected on an ongoing basis, service access and utilization can be examined over time (Evans, et al., 2010). With respect to network analysis, administrative data have an advantage over survey data in that interorganizational ties are observed from the patient perspective. Self-reports of organizational ties are subject to a variety of respondent biases including recall bias, reporting bias, and social desirability bias. Patient-level data allow researchers to construct service networks from the "ground-up" as opposed to the reports of program administrators who may or may not have adequate information about service-level linkages.

Research on continuity of service after detox is scanty. The present study makes a significant contribution to the substance abuse treatment literature because data was analyzed for all detox patients receiving care in California from 2008 to 2009. Given the large data set and the diversity in patient and program characteristics, the results of this study may be generalizable to detox programs outside California. The present study is the first to examine the influence of program linkages or interorganizational networks on detox readmissions. This study is also one of the first to apply network analysis to enhance the evaluation of substance abuse treatment outcomes. Finally, while this study examined systems integration within the drug treatment sector, the concepts and methods used are applicable to systems integration research in other health-related fields.

VIII. Future Directions

Structural hole theory states that actors who are in a position to bridge structural holes separating disconnected actors and groups have an advantage because they can access information and resources that are not available to everyone. I did not examine the role of detox programs as brokers within their networks, but this is an area for future research. Within the context of detox programs and their goal of transferring patients to treatment, it is not clear whether detox programs themselves need to function as brokers between non-redundant ties. This is where context blends with theory. Detox programs do not provide addiction treatment or rehabilitation. In the larger substance abuse treatment system, the value of detox is that it can connect patients to treatment. It is possible that detox programs do not need to function as brokers to help patients get into treatment, but have a direct connection to a treatment program that functions as a broker. Imagine that a detox program has one main residential program that it refers its patients to. If this residential program is highly central in the broader county network, the detox program enjoys the benefits of sending its patients to a residential program that ultimately takes on the job of treating the patients' addiction and possibly sending patients on for further care on an outpatient basis. The residential program is central because it has a lot of ties to other treatment programs, but it may also have more resources for treatment and quality services, which benefit patients.

An example of this can be found in the comparison of the two residential programs described in chapter 7. Structural hole theory would predict that the residential program with higher efficiency and higher betweenness (a brokerage measure) would better performance in the area of repeat detox admissions. However, it is the other program, the one with slightly lower efficiency and much lower betweenness, that has the better outcome in terms of a lower detox readmission rate. Upon further examination, I noticed that the program with the lower efficiency and betweenness is situated next to a residential program that has the highest betweenness scores in the whole county network. The advantage of having a tie to a highly central treatment program is that it can broker ties to other treatment programs. While the detox program is not involved in the work of the residential program, the detox program benefits from this bond because its patients can access diverse treatment programs. The implications are that detox programs can maximize their services through connections to other programs. In addition to a lack of redundancy within the ego-network, the types of ties a program has and the quality of these ties may also impact performance of detox programs. It may not be necessary or even productive to have a large number of direct ties if one's direct ties provide access to many indirect ties (Ahuja, 2000).

The above discussion suggests that the relationships detox programs have with their direct ties impact performance. Burt (2000) argues that network closure among direct ties allows actors to take advantage of resources available in outside networks. Building on this idea, Ahuja (2000) found in his study of innovation within the chemicals industry that firms benefit from both strong and weak ties; that is, strong ties may lead to resource sharing and knowledge spillover benefits, while weak or indirect ties provide access to strategic information. In sum, an integrated approach may be needed that includes elements of both network closure (e.g., strong ties) and structural holes (e.g., weak ties) (Burt, 2000). For detox programs, having strong ties to a few core treatment programs can help detox programs access indirect referral sources for their patients without having to manage many direct ties. An example of this can also be seen in the comparison of the two residential detox programs in chapter 7. The program with the lower readmission rate, i.e., better performance, has a stronger link to its own residential program. This program has fewer direct ties than the other detox program, but the same number of indirect ties to treatment programs. Having similar resources through indirect ties but smaller numbers of direct ties was found to be advantageous in the study by Ahuja (2000).

The present analysis would benefit from the perspectives of treatment staff members. In particular, staff members could examine the patient transfer maps showing their linkages to other programs and identify the programs they interact with around referrals. Staff members could provide contextual information to help illuminate the discrepancies between reported referral ties and patient transfer linkages. Such feedback from staff members would help determine the utility of patient transfers as a proxy for interorganizational ties.

Upon completing my dissertation, my plan is to share the network maps at the next meeting of the County Alcohol and Drug Program Administrators' Association of California. In addition, I plan to have an in-depth discussion with a few administrators and treatment providers in Santa Clara County to better understand the conditions that foster patient transfer networks.

Santa Clara is the county whose residential detox programs I began to investigate more closely at the end of my analysis work. I am interested in examining the utility of the network maps for identifying clusters of programs that are successfully coordinating care for detox patients.

IX. Conclusions

In addition to rehabilitation from substance use disorders, substance abuse treatment programs are expected to address a comprehensive set of service needs including mental health therapy, housing, and vocational training. The need for "systems of care" is a metaphor commonly used by policymakers in the field to promote the idea of services integration. The Substance Abuse and Mental Health Services Administration developed the "Recovery Oriented Systems of Care" model, which proposes that "treatment for substance use conditions is only one element in which systems (e.g., treatment/recovery, family, medical, housing/homeless, child welfare, criminal justice, educational) are integrated to offer a fully coordinated menu of services and supports to maximize outcomes" (SAMHSA/CSAT, 2010). In addition to the range of treatment-related services that patients need, there are also various stages within the recovery process that require different levels of care.

Given the interest in systems approaches to substance abuse treatment, there is a need to expand the scope of current conceptual models of treatment to include the role of interorganizational networks. This study defined substance abuse treatment systems as interorganizational networks among treatment programs. Interorganizational networks can be observed through patient transfers. Patient transfers are an objective source of information that documents where and when patients receive treatment.

This study contributes to the literature on readmissions to detox in public-sector substance abuse treatment systems. I found an independent association between non-redundant ties with detox programs' networks, a program-level factor, and readmission to detox within one year, a patient-level outcome. If performance of detox programs is reflected by patient readmissions, this finding suggests that performance of detox programs is embedded in social relations between programs. The finding supports the central premise of network theory that social structure predicts performance at the individual and organizational levels (Granovetter, 1985). Research documenting the association between network structures and patient outcomes is limited. This study represents an important first step in examining program linkages as predictors of patient outcomes in the health field.

Interorganizational networks in the substance abuse treatment sector are created by program staff and patients voluntarily through informal relationships. Patient transfers include both direct and indirect ties between programs. As a result, program staff may not be aware of all of their ties to other programs. Based on the results from this study, non-redundant ties within the detox programs' networks can be considered hidden assets because non-redundant ties connect detox programs to other treatment programs and expand the range of services available to patients. This study suggests that detox programs may transition more patients to rehabilitation and improve their outcomes if they gain awareness of their direct and indirect ties to treatment programs and formalize these relationships to promote greater coordination of care.

APPENDIX A

List of Counties Included in the Dataset

County name	County code
Alameda	1
Butte	4
Contra Costa	7
Fresno	10
Humboldt	12
Imperial	13
Kings	16
Los Angeles	19
Marin	21
Mendocino	23
Merced	24
Monterey	27
Napa	28
Orange	30
Placer	31
Riverside	33
Sacramento	34
San Bernardino	36
San Diego	37
San Francisco	38
San Joaquin	39
San Luis Obispo	40
San Mateo	41
Santa Barbara	42
Santa Clara	43
Shasta	45
Solano	48
Sonoma	49
Stanislaus	50
Tulare	54
Ventura	56
Yuba	58

APPENDIX B

Coding of Transfers

To code transfers between all services for the network analysis, I sorted the data by admission date and created a wide file. Using the “service type” variable in the long file, the wide created a new “service” variable for each admission and discharge record. For example, “service 1” is the service documented in the first admission record. “Service 2” is the service listed in the discharge record for the first admission, e.g., the same as “service 1”. Following this pattern, “service 3” is the service documented for the second admission record. There are as many “service” variables as records in the original dataset.

A transfer is defined as two services that are linked together by less than 14 days. To code the transfer, the date of the first discharge is subtracted from the date of the second admission. If the number of days is less than 14, a new variable is created, e.g., “transfer 1”, and is coded 1 if a transfer occurred and 0 if a transfer did not occur. I allowed for up to 15 unique services in my coding of transfers. After coding transfers, I created new variables to capture the pairs of providers involved in each transfer; that is, if a transfer occurred between service 1 (first admission) and service 3 (second admission), the treatment provider for service 1 and the treatment provider for service 3 are tied. We can say that the treatment provider from service 1 sent a patient to treatment provider 3 (provider 1 is the “sender” and provider 3 is the “receiver”). See the table below for a description of the coding process for the first transfer.

Service 1		Service 3*		Transfer 1		
Record 1	**Record 2**	**Record 3**	**Record 4**	**Record 3 – 2****	**Send 1**	**Receive 1**
Admission date	Discharge date	Admission date	Discharge date	Transfer 1 = 1 if difference < 14 days	Provider of service 1 if transfer = 1	Provider of service 3 if transfer = 1

* Service 3 is actually the admission record for the second service.
****** Not all patients will have data in the first record of the wide file. For example, for some patients, record 2 will include the admission date for the first service as opposed to the discharge date for the first service. In this case, a separate transfer variable needs to be created and this variable will capture the amount of time between record 4 (admission date for the second service) and record 3 (discharge date for the first service).

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