Long-term Drug Treatment Outcomes in Maryland: *Results of the TOPPS-II Project*

Center for Substance Abuse Research (CESAR)

In collaboration with the Maryland Alcohol and Drug Abuse Administration (ADAA)

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Background on TOPPS-II

The Treatment Outcomes Performance Pilot Studies-II (TOPPS-II) initiative, administered by the federal Center for Substance Abuse Treatment (CSAT) of the Substance Abuse and Mental Health Services Administration (SAMHSA), provided an opportunity for Maryland to test an innovative approach to monitoring drug treatment outcomes. The project was a collaborative effort between the Maryland Alcohol and Drug Abuse Administration (ADAA), the recipient of the federal award, and a team of researchers from the Center for Substance Abuse Research (CESAR) at the University of Maryland, College Park.

Goals and Objectives of the Maryland TOPPS-II Project

The overarching goal of the Maryland TOPPS-II project was to determine the feasibility of measuring drug treatment outcomes by linking drug treatment data to other State agency data sources. This approach is complementary to traditional primary data collection efforts in which drug treatment patients are interviewed in-person at baseline and then at specific follow-up periods.

This approach took advantage of Maryland's already existing, well-developed in-treatment substance abuse management information system, SAMIS, that collects information at admission and discharge from drug treatment on all clients attending certified programs in Maryland.

The specific objectives of the project were to:

1. *Determine which other State agency databases could be linked to SAMIS data.*
2. *Develop a mechanism by which ADAA could cooperate with other State agencies to link data for the purposes of monitoring drug treatment outcomes.*
3. *Test different methods of linking SAMIS data to other State agency databases.*
4. *Understand the effect of treatment completion on the following long-term outcomes (at least one year post-discharge, after adjustment for an array of individual-level characteristics (e.g., age, sex, drug problem, prior employment history, etc.):* ***mortality,*** *the likelihood of* ***becoming employed, being arrested****, and* ***being readmitted to drug treatment.***

Highlights of Findings

Lessons Learned Regarding Adminstrative Data Linking

- More conservative linkage rates are obtained when one uses multiple sources of information to construct a unique identifier (partial social security number (SSN) + race + date of birth + sex) as compared to the full SSN.

- Administrative datasets, such as wage and arrest records from State agencies, contain valuable information that can be used to develop performance measurement outcome systems.

- The most labor-intensive part of establishing a drug treatment monitoring system that utilizes administrative data-linking methodology has been completed under the TOPPS-II project. This includes programming to concatenate individual records, defining variables, and recoding string variables from administrative datasets into meaningful outcome categories.

- It is necessary to execute formal data transfer agreements between State agencies so that information sharing and confidentiality protection procedures are established and understood by each agency.

- Hospital discharge and Medicaid utilization information could not be used in the TOPPS-II studies because of logistical constraints regarding obtaining and utilizing the data.

Mortality

- In a statewide sample of patients attending drug treatment in Maryland, 0.09% of patients died during a twelve month period following discharge from drug treatment.

- In a Baltimore City sample of patients attending drug treatment, patients who completed treatment were no different than non-completers with respect to their mortality rate following drug treatment.

- Among patients attending drug treatment in Baltimore City, injection drug users were almost five times more likely to die following drug treatment compared to non-injection drug users, after controlling for types of drugs used and an array of individual characteristics.

- Mortality following drug treatment is most likely related to preexisting health conditions. Drug treatment provides an opportunity to intervene regarding health care needs and HIV treatment, if needed.

Employment

- Twenty-seven percent of patients attending treatment in Baltimore City were employed before, during, and after treatment. Thirty-one percent were chronically unemployed, that is, they did not receive any wages before, during, and after treatment.

- In Baltimore City, treatment completion was associated with both increased wages following treatment and a 28% increase in the likelihood of becoming employed post-discharge, after adjustment for individual characteristics.

Arrests

- Among patients attending treatment across Maryland, 8.6% were arrested in the year following discharge, compared to 10% in the year prior to admission.

- Among a sample of patients attending treatment in Baltimore City, treatment completion was associated with a 54% decrease in the likelihood of being arrested post-discharge, after adjustment for individual characteristics.

- Among a sample of patients attending treatment in Baltimore City, non-completion of treatment was associated with a 55% increased likelihood of arrest for acquisitive, or income-generating, crimes.

Readmission

- Forty percent of patients admitted to treatment in Maryland during FY 1996 were readmitted to treatment at some point during a six-year follow-up period. Half of these readmissions occurred within 200 days; only 3.3% of the sample studied were readmitted to treatment more than once.

- In this same study, patients who completed drug treatment had a reduced chance of readmission.

Treatment of "Alcohol-only" Patients

- Patients presenting with only alcohol problems who attended programs across Maryland that had a high proportion of other alcohol-only clients (i.e., greater than or equal to two-thirds of other patients) had a greater chance of treatment completion as compared to patients who attended programs with less than one-third of patients having "alcohol-only" problems.

The Association between Distance Traveled and Program Completion

- Holding a wide variety of factors constant, traveling less than a mile to outpatient treatment in Baltimore City was associated with a 50% greater

II. Introduction

A. Purpose and Rationale

Costs of the Drug Problem

Alcohol and drug abuse and their related consequences exact a great emotional and financial toll on individuals, their families, and society. It is estimated that, on an annual basis, alcohol abuse costs Maryland more than 3.4 billion dollars, and drug abuse costs 2.2 billion dollars because of lost individual productivity, crime-related losses, healthcare emergencies, chronic illnesses, and a wide range of other problems (CESAR, 2003).

Treatment as a Cost-effective Way of Reducing the Drug Problem in Maryland

Alcohol and drug treatment has gained considerable appeal among policymakers across the US as a cost-effective strategy for reducing the burden associated with substance abuse. In Maryland, estimates suggest that 286,000 people some form of alcohol or drug treatment; about one-quarter of these individuals receive treatment services (CESAR, 2002). A primary goal of treatment is to reduce alcohol and other drug consumption; in other words, to address the drug dependence. Another secondary effect of drug treatment, and sometimes uniquely stated as treatment goals, is to increase an individual's chances of success in various areas of his/her life. Often, either because of conditions that existed previous to their involvement in alcohol and other drugs, or as a direct result of their drug consumption, many drug-dependent individuals experience loss of social support, trouble with their jobs, families, and finances, interactions with the criminal justice system, and numerous mental and physical health problems.

Drug treatment is considered to be a first step in changing the trajectory of a person's life. Many national outcome studies that followed individuals after discharge from drug treatment programs demonstrate that drug treatment can increase the likelihood of employment and decrease the likelihood of criminal activities and arrest. A more in-depth look at some of these studies can be found in Section II.D. In addition, data from national treatment outcome studies consistently demonstrate the cost-effectiveness of publicly funded drug treatment. For instance, one study reported that for every dollar spent on drug treatment, seven dollars was recovered, in large part, because of the relief on the criminal justice and health care systems and because productivity could be restored in the form of jobs.

The TOPPS-II study aimed to discover whether drug treatment in Maryland was associated with benefits to the individual and society. Moreover, TOPPS-II sought to demonstrate that these benefits whether these benefits were sustainable and not just present at discharge from drug treatment.

Setting Up New Cost-efficient Approaches to Monitoring Long-term Drug Treatment Outcomes in the U.S. and Maryland: The History of the TOPPS-II Initiative

As more and more research studies demonstrated the cost-effectiveness of drug treatment, many states found themselves in the position of needing ways of setting up and maintaining efficient data systems to monitor treatment outcomes. These systems, if they could demonstrate cost-savings at a local level, would justify the public dollars being spent on drug treatment.

Various options were available to the states. One option was to set up a system by which large samples of individuals in drug treatment would be interviewed at admission, and then followed over a finite time period. These individuals then could be re-interviewed and asked about their criminal activities, employment situation, health status and drug consumption following discharge. Urine samples could also be tested to confirm recent self-reports of drug use. These sorts of studies, using primary data collection efforts, are probably the most expensive method for monitoring drug treatment outcomes. Smaller, less expensive, studies of this type that were limited in their scope could be done, but they would be appropriate for special populations. Another possibility that existed was to link drug treatment client data with already existing data from administrative databases of other state agencies, such as employment data from the Department of Labor, Licensing and Regulation, or arrest data from the Department of Public Safety and Correctional Services. In this way, data could be analyzed such that one could compare outcomes before and after treatment, without having to invest resources to conduct face-to-face interviews with drug treatment clients. In addition, this method would yield a large sample size for analyses of subgroup variation that would not be possible with smaller studies.

In an era of scarce financial resources, the option to use administrative data linkage is important because it is a cost-effective way to monitor drug treatment outcomes. The project described herein represents Maryland's attempt to implement this option.

The Treatment Outcomes Performance Pilot Studies-II (TOPPS-II) initiative, administered by the federal Center for Substance Abuse Treatment (CSAT) of the Substance Abuse and Mental Health Services Administration (SAMHSA) provided an opportunity for Maryland to test this innovative approach to monitoring drug treatment outcomes. It was built upon TOPPS-I, which was a first attempt to examine drug treatment outcome issues. The project was a joint collaborative effort between the Maryland Alcohol and Drug Abuse Administration (ADAA), the recipient of the federal award, and a team of researchers from the Center for Substance Abuse Research (CESAR) at the University of Maryland, College Park. This approach to measuring drug treatment outcomes, via linkage to administrative data sources, is complementary to the primary data collection approach being used in several other states under the TOPPS-II initiative.

This approach took advantage of Maryland's already existing, well-developed in-treatment Substance Abuse Management Information System (SAMIS) that collects information at admission and discharge on all clients attending certified drug treatment programs in Maryland. SAMIS was the foundation upon which a monitoring system for post-discharge outcomes could be built.

The overarching goal of the Maryland TOPPS-II project was to determine the feasibility of this approach. Because the state had never attempted to match client information from SAMIS with other administrative data from other state agency databases (e.g., employment, arrests, and hospital utilization), the feasibility and potential issues encountered in implementation were unknown.

As will be described in this report, the project was successful in demonstrating the feasibility of the approach, as well as clearly showing the benefits of drug treatment in reducing arrests and increasing the likelihood of employment. Much of the most intensive and costly initial work has already been accomplished through the TOPPSII project so that the system to assess post-discharge outcomes among drug treatment clients can be ongoing and cost-efficient. In addition, the lessons learned from TOPPS-II, as described below, will be useful for maintaining and expanding the system to meet Maryland's needs.

Box 1 summarizes the advantages and disadvantages of the two main approaches to monitoring drug treatment outcomes. Linking drug treatment experience data with administrative databases overcomes one of the most common methodological problems with primary data collection, namely, the problem of attrition and biased results based on individuals who were able and willing to present for follow-up interviews. In addition, collecting data via face-to-face interviews on topics such as employment and criminal history can be somewhat sensitive, and although we have made advances in the techniques for improving the validity of such data, primary data collection must rely on self-report. The administrative data approach, with its reliance on already gathered data, greatly reduces bias associated with self-report. The main disadvantage to the administrative data linking approach lies in its inability to assess actual drug consumption following treatment. Moreover, because administrative data was not collected for research purposes, its utility for assessing outcomes was not known as this study began.

Why Maryland Should Maintain a Drug Treatment Outcome Monitoring System

As mentioned above, most of the up-front capital expenditures have been made through the initial work of this TOPPS-II project. Maintenance of the system will be relatively inexpensive compared to the initial work. It is important to continue to monitor drug treatment outcomes for several reasons. First, having a treatment monitoring system can help improve drug treatment services. Analysis of data from the monitoring system can identify the types of treatment that work well for different groups of people. This information is extremely valuable for improving service delivery for people in need of alcohol and other drug treatment services.

Second, a treatment monitoring system improves our understanding of the cost savings incurred by making treatment available to those who need it. Without quantifying the long-term benefits of treatment, we do not know how much we are saving in terms of criminal justice costs, as well as gains in employment and other societal benefits.

Box 1. Advantages and Disadvantages of Different Methods to Establish Drug Treatment Outcomes Monitoring Systems.

Method and Definition	Strengths	Limitations
"Primary" Data Collection: Individuals in treatment are interviewed in person before, during, and after treatment about various aspects of their lives	• A large quantity of information can be gathered on various aspects of their lives • Measures of drug use can be gathered at follow-up	• Expensive and covers a short follow-up period • Subject to the possibility that the client is recalling their history incorrectly • The client population is often difficult to follow in time; many clients cannot be located • Small sample size
"Secondary" or Administrative Data Collection: Records of individual clients are linked to administrative databases available to the State (e.g., employment and criminal justice records)	• Once up-front costs are expended, relatively inexpensive • Measurements can be made over long period of time before, during, and after treatment • Large sample size	• Measures of drug use cannot be gathered at follow-up • Requires the availability of administrative data and the cooperation of state officials in linking the data • Need unique identifier to link databases
"Hybrid:" A mixture of primary and secondary data collection	• Ideal in terms of overcoming methodological flaws	• Moderately expensive

Goals and Objectives of Maryland's TOPPS-II Project

The overall goal of the project was to demonstrate the feasibility of using the administrative data linking strategy for Maryland to examine long-term drug treatment outcomes.

The specific objectives pertaining to methodology were to:

1. *Determine which State agency databases existed that could be linked to SAMIS data.*
2. *Develop a mechanism by which ADAA could cooperate with other State agencies to link data for drug treatment outcome monitoring.*
3. *Test different methods of linking SAMIS data to other State agency databases; (e.g., to determine whether linkage rates differed for matches obtained via the last four digits of the social security number + date of birth + race + sex vs. the full social security number).*

The specific objectives pertaining to drug treatment effectiveness were to:

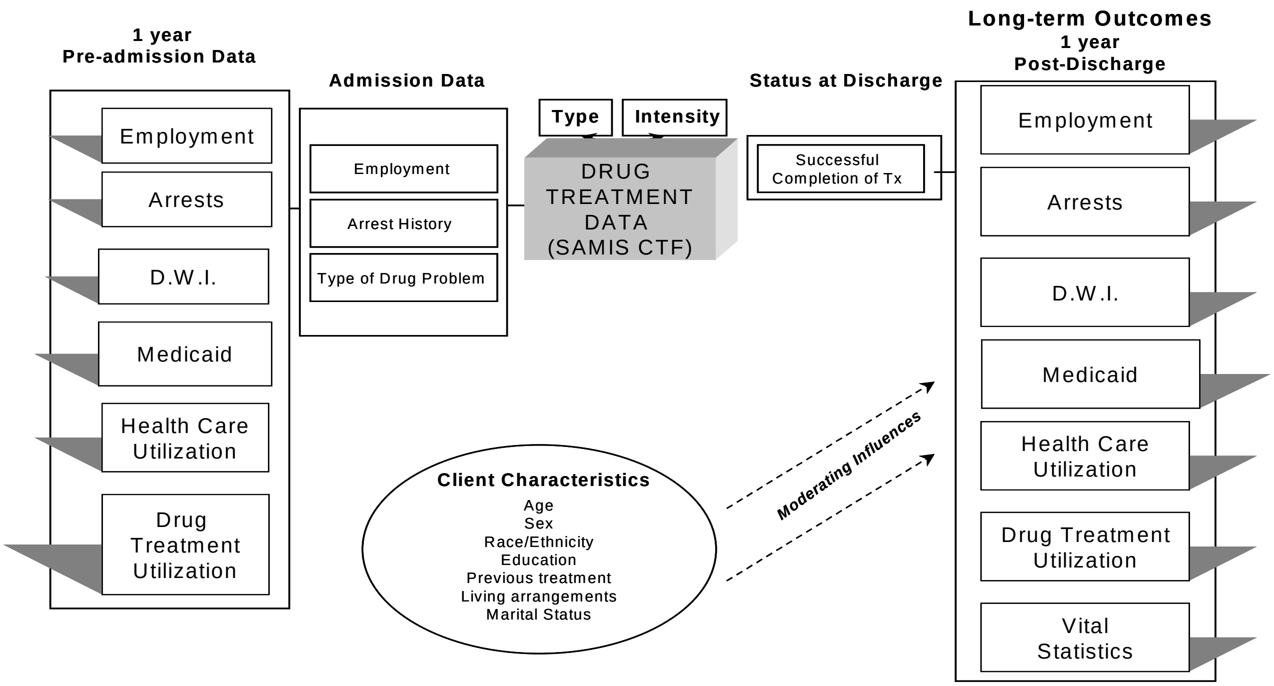
1. *Understand the effect of treatment completion on the likelihood of becoming employed one-year post-discharge, after adjustment for an array of individual-level characteristics (e.g., age, sex, drug problem, prior employment history, etc.).*
2. *Understand the effect of treatment completion on the likelihood of being arrested, for any crime, income-generating crimes, and DWI in particular, at one year post-discharge, after adjustment for an array of individual-level characteristics (e.g., age, sex, drug problem, prior arrest history, etc.).*
3. *Determine the proportion of clients who die 12 and 18 months after discharge from drug treatment and explore the association between noncompletion of treatment and mortality, after adjustment for an array of individual level characteristics (e.g., age, sex, drug problem, injection history, etc.).*
4. *Determine what proportion of clients are readmitted to drug treatment after discharge and what characterizes individuals who are readmitted to treatment.*
5. *Determine to what extent other variables influence treatment completion and how these variables should be controlled for in future studies of long-term drug treatment outcomes.*

B. Description of Studies

Figure 1 illustrates the overall conceptual model that guided Maryland's TOPPS-II study. The starting point for data collection was the SAMIS Client Treatment Form (CTF), shown by the shaded box in the center of the figure. After decisions were made concerning time periods for pre-admission and follow-up periods, and definitions of the variables to include in analyses (see Section II.D. for more information), we attempted to link SAMIS information to employment, arrests, and health care indicators for two time periods (one year pre-admission and at least one year post-discharge from drug treatment). For obvious reasons, the vital statistics database (e.g., mortality) was only searched for the post-discharge time period. As will be described below, it was not possible to use Medicaid data or to obtain hospital discharge data.

Figure 1. Overall Data Linking Strategy to Examine Drug Treatment Outcomes Using Administrative Databases.

In addition, the Inter-State Cooperative Study (ICS) was formed to share



experiences and information among the three states that opted to pursue an administrative data linking strategy for measuring long-term drug treatment outcomes (Washington, Oklahoma, and Maryland). This cooperative study has been highly successful and has resulted in two scientific manuscripts being submitted for publication in peer-reviewed journals. The results of Maryland's project as well as those of the other states, will help the states to standardize both independent predictor variables and longer-term outcome variables in the drug treatment field.

The main research question regarding the effect of treatment completion on outcomes could be answered using multivariate statistical analyses, where the strength of the association between completing treatment and "successful" outcomes (e.g., being employed, having no arrests, etc.) is estimated after adjustment for a number of demographic characteristics (e.g., age, sex, marital status, etc.), treatment process information (treatment modality, time in treatment, presenting drug problem, etc.). This approach, sometimes called "case-mix" adjustment. The analyses compare those who complete treatment with noncompleters to determine differences in long-term outcomes.

C. Relationship of TOPPS-II Activity to Maryland's Drug Treatment Performance Measurement System

Maryland law (Health General Section 8-402.F), directs the Maryland Alcohol and Drug Abuse Administration (ADAA) to determine the degree to which individuals are successfully discharged from treatment programs and the extent to which they are successful in controlling their drug problem after discharge.

Simultaneous with the TOPPS-II project, ADAA initiated the establishment of a performance outcome measurement system to assess the effectiveness of substance abuse treatment in Maryland and to improve the delivery of treatment services for all DHMH-certified drug and alcohol treatment programs. Starting with the Alcohol and Drug Treatment Task Force in 2000, and continuing with the efforts of the Maryland Drug and Alcohol Council, the State adopted a core set of performance measures. These include measures of current alcohol and drug use, criminal involvement, employment status, and living arrangements. These recommended performance measures reflect expectations of Maryland's drug treatment provider community and relate to national performance measurement efforts, as they are the same as those used in national treatment outcome studies. These linkages give Maryland's drug treatment community the opportunity to connect to national effectiveness efforts.

In the performance measurement system, data would be gathered at intake, discharge, and after treatment and would be collected electronically via a new system called e-SAMIS, an electronic Web-enabled system of SAMIS. The TOPPS-II experience has been useful for ADAA since one of the objectives of e-SAMIS is to coordinate the linkage of drug treatment data with various administrative data sources in the State to measure treatment outcomes. In addition, as was done in TOPPS-II, e-SAMIS will allow for the modeling of drug treatment outcomes as a function of a multitude of independent variables available on e-SAMIS. Some independent variables include demographic characteristics, drug use patterns and severity of drug problems, and treatment characteristics such as length of stay and modality.

D. Literature Review

Several major drug treatment outcome studies have been conducted over the past two decades that have provided strong evidence for drug treatment effectiveness. Moreover, these studies have demonstrated the importance of retention (as measured by longer lengths of stay and program completion) for increasing the likelihood of successful outcomes. Treatment retention is one of the most consistent predictors of positive post-discharge outcomes (Anglin & Hser, 1990; Simpson, Joe, & Brown, 1997; Etheridge et al., 1999). Longer periods of time in drug treatment have been associated with improved outcomes in several large-scale studies that compared the patient's own pre-treatment behaviors with behavior post-discharge, and in other studies that used other comparison groups (Etheridge et al., 1999; Simpson, 1981; De Leon, 1989; Simpson et al., 1997; Gossop et al., 1999). The same effect has been reported for program completion (Moos, Finney & Cronkite, 1990). In fact, McLellan et al. (1997) suggested that "those patients who stay in treatment longer and who complete a standard course of care… show the best outcomes (regardless of the outcome measure)" (p. 27).

Follow-up analyses from the Drug Abuse Reporting Program (DARP) revealed more favorable post-treatment outcomes as the time spent in treatment increased above 90 days (Simpson & Sells, 1982). In the Treatment Outcome Prospective Study (TOPS), time in treatment was an important predictor of post-treatment drug abuse across all drugs and treatment modalities and was a weaker predictor of post-treatment employment, lower criminal involvement, and readmission to treatment for some modalities (Hubbard et al., 1989). Time in treatment was also an important predictor of heroin, cocaine, and marijuana use, full-time employment, and predatory crimes for therapeutic communities in TOPS (Condelli & Hubbard, 1994). TOPS results were replicated in the Drug Abuse Treatment Outcome Study (DATOS). Clients who were in long term residential treatment for at least three months had decreased drug use, were less likely to be arrested, and more likely to be employed during the 12-month follow-up period (Simpson et al., 1997). Similar positive correlations between treatment retention and positive outcomes after discharge were also seen in the Services Research Outcomes Study (SROS) (SAMHSA, 1998), the National Treatment Improvement Evaluation Study (Gerstein & Johnson, 1999), and the British National Treatment Outcome Research Study (Gossop, Marsden, Stewart, & Rolfe, 1999).

Here we present a brief review of the literature as it pertains to the outcomes of interest in Maryland's TOPPS-II project: 1) mortality; 2) employment; 3) criminal activity and arrests, including driving while impaired (DWI) offending; and, 4) readmission to drug treatment.

Mortality

Despite the evidence that drug use is associated with a high risk of premature death (de la Fuente, Barrio, Vicente, Bravo, & Santacreu, 1995; Oppenheimer, Tobutt, Taylor, & Andrew, 1994), few systematic investigations have been conducted that examine mortality as an outcome following drug treatment. Much of what is known about the association between drug treatment and mortality comes from studies of methadone maintenance patients. One such study found that patients who were discharged with medical consent from a methadone maintenance program had similar mortality rates on follow-up to those in treatment, while patients who were involuntarily discharged had mortality rates similar to street users (Gronbladh, Ohlund, & Gunne, 1990).

Other studies of methadone maintenance clients have observed that heroin users are two to four times more likely to die after discharge than during drug treatment (Appel et al., 2000; Caplehorn, Dalton, Cluff & Petrenas, 1994; Caplehorn, Dalton, Haldar, Petrenas, & Nisbet, 1996; Davoli et al., 1993). Further studies have shown that individuals in drug treatment are significantly less likely to die from heroin-related causes than those discharged from treatment, while others have not found differential death rates. In-treatment methadone patients appear to have lower mortality rates than injecting heroin users (Poser, Koc, & Ehrenreich, 1995), street users, and patients who receive only detoxification services (Gearing & Schwithezer, 1974).

A positive association between drug treatment duration and survival was found by Segest et al. (1990) in an eight-year follow-up study of methadone maintenance patients. In this study, 39 of the 178 sampled died during the observation period and, of those that died, longer retention was related to longer survival. However, this particular study did not control for individual characteristics or any other treatment process variables except time in treatment. Conversely, Moos et al. (1994) found that longer treatment episodes were correlated with higher mortality rates in patients who were at least 55 years old and attending Veteran's Affairs drug treatment units.

In a four-year follow-up study of a DARP cohort, Joe et al. (1982) found that time in treatment was not predictive of survival post-discharge. Similar results were observed in the SROS study, although the difference in time in treatment between survivors and decedents approached statistical significance (SAMHSA, 1998). Unfortunately, these studies did not statistically control for either drug problem severity or demographic variables.

Criminal Activity and Arrests

Both general criminal justice involvement and arrests are important outcomes for states to monitor for two primary reasons: first is the connection between drug and alcohol use and crime. The strong association between illegal drug use and criminal behavior has been shown in many studies (Inciardi, 1979; Speckart & Anglin, 1986; Chaiken & Chaiken, 1990; Hall et al., 1993). This association is especially marked when drugs are used as part of a pattern of dependent drug use. Both involvement in crime and the amount of crime committed during periods of addiction far exceed that committed during periods of non-addiction (Ball et al., 1983; Nurco et al., 1989).

The types of crime that are most often associated with drug dependence include income-generating crimes such as shoplifting, fraud and theft (Speckart & Anglin, 1985; Ball et al., 1985; Stewart et al., 1999), although drug-selling offenses are also common (Gossop et al., 2000). Surveys of arrestees in the US have shown high levels of drug use prior to arrest. For example, in both Seattle and Oklahoma City, more than 62% of those surveyed tested positive for use of at least one illicit drug in the week prior to arrest, while more than 20% tested positive for the use of multiple drugs (Taylor et al., 2001).

The second reason for monitoring criminal justice outcomes is the potential impact of treatment on justice system expenditures. This impact is potentially significant since national criminal justice system costs have risen from an overall total of just over $79 billion in 1990 to nearly $130 billion in 1997, an increase of 65%. Expenditures for correctional activities have risen even more, nearly 71% over the same period of time (Bureau of Justice Statistics, 2000). Also, state and federal incarceration rates grew over 200% between 1980 and 1996, with the largest contributing factor in that growth being the increased incarceration of drug offenders (Blumstein & Beck, 1999). Because of these rapidly increasing costs and rates of incarceration, any intervention that might ease pressures on the criminal justice system is important to policymakers.

Research concerning how drug treatment interventions influence criminal behavior is important both for implementing and evaluating treatment programs and for developing policies to tackle drug-related crime. Studies using primary data collection methods have examined the relationship between drug treatment and crime and have found marked reductions in criminal behavior after treatment (Ball & Ross, 1991; Hubbard et al., 1989; Gerstein & Johnson, 1999; Gossop et al., 2000). Hubbard (1989) found that the proportion of clients committing property crimes during drug treatment fell to about 10% of pre-treatment levels, and to about one-third of pre-treatment levels during the year after treatment. In the United Kingdom, Gossop et al. (2000) found that acquisitive crimes committed by clients treated in both residential drug treatment programs and in outpatient methadone programs fell to about one third of the levels reported prior to intake.

Several studies have suggested that reductions in crime are related to time in drug treatment. Hubbard et al. (1997) reported findings to support the importance of time in long-term residential drug treatment programs for reductions in criminal behavior.

Similar findings were reported from the UK by Gossop et al. (1999), who found that longer periods of time spent in residential treatment programs were associated with significant reductions in acquisitive crime. Hubbard et al. (1999) also found that longer periods of drug-free outpatient treatment were linked to reduced rates of predatory crime (e.g. robbery, burglary, larceny).

The relationship between time in treatment/program completion and criminal behavior has been less thoroughly investigated. Specifically, Hubbard (1989) found that the proportion of clients committing property crimes during drug treatment fell to about 10% of pre-treatment levels, and to about one-third of pre-treatment levels during the year after treatment. In the UK, Gossop et al. (2000) found that the number of acquisitive crimes committed by clients treated in both residential drug treatment programs and in outpatient methadone programs fell to about one-third of the levels reported prior to intake.

Employment

Outcome research on employment has been conducted using a variety of designs and study groups. Several large epidemiological studies have sampled patients from sites across the nation to assess the relationship between treatment and employment (Hubbard et al., 1984; Leshner, 1997). Results from TOPS showed a small but significant positive effect on subsequent earnings after patients received outpatient drug treatment (Hubbard et al., 1984; French et al., 1991). However, for patients who received inpatient or methadone treatment, no such result was found (French & Zarkin, 1992). Other analyses using TOPS data showed a positive and significant impact of time in treatment on two important labor market outcomes: earnings and weeks worked in a 12-month follow-up period (French et al., 1991). Hubbard et al. (1997) found that after a one-year follow-up there was a significant relationship between time in drug treatment and employment outcomes. Specifically, patients in long-term residential programs who stayed six months or longer in treatment had a 10% increase in their rates of full-time employment compared to those who had shorter stays.

Results from the National Treatment Improvement Evaluation Study (NTIES) documented increases of 16-32% in the proportion of patients receiving some wages after treatment among patients attending non-methadone programs. (Gerstein & Johnson, 1999). Several state-level outcome studies using administrative data have shown beneficial effects of drug treatment for employment. In Washington State, studies found positive associations between treatment and employment (Wickizer et al., 2000; Luchansky et al., 2000; Brown et al., 1997).

These studies evaluated several programs, as well as different subgroups of patients. Longhi et al. (1994) reported on drug treatment outcomes of patients in Washington with alcohol or other drug addiction and who are judged to be indigent, unemployable and incapacitated due to their substance abuse. Monthly data over a four-year span (before, during, and after treatment) for individual patients were matched across state agencies' records. Using data from several administrative information systems, the researchers reported that patients had a higher occurrence of employment, an increase in earnings, and a decrease in publicly-funded services such as medical care and income assistance after drug treatment. In Oklahoma, the CSAT-funded Treatment Outcomes and Performance Pilot Studies results found service recipients' median income gains from pre-treatment to one and two years post-treatment were significantly greater than the median income gain in the general population (Oklahoma Department of Mental Health and Substance Abuse Services, 2000). Gains were also greater than the increase in the consumer price index. Sixty-two percent of the patients in the two-year follow-up were found to have income gains.

In Oregon, Finigan (1996) found higher wages in a three-year follow-up period for patients who completed treatment compared to those receiving few or no services. A study period of two years pre-treatment and three years post-treatment was used to ensure long-term treatment effects were measured. Finigan states that "the accrual of positive societal outcomes resulting from alcohol and drug treatment were found to be significant for a period of at least three years." These results were consistent across care provided in outpatient and residential settings.

Treatment Readmissions

Research on treatment readmissions specific to patients attending drug treatment programs has only begun to emerge in recent years. In the past, treatment readmission research focused on psychiatric patients, with substance abuse as a possible contributing factor. These studies often attempted to identify "revolving door patients," who cycle in and out of treatment facilities frequently, and stated that the best predictor of readmission after discharge was prior treatment system use (Graham & Brook, 1985). This "revolving door" phenomenon has been called into question on the basis of more recent studies. Moreover, as we begin to learn more about factors that contribute to treatment readmission, independent of program characteristics, it is important to appreciate that treatment readmissions may not be an appropriate measure of program performance per se (Humphreys & Wiengardt, 2000; Lyons et al., 1997).

The main point to be made is that we are limited by the readmission research study designs that use administrative data that can only tell us something about those who readmit and does not inform about those who do not readmit.

Studies report a wide range of readmission rates. Not surprisingly, studies with longer follow-up periods report higher readmission rates. For example, studies that use follow-up periods of one to two years report readmission rates of 24% to 38% (Luchansky et al., 2000; McCusker et al., 1998; Booth et al., 1991), while studies with four to ten year follow-up periods have higher readmissions rates of 57% to 70% (Sanchez-Carbonell & Vilaregut, 2001; Moos, Mertens & Brennan, 1994).

Several factors, including both patient and program characteristics, have been associated with the probability of readmission. Frequently cited patient characteristics associated with higher rates of readmission include being unmarried (Thakur et al., 1998; Rabinowitz et al., 1995; Moos, Brennan, & Mertens, 1994; Moos, Mertens, & Brennan, 1994), younger (al-Nahedh, 1999; Moos, Mertens, & Brennan 1994; Lewis & Joyce, 1990), and having a co-occurring disorder (Luchansky, 2000; Tomasson & Vaglum, 1998; Moos & Moos, 1995). It has also been observed that patients who complete treatment have an average 25% lower risk of readmission than non-completers, and when patients do readmit to treatment, they typically readmit to outpatient programs (Luchansky, 2000).

Patient quality of life and lifestyle also appear to affect treatment readmissions. Family support and reassurance of worth, in addition to involvement in the treatment process, decrease readmission rates (Booth et al., 1992). On the other hand, general social stresses can increase readmissions (al-Nahdeh, 1999). Luchansky (2000) noted that patients who had an arrest one year prior to the index treatment episode had increased readmission rates. Finally, alcohol use increases the risk of readmission (Luchansky, 2000; Thakur, 1998; Schonfeld, 1989).

Readmission rates also vary by treatment modality. Residential programs have higher readmission rates than outpatient programs (Luchanksy, 2000; Hubbard et al., 1989), and community-based residential programs have lower readmission rates than hospital-based residential facilities (Moos, King, & Patterson, 1996). Other drug treatment program attributes that are associated with readmission rates include smaller programs and those that encourage a longer length of stay (Barnett & Swindle, 1997; Moos & Moos, 1995; Peterson et al., 1994), programs with fewer discharges, and programs encouraging patient participation in aftercare (Peterson et al., 1994).

Studies have also shown that treatment enhancements within programs can lower patient readmissions. According to Shwartz et al. (1999), patients treated in outpatient acupuncture detoxification programs had lower detoxification readmission rates than short-term residential detoxification programs six months after discharge (18% vs. 36%). Mental health service utilization during treatment (Moos, Pettit, & Gruber, 1995) and immediately post-discharge (Swindle et al., 1995) is also associated with lower readmission rates.

Assessment and Treatment of DWI Offenders

In most states, DWI offenders receive an assessment that guides their placement or assignment into either an educational program or a treatment facility as they pass through the criminal justice system. States vary significantly with regard to the procedures that are followed and the criteria that are used to assign individuals to treatment. Typically, the assessment is multi-modal and includes the results of standardized assessment tools, such as the Michigan Alcoholism Screening Test (MAST) or the Alcohol Use Inventory (AUI), information on prior DWI convictions, and the BAC at the time of arrest. Moreover, although states have written legislation that governs the assessment process, these assessment protocols are not consistently followed. Many individuals fall through the cracks, escape detection by the assessment process, and do not complete treatment.

As more states formalize their assessment procedures, there is an increased need to know what designates an appropriate placement, and whether or not individuals who are assigned to a particular type of treatment have successful outcomes. Aside from our own preliminary work (Arria et al., 2002) showing that demographic characteristics are predictive of treatment assignment, few other studies have been conducted in this area. Likewise, few long-term studies of treatment outcomes among DWI offenders have been published. However, one recent five-year follow-up study reported that clients who completed a DWI treatment program in New Mexico had re-arrest rates that were 17% less than clients who did not participate in a treatment program (Kunitz et al., 2002). In contrast to “mainstream” alcoholism treatment, where the primary goal is to reduce problematic drinking, specific treatment for DWI offenders involves providing education and guidance to reduce recidivism.

Although an early review of DWI treatment literature from 1980-1991 concluded that alcohol-related crashes are not significantly reduced by treatment and rehabilitation programs (Jones & Lacey, 1991), other studies have supported the effectiveness of treatment (Kunitz et al., 2002; Nochajski et al. 1997; Hubbard et al, 1984). Unfortunately, the literature on this topic is incomplete and the studies are plagued with methodological problems, including small sample sizes, high attrition rates and a lack of generalizability. Wells-Parker et al. (1995) concluded, from a more recent meta-analysis of the efficacy of treatment and rehabilitation programs, that the "better" studies suggested that treatment reduced DWI recidivism by an average of 8% to 9% over no treatment. Some studies have also examined the efficacy of treatment specifically for repeat offenders. The results indicate that these treatment groups only perform marginally better than comparison groups (DeYoung, 1997; Langworthy & Latessa, 1993; Peck et al., 1994).

One consistent finding from DWI treatment literature is that, in the absence of legal actions, treatment might have little impact on the subsequent crash rates of either first-time or repeat offenders (e.g., Nichols & Ross, 1990; Sadler et al., 1991). Results show that for all levels of prior DWI convictions, combining alcohol treatment with either driver license restriction or suspension is associated with the lowest DWI recidivism rates (DeYoung, 1997).

III. Research Design and Methods

A. Data Linking Methodology

One of the first tasks of the project was to determine which State agency databases would prove suitable for linking with SAMIS data and useful for understanding the impact of drug treatment. Several agencies were approached and meetings were held to determine the structure of the agency databases and the agency's willingness to execute data transfer agreements with CESAR and ADAA (see Appendix 1 for a sample data transfer agreement).

CESAR executed a formal data transfer agreement with ADAA to obtain SAMIS data for the purposes of linking with other databases and to examine readmission patterns and characteristics, and also to obtain DWI assessment data on all individuals in Maryland arrested for DWI. Successful data transfer agreements were executed between CESAR and ADAA with the following agencies:

- Baltimore Substance Abuse Systems, Inc. to obtain data from the Centralized Intake and Referral Management Information System (CIRMIS);
- The Division of Health Statistics in the Department of Health and Mental Hygiene to obtain vital statistics data (i.e., mortality);
- The Office of Unemployment Insurance in the Department of Labor, Licensing and Regulation (i.e., employment data), administered through the Jacob France Center of the University of Baltimore;
- The Information Technology and Communications Division of the Department of Public Safety and Corrections (i.e., arrest data).

It was not possible to link SAMIS data with Medicaid data held by the Planning, Development and Finance Administration in the Department of Health and Mental Hygiene due to logistical constraints. Also, it was discovered that health care utilization data held by the Maryland Health Resources Planning Commission did not contain individual-level information that could be used to link with SAMIS data.

The following general procedures for data transfer was agreed upon:

1. Data was transferred from the Centralized Intake and Referral Management Information System (CIRMIS) from the Baltimore Substance Abuse Systems, Inc. and from the Substance Abuse and Management Information System (SAMIS) from ADAA to CESAR.
2. Algorithms were developed from the drug treatment datasets to determine if entries from different databases were those of the same person. The dataset was transformed so that each unique individual treatment data episode was represented as a row, and if multiple admission data existed, those data were represented as additional treatment episodes of the row.
3. CESAR produced a dataset containing only the client identifiers necessary for matching, plus a percentage of bogus identifiers. In this way, it was impossible for the State agency to discern which identifiers were bogus, and which were real; the agency therefore did not know which of the identifiers denoted individuals in drug treatment.
4. The client identifier dataset was transferred to the State agency.
5. The State agency linked the identifier data to information available from its database.
6. The dataset was transferred back from the agency to CESAR for analysis.
7. CESAR merged the State agency dataset with SAMIS variables.
8. Once merged, all identifiers were dropped from the analytic database.
9. CESAR staff reviewed the data to ensure that key variables were valid and cleaned the databases, as appropriate. CESAR staff created analytical variables to be used as outcome measures.
10. Statistical analyses were performed by CESAR staff.

Sensitivity Analyses of Different Linkage Methods

Once data transfer agreements were in place, it was necessary to test the feasibility of different linkage methods. Currently, the statewide information system, SAMIS, managed by ADAA, only records the last four digits of the social security number. Baltimore Substance Abuse Systems, Inc. (BSAS) collects the treatment information required by ADAA for all individuals receiving treatment in Baltimore City treatment programs through its Centralized Intake and Referral Management Information System (CIRMIS). CIRMIS contains all of the data fields required to be reported to SAMIS and includes the full social security number.

This provided the opportunity to perform a test, or sensitivity analysis, using the data from the City of Baltimore with mortality data. The results of the following two data matching strategies were compared: 1) linking the drug treatment clients' full Social Security Number with mortality data and 2) linking drug treatment data with mortality data using the last four digits of the client's Social Security Number plus his/her date of birth with race and sex.

B. Sample

Sampling Frame

CIRMIS data included all Baltimore City adult treatment clients attending publicly-funded treatment programs, who were admitted and discharged within FY 1998. ADAA data included all adult treatment clients attending publicly-funded treatment programs, admitted and discharged within FY 1997. Specific studies and other analyses used specific time frames and follow-up periods that were unique to each research question. These are specified in the Results section under each analysis.

Data Source (SAMIS)

The Maryland ADAA requires all certified addiction treatment programs in Maryland to report to the Substance Abuse Management Information System (SAMIS) on a monthly basis. Information on treatment clients is reported to

SAMIS at two points -- admission to treatment and discharge from treatment. Clients who are recorded in SAMIS must be formally admitted and have individualized treatment plans. They must receive at least one direct treatment service every 30 days in order for their record to remain active. Forms are sent to ADAA and entered into an SPSS database. ADAA staff hold regional training sessions in each of the six regions of the state to provide instructions to program staff on how to correctly complete the SAMIS forms.

The SAMIS CTF contains data items collected at intake/admission to and discharge from treatment, such as demographics (e.g., date of birth, sex, race, ethnicity, number of dependent children, living arrangement, residence, employment, education, and income); substance use patterns at admission and discharge (e.g., drug of choice, frequency of use, route of administration, and severity); ASI composite scores for adult clients (i.e., medical status, employment and financial support status, drug use, alcohol use, legal status, family and social relationships, and psychiatric status); number of prior admissions, service category, source of referral, days waiting to enter treatment, number of counseling sessions delivered during treatment; and number of urinalysis tests conducted during treatment. A copy of the SAMIS CTF is included in Appendix 2.

The SAMIS CTF was developed to permit analyses of patterns of repeated treatment episodes and tracking of clients throughout the system. The last four digits of the client's social security number are included, which when combined with the date of birth, race, and sex provide a client identification number.

Validity of SAMIS Data

Extensive edit checks are conducted on SAMIS at the state-level, and the data also undergo federal Treatment Episode Data Set (TEDS) edit checks. In addition, the Maryland ADAA has instituted a SAMIS validation process whereby on-site reviews of program records are conducted to establish the validity of information provided to SAMIS.

The Licensing and Certification Unit visits the programs either once a year or once every two years and reviews a selected number of records. This review of the client records validates the admission and discharge of addiction clients seen at the program. The field services unit of the ADAA visits the ADAA-funded programs quarterly and reviews a select number of records. This review monitors the admission and discharge of clients and validates whether the client has been seen every thirty days.

The SAMIS editing software was modeled after the original software created for the federally mandated Client Oriented Data Acquisition Process (CODAP). Two types of errors are identified--flagged errors that include blanks and internal inconsistencies and rejected errors that include discharges without admissions, duplicate forms, invalid clinic identifiers, and re-admissions without intervening discharges. These latter errors result in the rejection of the form and placement on an error file, which can be modified and which is automatically resubmitted each reporting cycle. The SAMIS admission and discharge are on a single form and are matched in the master file by the unique form serial numbers. This all but eliminates the problem of unmatched discharges. In effect, each discharge submitted has the admission information duplicated on the top half of the form, so if the admission cannot be located in the master file, it can easily be resubmitted.

With each monthly submission of SAMIS forms, each program also submits an Active Client List that enumerates each client in treatment on the last day of the month according to clinical files. These lists are matched to the SAMIS master file and discrepancies are investigated by a staff of five analysts, each carrying a caseload of programs. With monthly monitoring, program census counts and SAMIS Active Client Lists rarely differ by more than five percent. In addition, the SAMIS staff includes a validator who examines client records on site and compares SAMIS information to information documented in client files. This further reduces the likelihood of “phantom clients” or inappropriately active records. Although counseling sessions reported on SAMIS may vary in length depending on each program’s accepted standard, they must be documented in the clients’ progress notes. Although manpower intensive, SAMIS editing procedures provide substantial confidence in the accuracy and completeness of data files.

Exclusionary Criteria

The following clients were excluded for analysis under the TOPPSII project: 1) Clients attending programs that did not receive at least some ADAA block grant funding; 2) Clients receiving only detoxification services; 3) Clients receiving only medication-assisted treatment services; 4) Clients who were incarcerated at discharge; 5) Clients who had died during their course of treatment.

C. IRB Considerations

Although no direct contact with human subjects was required because Maryland has chosen a secondary data approach, a protocol still needed to be reviewed by the University of Maryland Institutional Review Board (UMD IRB) and the Institutional Review Board of the Maryland Department of Health and Mental Hygiene (DHMH IRB). These protocols were reviewed and approved by both IRBs. Copies of the protocols are contained in Appendix 3.

D. Measures

Dependent Variables

The outcomes were operationalized in the following ways:

1. ***Mortality:*** The database contained information on the date of death, and up to 19 causes of death, as coded by the International Classification of Diseases-9th Version (ICD-9). For our purposes, we coded whether or not the person died, the primary cause of death, as determined by a review of all causes, and the time elapsed between discharge from drug treatment and the date of death.
2. ***Employment:*** The database contained information on the amount of earnings by quarter for each individual and an employer identification number for each respective quarter. Federal reporting requirements mandate that every state maintain a database that contains the records of anyone receiving taxable wages and contributing to the unemployment insurance fund. Each quarter, employers are required to report the wages earned by each of their employees. For our purposes, we coded whether or not the person was employed, as denoted by having any wages during the four quarters before admission, and the four quarters after discharge from drug treatment. In addition, we calculated the total sum of wages in the four quarters following discharge. Because full Social Security Number was the only variable available with which to match SAMIS data, employment analyses could only be conducted for Baltimore city data.

3. ***Arrests:*** Among many other variables, the database contained information on the date of arrest and the type of charges. For our purposes, we coded whether or not the person had any arrests in the 12 months preadmission or in the 12 months post-discharge. In addition, we conducted a special analysis of acquisitive crimes or incoming-generating crimes, such as theft, forgery, or robbery, with the Baltimore City data.

Independent Variables

The administrative treatment data contained a record for each admission to publicly-funded substance abuse treatment. Some patients had multiple admissions to treatment during the study period. Successive admissions could have been close together in time, or separated by several months. Rather than analyze the outcomes of single admissions to treatment, episodes were constructed from admission and discharge records to more accurately capture continuous care for substance abuse. The point of doing this was to ensure that evaluation of outcomes would not begin until continuous care was over. Without constructing episodes, it would have been impossible to distinguish intervention periods from outcome periods.

Episodes were constructed as follows. For patients with a single admission to treatment in the study period, the episode began on the admission date and ended on the discharge date. A minority of patients had multiple admissions in the study period. These multiple admissions were linked and became a part of the same episode only if there was no more than a 30-day gap between discharge from one program or level of treatment and the new admission to another. If that gap exceeded 30 days, then multiple admissions would constitute multiple episodes. After treatment episodes were constructed, the last episode in the treatment year was selected to be the index episode. Employment outcomes were tracked after the end of this index episode. The creation of episodes was important, because they more accurately represented the total treatment for which effects (change in employment and income) were being measured.

The two main independent variables were completion of treatment and length of stay. These variables were operationalized as follows:

1. ***Completion of Treatment***: Treatment completion was determined from discharge codes reported by provider facilities to the ADAA on the SAMIS form. For patients with one admission in their index episode, the code corresponding to that single admission was used as the treatment completion indicator. For patients with multiple admissions in their index episode, the discharge code linked to the last discharge was used to determine completion. It indicates whether the patient successfully completed treatment, defined as those who completed their treatment plan objectives and 1) did not use any substance during the 30 days prior to discharge or 2) used some substance during the 30 days prior to discharge but the clinician did not consider the use to cause any problem or dysfunction in the patient's life.

2. ***Length of Stay:*** For patients with a single admission in their episode, *length of time in treatment* was calculated as the difference in days between the admission date and the discharge date. For those with multiple admissions, length was calculated as the difference between the first admission date and the final discharge date. Length of time in treatment was then categorized as either less than or equal to 90 days or greater than 90 days.

Covariates

Values for age, sex, race/ethnicity, and living situation were taken from the first admission record of the treatment episode. Other variables of interest were substances used, prior arrest history, and prior employment and wage history. *Type of drug problem* was categorized as alcohol only, marijuana only, alcohol and marijuana, alcohol and another drug (not marijuana), and multiple drugs. These mutually exclusive groups represent the substance or substances of choice that the patient reported at the time of admission.

IV. Data Analysis Procedures

A. Logistic Regression

Because it is possible to conceptualize all of the proposed outcomes as binary, we will first employ logistic regression to quantify the evidence in support of each of the research questions. The model for each outcome will examine whether or not the main effect is associated with the outcome and can be represented as:

$$\ln\{ P / 1- P \} = b_0 + b_1 Covariate_1 + \ldots + b_p Covariate_p + gMainEffect ,$$

where P designates the probability that the outcome is positive (i.e., equals one) given the values of covariates 1 through p. The p covariates are included to hold constant their effect on the probability of the outcome. In the course of estimating models, it may become evident that further covariates need to be included. The exponentiated regression coefficient exp(g) represents the odds ratio for the main effect. If the main effect can be represented by one or several binary variables, exp(g) quantifies the odds that the outcome is positive among those with the main effect (e.g., successful completion of treatment) relative to the odds that the outcome is positive among those in the reference group. In other words, the odds ratio indicates that clients with the main effect are exp(g) times as likely to be positive on the outcome as those in the reference group. If the main effect is continuous, the odds ratio indicates that clients whose main effect equals X are exp(g) times as likely to be positive on the outcome as those whose main effect equals X – 1.

Subjective evaluation will determine if odds ratio for the main effect is of substantive interest. In order to explore subgroup variation we will estimate the logistic model separately for each of the subgroups. As statistical significance is meaningless in this context, subjective evaluation will determine if there are meaningful differences between the separate estimates of the odds ratio for the main effect.

In non-technical terms, logistic regression answers the question of whether, for some explanatory variable (the Main Effect), the number of individuals for whom a given outcome occurs differs from the number of individuals for whom the outcome does not occur, removing the potential confounding influence of other variables (the Covariates). The coefficient associated with the Main Effect, g, is a measure of the impact of the Main Effect on the outcome variable.

B. Linear Regression

Some outcomes, such as total wages earned in the year following discharge from treatment, can also be conceptualized as continuous outcomes. For this reason, we will also use linear regression. The model for each of the respected outcomes will examine whether or not the main effect is associated with the outcome and can be represented as:

$$Outcome = b_0 + b_1 Covariate_1 + \ldots + b_p Covariate_p + gMainEffect,$$

The linear regression models will include the same p covariates as the logistic regression models. If the main effect can be represented by one or several binary variables, the regression coefficient g represents the difference between the level of the outcome for those with the main effect and those in the reference group. If the main effect is continuous, it represents the difference between the level of the outcome for those whose main effect equals X and those whose main effect equals X - 1. As with the logistic regression models, subjective evaluation will determine if magnitude of the main effect is of substantive interest and subgroup variation will be examined by estimating separate models for each subgroup.

In nontechnical terms, linear regression answers the question of the degree of relationship between some outcome variable and an explanatory variable (the Main Effect), removing the potential confounding influence of other variables (the Covariates). The coefficient associated with the Main Effect, g, is a measure of the amount of change in the outcome variable when there is a change of one unit in the explanatory variable.

C. Proportional Hazards Regression

Some outcomes can also be conceptualized as time from discharge to an event. For this reason, we will also use proportional hazards regression. The model for each of the respective outcomes will examine whether or not the main effect is associated with time until the outcome and can be represented as:

$$l(t \mid x) = l_0(t)\exp[b_1\text{Covariate}_1 + \ldots + b_p\text{Covariate}_p + g\text{MainEffect}] ,$$

where $l_0(t)$ is an unknown function representing the instantaneous risk of the outcome.
The exponentiated regression coefficient exp(g) represents the relative risk for the main effect at time t. If the main effect can be represented by one or several binary variables, exp(g) quantifies the risk of the outcome at time t for those with the main effect relative to the risk at time t for those in the reference group. For example, if the outcome is time to employment and the main effect is whether or not a client is male and exp(g)=2, the proportional hazards regression will tell us that male clients are two times as likely to be employed at time t as female clients. If the main effect is continuous, the relative risk exp(g) represents the risk of the outcome at time t for those whose main effect equals X relative to those whose main effect equals X - 1. As with the other regression models, subjective evaluation will determine if magnitude of the main effect is of substantive interest and subgroup variation will be examined by estimating separate models for each subgroup.

In nontechnical terms, proportional regression answers the question of the degree of relationship between the time until occurrence of some event and an explanatory variable (the Main Effect), removing the potential confounding influence of other variables (the Covariates). The coefficient associated with the Main Effect, g, is a measure of change in the outcome variable when there is a change of one unit in the explanatory variable.

D. Statistical Software Usage

The analyses described above were executed using SPSS and SAS.

V. FINDINGS

This section is organized into three main sections. First, many administrative, methodological and analytical challenges were overcome in completing this study. Because of the emphasis on feasibility, the first section highlights some of the more important lessons learned during this process. Second, we describe the characteristics of patients attending Maryland's publicly-funded treatment system. Third, we describe the results of several studies that exemplify the types of treatment outcome studies that can be conducted using administrative data linking methodology. In this section, we describe three studies on mortality, two on employment, and two on arrest outcomes. Also, because completion of treatment was found to be significantly associated with successful long-term drug treatment outcomes, this section describes two additional studies that discuss important correlates of completion of treatment.

A. Lessons Learned

Establishing and maintaining working relationships with State agencies: A drug treatment monitoring system that utilizes administrative data linking must rely on successful working relationships with key personnel from State agencies, including the gatekeepers of administrative databases. In this project, it was necessary to:

- Identify key individuals, such as the leaders of State agencies, and also the technical staff involved in creating and maintaining databases;
- Establish clear communication channels;
- Draft formal agreements and have them approved and signed off by the leaders of agencies, ADAA and CESAR research personnel. An example of a formal data transfer agreement is included in Appendix 1.
- Convey the value of the project to the leaders of the State agency, and in many cases, with staff turnover and leadership changes, it was necessary to have several meetings to present the goals and objectives of the project. Two major issues that continually were discussed included: 1) the extra burden imposed on State agency staff to link data electronically, for which payment for time and administrative fees were necessary to resolve; and 2) confidentiality issues, which could be resolved via standard confidentiality protocols that were reviewed and approved by two Institutional Review Boards.

Linking databases with the use of a unique patient identifier: When the project started, it was impossible to know if it would be feasible to link databases based on full or partial social security numbers (SSN). The percentage of records that were indefinite or unlinkable because of missing or incorrect social security information was not known. As mentioned earlier, CIRMIS data from Baltimore City afforded an opportunity to compare linkage rates using two methods: 1) the full SSN; and 2) the last four digits of the SSN with date of birth, sex, and race. The results of a sensitivity analysis performed between CIRMIS data and mortality data revealed that the method using the full SSN yielded a higher linkage rate. Of the 112 matches that were made from 4,001 patients, 94 (83%) matches were made with either method. An additional 16 matches were made if one used only the full SSN; and another two matches were made using the partial SSN and the date of birth, sex and race. Therefore, this finding suggests that if multiple sources of identification are used to create a unique patient identifier, a lower or more conservative linkage rate will be achieved.

Assessing the content and quality of each outcome database: This project found that, in general, the State agency databases were an excellent and rich source of information. Although the data files required some cleaning to eliminate missing or incomplete data, or invalid data fields, meaningful analyses could be performed with administrative data from a variety of State agencies. Recoding variables for meaningful analyses was the most time and labor-intensive. For instance, the mortality database had hundreds of numeric cause-of-death codes. These numeric codes had to be examined, sometimes by hand, and then five meaningful, collapsed categories were developed for outcomes analyses.

Concatenating treatment episode data: A method had to be developed to resolve the problem of dealing with multiple admissions to drug treatment. The SAMIS data were organized in an admission format, with every admission being a unique “row.” For administrative data linking, it was important to specify which admission among multiple admissions would be chosen. To resolve this problem, Maryland turned to other states that had previous experience with administrative data linking (e.g., Washington and Oklahoma) for advice. These states advised CESAR to convert drug treatment data into treatment episodes as the primary unit of analysis. Treatment episodes were defined as a series of service delivery units (SDU), which are defined as one admission and one discharge, with no more than 30 days in between the last discharge and the next admission. The admission date of the first SDU was used as the starting point of the treatment episode and the discharge date of the last SDU in the fiscal year was used as the endpoint of the treatment episode.

Patients were first matched within SAMIS so that a patient with more than one admission would be identified as the same patient in order to define an episode of treatment. CESAR developed an SPSS program that matched patients on the last four digits of their SSN plus their date of birth plus their sex, and their race. CESAR initially tried matching on the last four digits of the SSN plus the date of birth, but this method did not uniquely identify patients. For example, there were several patients with the same last four digits and date of birth. Sex was added as an identifier, but this also did not uniquely identify patients, but when race was added, each combination of numbers referred to one unique patient. One patient-identifying variable was thus created using the last four digits of the SSN, the date of birth, sex, and race. Once this was done, CESAR developed a reiterative SPSS program that accounted for all possible combinations of SDUs and episodes to convert the SAMIS dataset from a SDU unit of analysis to an episode unit of analysis. The year prior to the start of the treatment episode was compared to the year after discharge in analyses of treatment outcomes.

Choosing dates to utilize for analyses: Most State agency databases have improved in quality over time. For example, CIRMIS came under the control of BSAS in 1997, when several programs were being added to the database reporting system. BSAS, therefore, was more confident in the accuracy and completeness of data collected during and after calendar year 1998.

Finding an absence of demographic variables to use for matching processes: An outcomes monitoring system that relies on administrative data linking requires a unique patient identifier that is exactly the same between the two databases being matched. The Department of Labor, Licensing and Regulation does not maintain date of birth (or any other individual demographic trait) on its database, but does maintain full SSN. The wage records database only includes three variables for each individual: employee's full SSN, the reporting employer's Maryland unemployment tax account number, and the amount of earnings paid to that employee by the reporting employer during the reference year/quarter. Therefore, only Baltimore City drug treatment data could be used to link to employment data, since CIRMIS, but not SAMIS collected the full SSN, the only common identifier within the wage records database.

Finding some databases that did not include SSN to use for matching processes: Hospital discharge data could not be used for the TOPPS-II project, because this database did not contain either the full or partial SSN. Since the matching process involved SSN, probabilistic matching software would have been required to utilize this database. A probabilistic matching process would use the common demographic variables of both databases to match individuals. Only then could hospital discharge outcome data be obtained.

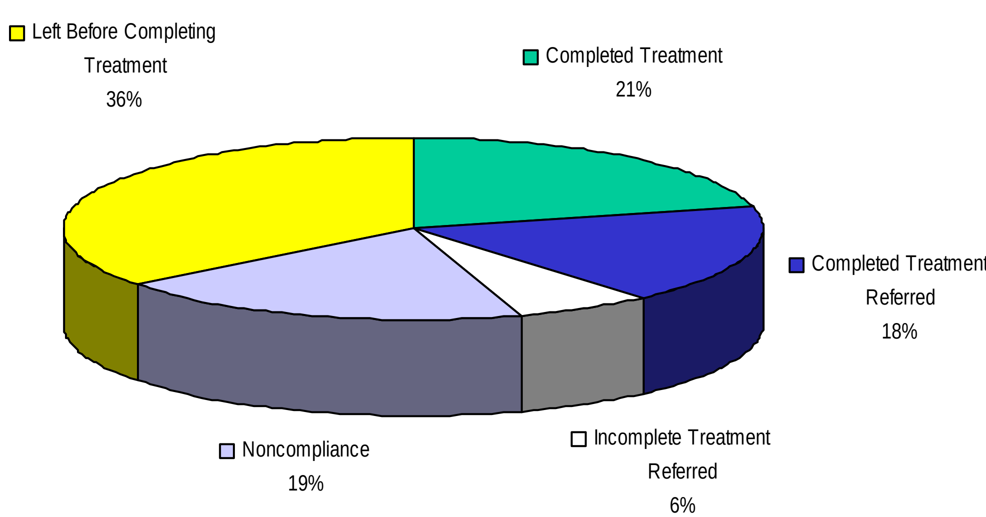
B. Description of the Sample

This section describes the general characteristics of Maryland's treatment system in FY 1997, the target year for which long-term outcomes were measured. The results presented in the section represent only a subset of all patients admitted to Maryland treatment programs because the TOPPS-II project required that certain groups of patients be excluded for a variety of reasons. In 1997, there were 26,336 adult discharges from the SAMIS system. When the sample was restricted to adults who were admitted and discharged in FY1997, whose reason for discharge was not death or incarceration, and then was concatentated to represent unique SDUs, 14,808 individuals remained in the sample. The following results pertain to this sample of individuals.

Reason for Discharge

Figure 1 displays the various reasons for discharge among patients in the sample. About 40% of the sample completed treatment; another 19% were discharged due to non-compliance and about a third left on their own before completing treatment.

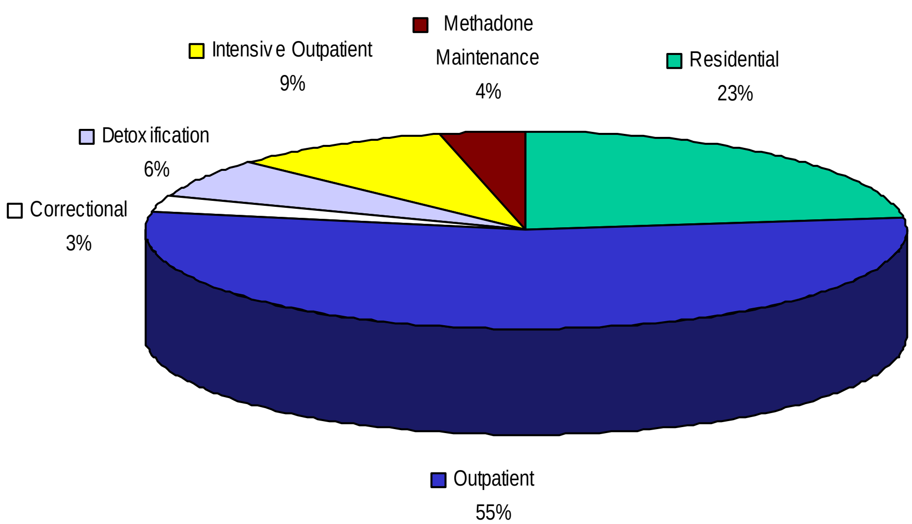
Figure 1. Reason for Discharge in the TOPPS-II Sample of Patients Attending Treatment Programs in Maryland During FY1997 (n = 14,808).



Treatment Modalities

Figure 2 displays the distribution of discharges during FY1997 with respect to various treatment modalities. It can be seen that 55% of the adult patients in Maryland were attending outpatient treatment programs. Because the TOPPS-II project was focused on long-term treatment outcomes, it was decided that individuals attending detoxification programs would be excluded, since there is controversy over whether or not detoxification can be considered "treatment". Also, because the TOPPS-II analyses required a set pre-admission (12 months) and post-discharge (12 months) period to conduct pre- and post-comparisons, patients who attended methadone programs were excluded for many of the TOPPS-II analyses. Many methadone patients are in programs for much longer than a year, making it difficult to establish these pre- and post-periods for analyses.

Figure 2. Distribution of Treatment Modalities in the TOPPS-II Sample of Patients Attending Treatment Programs in Maryland during FY1997 (n = 14, 808).



Presenting Drug Problems

Patients in Maryland present with a variety of drug problems. About two-thirds (67%) of patients presented with an alcohol problem; 52% with a cocaine problem; 30% with a heroin problem; and 36% with a marijuana problem. Striking regional differences occurred with respect to the types of presenting drug problems. More information on this topic is available from CESAR. Given that multiple drug problems was the norm rather than the exception, a cluster analysis was performed to best capture multiple drug use. In this way, each individual could be described by their membership in a "drug cluster". These mutually exclusive drug clusters were used in analyses where appropriate.

Demographic Characteristics of Patients by Treatment Modalities

Table 1 shows the demographic characteristics of patients attending the three modalities that were used in TOPPS-II analyses. Females were more likely to attend residential or intensive outpatient programs as compared to outpatient programs (37.0% and 40.6% vs. 23.6%, respectively). With respect to race, individuals who attended intensive outpatient programs were more likely to be Black as compared to White; however, this finding may be a function of the geographic distribution of intensive outpatient programs. Modalities did not significantly differ with respect to the marital and educational status of patients, with the exception that intensive outpatient programs had a lower proportion of individuals with a high school degree or more.

C. Description of Specific Studies

This section details ten studies conducted under the TOPPS-II project that exemplify the types of analyses that can be done using administrative data linking methods. Some sought to provide Maryland with descriptive information about long-term drug treatment outcomes. Other studies were designed not only to provide Maryland with basic information, but also to fill gaps in the research literature about particular issues. The large sample size afforded by administrative data linking methods was especially useful to answer questions about the correlates of long-term drug treatment outcomes. The ten studies were:

1. Mortality following Drug Treatment: General Findings
2. Mortality following Drug Treatment in Baltimore City: The Importance of Injection Drug Use
3. A Closer Look at the Causes of Mortality in Cocaine Users across Maryland
4. Employment following Drug Treatment in Baltimore City: General Findings
5. Employment Patterns Before, During and After Drug Treatment
6. Arrests following Drug Treatment in Maryland: General Findings
7. Reduction in Acquisitive Crime following Drug Treatment in Baltimore City
8. Readmission to Drug Treatment in Maryland: General Findings
9. Client Homogeneity and Treatment Completion among Patients with Alcohol Problems in Maryland
10. The Impact of Distance Traveled on Treatment Completion in Baltimore City

Table 1. Distribution of Demographic Characteristics in the TOPPS-II Sample of Patients Attending Treatment Programs in Maryland During FY1997 (n = 12, 657).

Variables	Outpatient (n = 8138)		Residential (n = 3412)		Intensive Outpatient (n = 1377)	
	n	%	n	%	n	%
Sex						
Male	6220	76.4	2148	63.0	818	59.4
Female	1918	23.6	1264	37.0	559	40.6
Race						
White	4239	52.1	1499	43.9	365	26.5
Black	3643	44.8	1844	54.0	1005	73.0
Other	256	3.1	69	2.1	7	0.5
Marital Status						
Never Married	4766	58.6	2032	59.6	913	66.3
Married	1306	16.0	383	11.2	127	9.2
Other	2066	25.4	997	29.2	337	24.4
Highest Level of Education*						
Less than High School	2919	35.9	1165	34.1	644	46.8
High School Graduate	3759	46.3	1575	46.2	561	40.8
More than High School	1437	17.7	671	19.7	170	12.4

* Due to missing data, the numbers do not sum to the total number of patients in each modality.

1. Mortality following Drug Treatment: General Findings

Purpose: To examine the rate of mortality among a statewide sample of patients 12 months post-discharge from drug treatment in Maryland.

Sample: Data from 14,808 patients in the SAMIS database who were admitted and discharged during FY 1997 were merged with data from the Department of Vital Statistics. For this analysis, all modalities were included, as were all race categories.

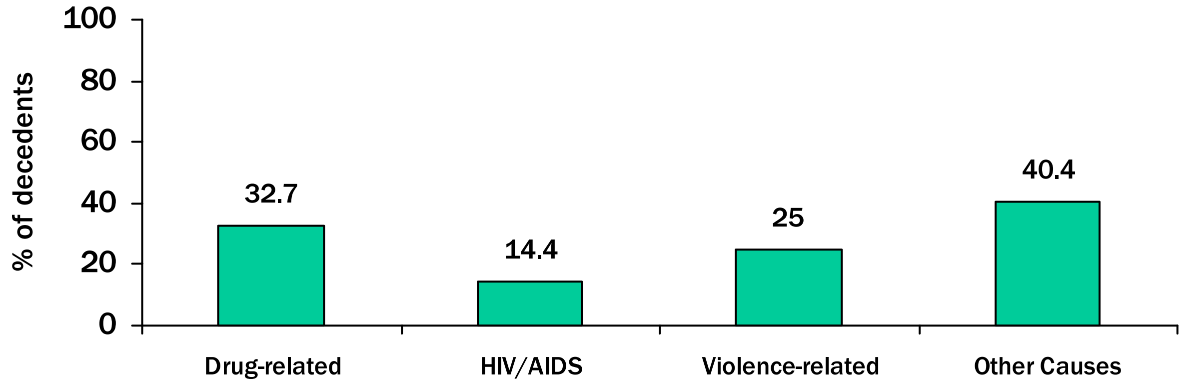
Only the following individuals were excluded from the analyses:

- Non-primary patients
- Adolescents (under age 18)
- No drug listed at admission
- Patient came from an adolescent program, but was over 21
- Patient was referred from juvenile services or school, but was over 21
- Social security numbers were missing or the last four digits were 9999.
- Patients whose reason for discharge was "death"- because a death discharge would obviously eliminate the risk of death after discharge.
- Patients whose reason for discharge was "incarcerated"- because the risks of death in that group may be different.

Methods: For the purposes of this study, a record match of the treatment patient indicates death within the 12-month period after discharge. When no match is found in the mortality database, the patient is assumed to have survived. The assumption is conservative because a person without a match may have actually died, but: 1) s/he died in another state; 2) the records did not match because the identifying information was different in the two databases; or 3) the death information was not entered into the database yet.

Results: Of the 14,808 patients in the analysis, 104 (.09%) died within 12 months of discharge from drug treatment. Figure 3 displays the major causes of death among this sample. It is important to note that this descriptive analysis allowed for multiple causes of death for any one individual. Drug-related causes were mentioned in about one-third of the decedents; other causes included a wide variety of medical conditions and were mentioned in 40% of the cases that died.

Figure 3. Causes of Mortality among a Statewide Sample of Drug Treatment Patients in Maryland (n = 104).



General Limitations of Studies using Administrative Mortality Databases

- The mortality database does not include Maryland residents who died outside of Maryland. For example, people who died in Virginia, Pennsylvania, and Delaware are not included. However, people who died in the District of Columbia *are* included because Maryland has an agreement with the District.
- Information recorded in the mortality database is derived from death certificates. Up to 20 causes of death and an underlying cause are recorded for each decedent, using ICD-9 or ICD-10 codes. Sometimes death certificates can have missing or incomplete information, especially in the cases of drug-related deaths.

2. Mortality following Drug Treatment in Baltimore City: The Importance of Injection Drug Use

Purpose: To examine the correlates of and, in particular, the effect of injection drug use, on mortality 18 months post-discharge from drug treatment among patients attending Baltimore City drug treatment programs. In addition, we aimed to more closely examine the principal causes of death in this restricted sample. Baltimore City data were used for this analyses because of the over-representation of injection drug users in this urban population as compared to the rest of Maryland.

Sample: Data from 4,002 cases in the CIRMIS of the Baltimore City treatment database in FY 1998, were merged with data from the Department of Vital Statistics. The same set of exclusionary criteria was used as described in Section C.1. The set included individuals whose SAMIS race category was something other than black or white, since the number of these individuals was too small (less than 1%) for meaningful separate statistical analyses. Because some patients belonged to more than one of these exclusionary groups, 3,887 patients remained in the final sample for analysis.

Methods: Bivariate (unadjusted) logistic regression models were developed for demographic, drug use, and treatment variables with a suspected association with mortality. An odds ratio and 95% confidence interval were calculated to measure the likelihood of mortality for each variable. Age, employment status, source of referral to treatment, heroin use, injection drug use, and prior admissions to treatment were significant (p=.05). Basic demographic characteristics (sex, race, and age) and the variables that were significant in the bivariate logistic regressions were included in a multivariate (adjusted) logistic regression model to predict death versus survival. The basic demographic characteristics were included as controls for consistency across different analyses.

Results: Of the 3,877 patients in the analysis, 98 (2.5%) died within 18 months of discharge from drug treatment. Table 2 shows the characteristics of the 98 individuals that died within an 18-month period following discharge from drug treatment in Baltimore City.

Table 2. Characteristics of Decedents among a Sample of Drug Treatment Patients in Baltimore City (n = 98).

VARIABLE	n	%
Time to death after discharge		
Died within 6 months	34	34%
Died within 6 months to 1 year	39	40%
Died within 1 year to 18 months	25	26%
Primary cause of death		
Drug poisoning/overdose	35	38%
HIV/AIDS	24	25%
Other Illness	24	24%
Violent Death	9	8%
Accidental Injury	3	3%
Other	3	3%

Table 3 displays the results of the unadjusted and adjusted logistic regression models to predict death versus survival. In the multivariate logistic regression, the following variables were significantly associated with mortality following drug treatment: age, source of referral to treatment, and injection drug use. Source of referral was significantly associated with subsequent mortality. Specifically, patients referred by other treatment or health care providers as compared to patients referred to treatment by the criminal justice system or who were self-referred were more than two times more likely to die within 18 months following discharge. Injection drug users were almost five times more likely to die within the 18 months following treatment, after controlling for several other potentially confounding covariates. It is important to note that the route of administration (i.e., injection) was more significant in affecting subsequent mortality than heroin use alone, as heroin use becomes non-significant in the multivariate model, and injection drug use remains significant.

Similar analyses were performed on drug poisoning/overdose decedents versus survivors. There were 35 drug poisoning/overdose deaths in the sample, and the only variable significant in the multivariate analysis of drug poisoning/overdose was injection drug use. Drug injectors were approximately 3.7 times more likely to die of drug poisoning/overdose than non-injectors.

Table 3. Results of Logistic Regression Models to Predict Mortality in a Sample of Drug Treatment Patients in Baltimore City (n = 3,887).

Variables	Decedents		Survivors		Unadjusted Model		Adjusted Model	
	n	%	n	%	OR	95% C.I.	OR	95% C.I.
Sex								
Male	37	38	1487	39	1.0	—	1.0	—
Female	61	62	2292	61	1.1	0.71-1.62	1.2	0.74-1.79
Race								
White	16	16	618	16	1.0	—	1.0	—
Black	82	84	3161	82	1.0	0.58-1.72	1.1	0.65-2.01
Age								
18-24	8	8	405	11	1.0	—	1.0	—
25-34	18	18	1574	42	0.6	0.25-1.34	0.5	0.20-1.14
35-44	53	54	1328	35	2.0	0.95-4.28	1.2	0.54-2.62
45 and over	19	19	472	12	2.0	0.88-4.71	1.1	0.44-2.53
Employment								
Employed	7	7	831	22	1.0	—	1.0	—
Not Employed	91	93	2948	78	**3.7***	1.69-7.93	**2.4***	1.10-5.40
Source of Referral								
Individual	16	16	1056	28	1.0	—	1.0	
Criminal Justice System	22	22	1561	41	.9	0.49-1.78	1.0	0.51-1.93
Other Health Care/AOD Tx Provider	60	61	1162	31	**3.4***	1.95-5.95	**2.3***	1.33-4.16
Drug Use								
Alcohol	34	35	1455	39	0.8	0.56-1.29		
Heroin	78	80	2524	67	1.9*	1.18-3.18	0.6	0.32-1.20
Cocaine	62	63	2247	60	1.2	0.78-1.78		
Multiple Drugs	71	72	2519	67	1.3	0.84-2.06		
Injection Drug Use	70	71	1199	32	**5.4***	3.45-8.38	**4.6***	2.55-8.32
Number of Prior Treatment Admissions								
None	32	33	1583	42	1.0	—		
One	34	35	1049	28	1.6	0.98-2.62		
Two or More	32	33	1147	30	1.4	0.84-2.27		
Treatment Completion Status								
Completed Treatment	7	7	377	10	1.0	—		
Referred	24	24	1035	27	1.2	0.53-2.92		
Did Not Complete Treatment	67	68	2367	63	1.5	0.69-3.34		

*Denotes a statistically significant odds ratio (OR).

3. A Closer Look at Causes of Mortality in Cocaine Users across Maryland

Purpose: To examine the correlates of mortality over a four-year follow-up period post-discharge from drug treatment in a sample of patients presenting with cocaine problems. While much research has examined the relationship between heroin use and general drug use to subsequent mortality, little is known about the extent to which cocaine use might contribute to mortality in drug-using populations. Moreover, little is known about factors that might potentially raise the risk of mortality among cocaine-using patients.

Sample: The subjects in this study were 10,504 adult drug treatment patients presenting for treatment with a cocaine problem who were discharged from a Maryland drug treatment program that received at least some ADAA-funding during FY 1997 (July 1, 1996 to June 30, 1997). If a patient had multiple treatment discharges for cocaine problems in fiscal year 1997, data associated with the last admission was used. All subjects were followed up until October 2001 via administrative data matching to determine the proportion who had died and the causes of death. The same set of exclusionary criteria was used as described in Section C.1.

Methods: A multivariate logistic regression was used to examine risk factors associated with mortality. The total mortality dataset that was searched for record matches included death records of Maryland residents who died in Maryland or in the District of Columbia between July 1996 and October 2001. The treatment data were matched to the mortality data when an exact match occurred on the subject's last four digits of the social security number, date of birth, race, and sex. For the purposes of this study, a record match of the subject indicated death during the follow-up period. When no match was found in the mortality database, the patient was assumed to have survived.

The substance use variables examined in this study were all measured at admission to treatment. The severity of the cocaine problem was determined by a clinician's assessment at admission. Daily use of cocaine was based on a patient's self-report in reference to the 30 days prior to admission. Route of cocaine administration was also obtained through self-report and refers to the most recent usual route prior to admission. Age of first use of cocaine represents the self-reported age of first use. While all individuals in this sample presented to treatment with a cocaine problem, up to two other substances could also be recorded as presenting problems. Variables for alcohol, marijuana, and heroin problems were created.

The existence of medical problems was computed from the Addiction Severity Index (ASI) composite medical score. For the ASI composite medical score, patients were asked how many days they had experienced medical problems in the past 30 days, how troubled or bothered they were by those medical problems in the past 30 days, and how important it was to them to receive treatment for those problems. A composite score of zero indicated no medical problems; scores greater than zero and up to one indicated some problems; and other scores were denoted as missing. If patients did not answer all of the questions, the composite score could not be calculated and was counted as missing.

Each independent variable was first tested for association with mortality in bivariate logistic regression models (unadjusted). Those characteristics that exhibited a significant association in the bivariate logistic regression models were then entered into a multivariate model (adjusted). Results for the models were interpreted in terms of odds ratios and 95% confidence intervals. The odds ratios were used as a measure of association, indicating how, and to what degree, the patient characteristics were associated with mortality in the follow-up period (e.g., an odds ratio of two for males would indicate that males were two times more likely to die in the follow up than females).

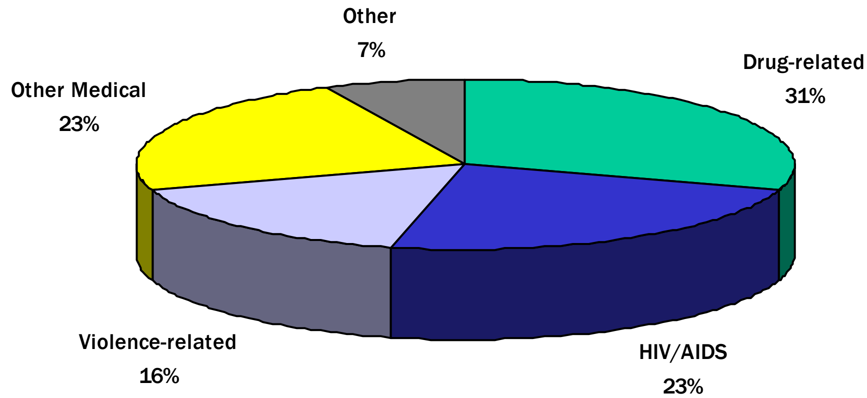
95% confidence intervals were used to measure the statistical significance of that association considering the standard errors. An odds ratio value of one would indicate the same likelihood of death in the follow up, 95% confidence intervals containing the value of one indicated that the variable did not have a statistically significant association with mortality. The characteristics associated with mortality in the bivariate analyses were then entered into a multivariate logistic regression equation to provide an estimated effect for each covariate that was statistically adjusted for all the other covariates included in the model.

Results

More than half (62%) of the patients were male, and 65% were black. The mean age of patients in the sample was 34. The predominant route of cocaine consumption was smoking. Many patients presented to treatment with drug problems in addition to cocaine (57% with alcohol; 40% with heroin; and 36% with marijuana). Twenty-seven percent of the sample had a documented medical problem upon admission to treatment.

Three hundred and forty-nine subjects died in the follow-up period, at an annualized rate of approximately 0.8%. Upon examining the causes of death among the 349 decedents, five general categories of death emerged: drug-involved, HIV/AIDS, other medical complications, violence, and other causes (see Figure 4).

Figure 4. Primary Causes of Death in a Statewide Sample of Patients with a Cocaine Problem Admitted to Treatment in Maryland (n = 349).



Almost one-third or 105 patients died from drug-involved causes. A subject was determined to have died from drug-involved causes when one or more of the listed causes of death was drug abuse or accidental drug poisoning. An exception to this was when the subject's underlying cause of death was violence or HIV/AIDS. The most common underlying causes of death among the subjects who died from drug-involved causes were: drug poisoning by narcotics and hallucinogens (37 cases); drug poisoning by analgesics, antipyretics, or antirheumatics (25 cases); and, drug poisoning by a drug that was not coded in the ICD (10 cases). In none of the cases was cocaine poisoning listed as an underlying cause of death.

Another 163 deaths could be attributed to medical causes. Half of these deaths, 82 cases, were due to HIV/AIDS, the remainder of patients died from other medical complications, such as malignant neoplasms (14 cases), pneumonia (7 cases), brain hemorrhage (5 cases), cardiovascular diseases (17 cases), liver-related disorders (9 cases), and septicemia (3 cases).

Deaths resulting from assaults, suicides, and injury by legal intervention (i.e., injuries inflicted by law enforcement agents in the course of duty or legal execution) were considered violent deaths. Fifty-seven subjects had violent events listed as the underlying cause of death. The most frequent causes of death in this category were: assault involving a firearm (24 cases); suicide involving a firearm (11 cases); and, assault involving a piercing weapon (5 cases).

The remaining 24 deaths did not fit into any of the above categories; these included traffic accidents (10 cases), alcohol-involved deaths (6 cases), and cases in which the cause of death was unclear (8 cases).

The causes of death are presented in Table 4 for four different combinations of drug problems: cocaine only (16 deaths), cocaine and alcohol only (33 deaths), cocaine and heroin combinations (235 deaths), and other combinations (65 deaths). A larger proportion of subjects who had problems with both cocaine and heroin died in the follow-up, 5.6%, relative to the subjects having other combinations of drug problems: 1.6% of cocaine only subjects, 1.7% of cocaine and alcohol-only subjects, and 1.9% of subjects using other combinations. A chi-square test determined that this difference was significant (P<.05).

Table 4. Causes of Death in Decedents from a Sample of Cocaine Users Attending Drug Treatment in Maryland During FY1997 by Polydrug Combination (n = 349).

Causes of Death	Cocaine Only	Cocaine and Alcohol Only	Cocaine and Heroin Combinations	Other Combinations	*TOTAL*
Drug-involved	4	9	82	10	***105***
HIV/AIDS	2	4	71	5	***82***
Other Medical	3	8	53	17	***81***
Violence-related	5	10	19	23	***57***
Other	2	2	10	10	***24***
	16	***33***	***235***	***65***	***349***

Among the decedents, medical causes other than HIV/AIDS were distributed evenly across the drug combinations (c^2=.571, P=.9). However, significant differences were found for each of the other causes of death (P<.05). Cocaine and heroin combinations had much larger than expected counts of drug-involved causes and HIV/AIDS. Thirty-five percent of the drug-involved deaths and 30% or the HIV/AIDS occurred among subjects who used both cocaine and heroin. Subjects who used cocaine only, cocaine and alcohol only, and all other combinations had about double the expected counts of violent causes.

Table 5 presents the results of the logistic regression models that were used to investigate predictors of mortality following discharge. In the adjusted multivariate model, it can be seen that being male, being older, injecting cocaine, using heroin (in addition to cocaine), and having a medical problem or missing medical data were significantly related to a increased likelihood of death following drug treatment. In contrast, having a severe cocaine problem was significantly associated with a decreased likelihood of mortality in the multivariate model. This finding is difficult to interpret without additional studies, but perhaps could be due to increased attention during treatment for medical issues.

Table 5. Results of Unadjusted and Adjusted Logistic Regression Models Predicting Mortality among a Statewide Sample of Patients with a Cocaine Problem Admitted to Drug Treatment in Maryland (n = 10,504).

Variables	Decedents		Survivors		Unadjusted Model		Adjusted Model	
	n	%	n	%	OR	95% C.I.	OR	95% C.I.
Age at Discharge (Mean, sd)	37.8	8.3	34.0	7.4	1.1*	1.05-1.08	1.0	1.02-1.05
Sex								
Female	109	31.2	3834	37.8	1.0	—	1.0	—
Male	240	68.8	6321	62.2	1.3*	1.06-1.68	1.4	1.10-1.79
Race								
White	95	27.2	3566	35.1	1.0	—	1.0	—
Black	254	72.8	6589	64.9	1.4*	1.13-1.84	1.0	0.79-1.33
Drug Problem in Addition to Cocaine								
Alcohol	153	43.8	5790	57.0	0.6*	0.48-0.73	0.9	0.68-1.11
Heroin	235	67.3	6194	61.0	3.2*	2.57-4.05	1.8*	1.30-2.45
Marijuana	89	25.5	3961	39.0	0.6*	0.46-0.75	1.0	0.79-1.37
Cocaine Problem Severity								
Mild/Moderate	120	34.4	2825	27.8	1.0	—	1.0	—
Severe	229	65.6	7330	72.2	0.7*	0.59-0.92	0.7*	0.54-0.88
Daily Use of Cocaine								
No	243	69.6	7752	76.3	1.0	—	1.0	—
Yes	106	30.4	2403	23.7	1.4*	1.12-1.78	1.1	0.86-1.44
Route of Cocaine Administration								
Other	46	13.2	1927	19.0	1.0	—	1.0	—
Smoking	127	36.4	6152	60.6	0.9	0.62-1.22	1.0	0.73-1.49
Injection	176	50.4	2076	20.4	3.6*	2.55-4.94	2.1*	1.43-3.03
Medical Problem								
No	141	40.4	6205	61.1	1.0	—	1.0	—
Yes	132	37.8	2689	26.5	2.2*	1.70-2.75	1.6*	1.20-2.26
Missing Data	76	21.8	1261	12.4	2.7*	1.99-3.53	1.8*	1.41-2.32

*denotes a statistically significant odds ratio

4. Employment following Drug Treatment in Baltimore City: General Findings

Purpose: To compare the proportion of patients who are employed in the 12 months pre-admission and 12 months post-discharge from drug treatment and to examine the effect of treatment completion on post-discharge employment and wages among a sample of patients attending drug treatment in Baltimore City.

Sample: Data from 4,002 patients in the CIRMIS database who were admitted and discharged in FY 1998, were merged with wage records from the Department of Labor, Licensing and Regulation. The resulting sample size was 2,959 patients, after excluding the following patients from the analyses:

- Patients admitted to a methadone program.
- Patients admitted to a detoxification program.
- Patients with missing Social Security Numbers.
- Patients whose reason for discharge was "death"- because a death discharge would obviously eliminate the opportunity for employment after discharge.
- Patients whose reason for discharge was "incarcerated"- because the opportunity for employment in that group may be different.
- Adult patients 65 years of age or older.

Methods: When no match was found for the record in the wage record database, the patient was assumed to have no employment. The wage record database was organized by quarter. Any employment was defined as having a record of wages earned in any of the four quarters following the end of the index treatment episode. Annual wages were defined as the sum of wages in the four quarters following the end of the index episode. Multiple logistic regression was used to quantify the association between treatment variables and employment, while controlling for patient demographics, types of presenting drug problems, and length of stay. Ordinary least squares regression was used for the subset of individuals who had at least some wages following treatment, also with adjustment for covariates.

Results: Of the 2,959 patients in the analysis, 58.8% received at least some wages in the four quarters following discharge from drug treatment. Figure 4 displays a comparison between the proportion of the sample that was employed before admission and after discharge for the total sample, and separately for individuals who completed treatment and those who did not complete treatment. It can be seen that completers were more likely to be employed both before and after treatment and that the relative increase in employment was greater for completers.

Figure 5. Proportion of Patients attending Drug Treatment in Baltimore City who were Employed Pre-admission and Post-discharge for the Total Sample and by Completion Status (n = 2,959).

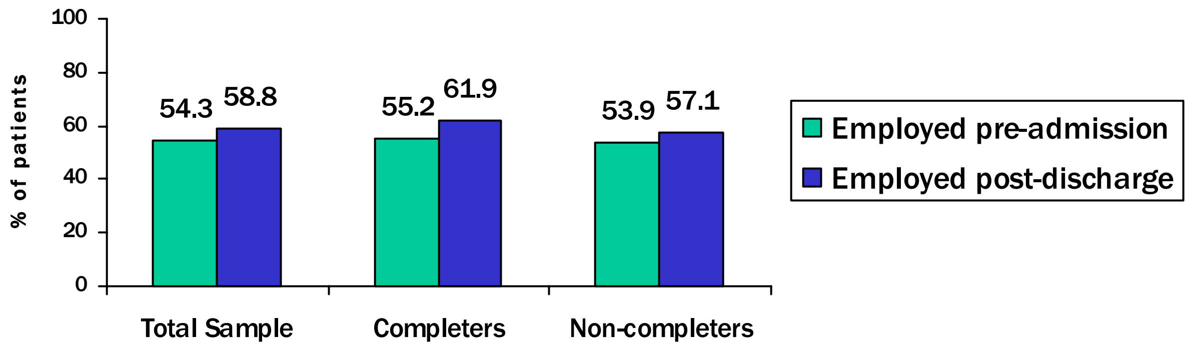


Table 6 presents the results of the regression models that predict post-discharge employment and the sum of wages among the subset of patients who were employed post-discharge. Treatment completers and patients with longer lengths of stay were approximately 25% more likely to be employed in the year following discharge than noncompleters and those with lengths of stay less than 90 days. Also associated with post-discharge employment were: younger age, being male, and having prior employment.

For the subsample who were employed post-discharge, higher wage levels were found for treatment completers, those with lengths of stay longer than 90 days, and individuals who were employed prior to treatment admission.

Table 6. Results of Logistic Regression Models Predicting Post-Discharge Employment and Total Wages in the Year following Discharge among Patients Attending Baltimore City Drug Treatment Programs (n = 2,959)

Variables	Employed (n = 1740)		Not Employed (n = 1219)		Adjusted model predicting Employment (n = 2,959)		Adjusted model predicting wages post-discharge (n = 1,736)	
	n	%	n	%	OR	P value	β	P value
Age								
>45	130	7.5	152	12.5	1			
18-30	607	34.9	394	32.3	1.75	*	-511.2	ns
31-45	1003	57.6	673	55.2	1.75	*	-7.18	ns
Sex								
Female	545	31.3	504	41.3	1			
Male	1195	68.7	715	58.7	1.34	*	728.0	ns
Race								
Non-white	1451	83.4	1039	85.2	1			
White	289	16.6	180	14.8	1.03	ns	851.3	ns
Living Arrangement								
Live alone	760	43.7	533	43.7	1			
Live with others	980	56.3	686	56.3	1.04	ns	632.1	ns
Prior Employment								
No	1033	64.2	885	65.5	1			
Yes	575	35.8	466	34.5	5.41	*	0.7	*
Prior Arrest								
No	672	38.6	450	36.9	1			
Yes	1068	61.4	769	63.1	0.94	ns	81.44	ns
Type of Drug Problem								
Alcohol Only	142	8.2	115	9.4	1			
Marijuana Only	64	3.7	55	4.5	0.88	ns	150.2	ns
Another Drug	408	23.4	262	21.5	1.19	ns	-1212.6	ns
Multiple Drugs	493	28.3	353	29.0	1.17	ns	-1280.6	ns
Alcohol & Marijuana	111	6.4	63	5.0	1.25	ns	-245.3	ns
Alcohol & Another Drug(s)	522	30.0	371	30.4	1.12	ns	-822.5	ns
Length of Treatment Episode								
Less than 90 days	1342	77.1	964	79.1	1			
Length of Episode > 90 days	398	22.9	255	20.9	1.25	*	2268.8	*
Treatment Completion								
No	1096	63.0	822	67.4	1			
Yes	644	37.0	397	32.6	1.24	*	1404.0	*

* denotes statistically significant odds ratio

General Limitations of Studies Using Administrative Employment Databases:

- The employment database does not include records of wages earned outside of Maryland.
- The wage record database includes only full SSN as a unique identifier. No other demographic data are available to utilize for matching.

5. Employment Patterns Before, During and After Drug Treatment

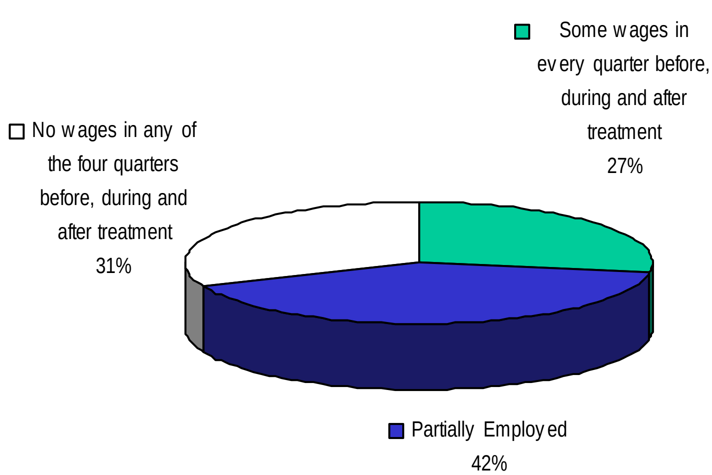
Purpose: To examine the patterns of employment among drug treatment patients attending Baltimore City programs.

Sample: Data from 4,002 cases in the CIRMIS of the Baltimore City treatment database in FY 1998 were merged with data from the Department of Labor, Licensing, and Regulation. The same set of exclusionary criteria was used as described in Section C4, with the exception that detoxification patients were included for this descriptive analysis.

Methods: A variable was created that designated full, partial, or no employment in the four quarters before and after treatment. Basic descriptive statistics were used to describe the sample.

Results: Of the 3,441 patients in the analysis, 27% were employed in every quarter before, during and after treatment; 31% did not receive any wages in any of the quarters before, during, and after treatment. Figure 6 displays these findings.

Figure 6. Employment Patterns among Patients Attending Treatment Programs in Baltimore City, FY 1998 (n = 3,441).



6. Arrests following Drug Treatment in Maryland: General Findings

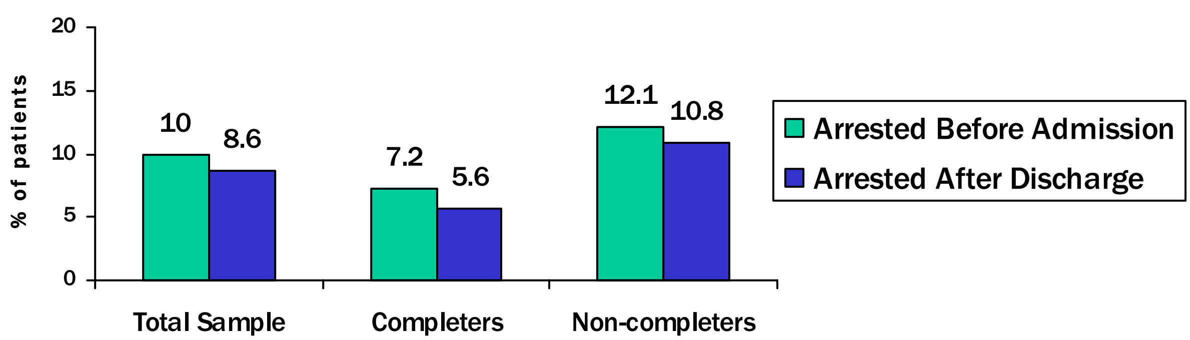
Purpose: To compare the proportion of patients who were arrested in the 12 months preadmission and 12 months post-discharge from drug treatment and to examine the effect of treatment completion on post-discharge arrest among a sample of patients attending drug treatment in Maryland.

Sample: Data from 11,841 patients in the SAMIS database who were admitted and discharged in FY 1997 were merged with arrest records from the Department of Public Safety and Correctional Services. The same exclusionary criteria used for the employment analyses (see Section C.4) were applied, with the exception that individuals older than 65 and patients whose reason for discharge was incarceration were included.

Methods: When no match was found for the record in the arrest database, the patient was assumed to have not been arrested during the follow-up period. Bivariate (unadjusted) logistic regression models were developed for demographic, drug use, and treatment variables with a suspected association with arrest. An odds ratio and 95% confidence interval were calculated to measure the likelihood of arrest for each variable. Basic demographic characteristics (sex, race, and age) and the variables that were significant in the bivariate logistic regressions were included in a multivariate (adjusted) logistic regression model to predict arrest.

Results: Of the 11,841 patients in the analysis, 8.6% were arrested in the 12 months following discharge from drug treatment. Figure 7 displays the comparison between the proportion of the sample that had been arrested before admission and after discharge for the total sample, and separately for individuals who completed treatment and those who did not complete treatment.

Figure 7. Proportion of Patients Attending Drug Treatment in Maryland Who Were Arrested Pre-admission and Post-discharge for the Total Sample and by Completion Status (n = 11,841).



It can be seen that completers were less likely to be arrested both before and after treatment and that the relative decrease was greater for completers. Table 7 presents the results of the regression models that predict post-discharge arrest. Treatment completers were 54% less likely to be arrested in the year following discharge than non-completers. Also associated with post-discharge arrest were being male and nonwhite. Some drug cluster groups also had a lower risk of being arrested relative to the heroin, cocaine, and alcohol group.

Table 7. Results of Logistic Regression Models Predicting Post-Discharge Arrest in the Year following Discharge among Patients Attending Drug Treatment Programs in Maryland (n = 11,841) (* denotes a statistically significant O.R.).

Variables	Arrested		Not Arrested		Unadjusted Model		Adjusted Model	
	n	%	n	%	OR	95% C.I.	OR	95% C.I.
Age	31.48	7.90	33.58	9.54	.97	.97-.98	.96	.96-.97
Sex								
Male	747	73.6	7,599	70.2	1.00	—	1.00	—
Female	268	26.4	3,227	29.8	.85*	.73-.98	.63*	.53-.74
Race								
Non-white	696	68.6	5,359	49.5	1.00	—	1.00	—
White	319	31.4	5,467	50.5	.45*	.39-.52	.75*	.63-.90
Type of Drug Problem								
Heroin, Cocaine, & Alcohol	94	9.3	500	4.6	1.00	—	1.00	—
Cocaine & Alcohol, & Marijuana	318	31.3	3,457	31.9	.49*	.38-.63	.73*	.56-.96
Heroin & Cocaine	259	25.5	1,229	11.4	1.12	.87-1.45	.98	.74-1.30
Alcohol	271	26.7	5,321	49.2	.27*	.21-.35	.56*	.42-.75
Heroin, Some Alcohol	73	7.2	319	2.9	1.22	.87-1.70	1.09	.76-1.56
Pretreatment arrest status								
Yes	287	28.3	901	8.3	1.00	—	1.00	—
No	728	71.7	9,925	91.7	.24*	.20-.27	.39*	.33-.47
Treatment Completion								
No	735	72.4	6,079	56.2	1.00	—	1.00	—
Yes	280	27.6	4,747	43.8	.49*	.42-.56	.54*	.45-.65
Length of Stay								
< 90 Days	810	79.8	7,302	67.4	1.00	—	1.00	—
≥ 90 Days	205	20.2	3,524	32.6	.52*	.45-.61	.94	.78-1.14
Source of Referral								
DWI/DUI	43	4.2	1,653	15.3	1.00	—	1.00	—
Voluntary	541	53.3	5,447	50.3	3.82*	2.79-5.23	1.39	.95-2.03
Other Criminal Justice	431	42.5	3,726	34.4	4.45*	3.23-6.11	1.20	.83-1.73
Treatment Modality								
Residential	322	31.7	2,817	26.0	1.00	—	1.00	—
Outpatient	693	68.3	8,009	74.0	.76*	.66-.87	1.28	.75-2.19

7. Reductions in Acquisitive Crime Following Drug Treatment in Baltimore City

Purpose: Acquisitive crimes, or income-generating crimes, are thought to be the types of crimes most commonly committed by drug users. This study investigated the association between treatment program completion and arrest for acquisitive crimes during the two-year period following discharge from a drug treatment program in Maryland. Also, we sought to examine whether the link between treatment completion and arrest is modified by prior history of acquisitive crime, type of drug problem, and length of stay in treatment.

Sample: Data from 4,002 cases in the CIRMIS of the Baltimore City treatment database in FY 1998 were merged with data from the Department of Public Safety and Correctional Services. The same set of exclusionary criteria was used as described in Section C.4 with the exception that detoxification patients and individuals whose reason for discharge was incarceration were included. Because some clients belonged to more than one of these exclusionary groups, 3,539 clients remained in the final sample for analysis.

Methods: The focus of the study was on rearrest events for acquisitive crime, which was coded in two ways: 1) whether or not the event occurred; and 2) the time to the event. The presence/absence of an arrest for acquisitive crime was examined using logistic regression models. The time to arrest was examined using survival analyses. Three categories of treatment completion were used: 1) completed treatment; 2) completed treatment and referred for more treatment; and 3) noncompletion of treatment.

Results: Table 8 shows the results of the logistic regression model to predict acquisitive crime in the two years following discharge from drug treatment. Treatment non-completion was associated with a 55% increase in the likelihood of post-discharge arrest for acquisitive crime as compared to treatment completion. Prior arrests for acquisitive crimes, having cocaine and heroin problems, and being exposed to less than seven days of treatment were associated with increased odds of arrest for acquisitive crime.

Table 8. Regression Models Predicting Acquisitive Crime in the Two Years following Discharge from Drug Treatment in Baltimore City (n = 3,539).

Variables	Arrested		Not Arrested		Unadjusted Model		Adjusted Model	
Treatment Completion	n	%	n	%	OR	95% CI	OR	95% CI
Completed	113	23.2	1,045	34.3	1.00	—	1.00	—
Did Not Complete	342	70.1	1,777	58.2	1.70*	1.38, 2.11	1.55*	1.23, 1.95
Referred	33	6.8	229	7.5	1.32	0.90, 1.95	1.43	0.96, 2.13
History of Acquisitive Crime								
No Arrests	287	58.8	2,661	87.2	1.00	—	1.00	—
Three or More Arrests	38	7.8	41	1.3	7.07*	4.59, 10.89	5.02*	3.20, 7.89
Two Arrests	41	8.4	60	2.0	5.11*	3.57, 7.30	4.20*	2.92, 6.05
One Arrest	122	25.0	289	9.5	3.10*	2.48, 3.87	2.66*	2.12, 3.35
Type of Drug Problem								
Alcohol & Marijuana	66	13.5	677	22.2	1.00	—	1.00	—
Cocaine & Heroin	207	42.4	1,040	34.1	2.00*	1.52, 2.64	1.99*	1.42, 2.79
Heroin Only	146	29.9	714	23.4	2.01*	1.51, 2.69	1.91*	1.37, 2.65
Cocaine Only	50	10.2	346	11.3	1.44	1.00, 2.09	1.81*	1.23, 2.66
Alcohol, Cocaine & Marijuana	19	3.9	274	9.0	0.73	0.44, 1.22	1.00	0.59, 1.70
Length of Time in Treatment								
More than 7 days	128	26.2	543	17.8	1.61*	1.32, 1.97	1.53*	1.24, 1.88
Less than or equal to 7 days	360	73.8	2,508	82.2	1.00	—	1.00	—

* denotes a significant O.R.

8. Readmission to Drug Treatment in Maryland: General Findings

Purpose: This study determined the proportion of patients readmitted to drug treatment in Maryland over a six-year follow-up period and examined the correlates of readmission.

Sample: 11,876 patients admitted to outpatient, intensive outpatient or residential drug treatment programs in Maryland during FY 1996.

Methods: Descriptive statistics were used to determine the proportion of patients who were readmitted at any time during the six-year follow-up period, the number of readmissions, and the number of days to the first readmission. Logistic regression models were developed to understand how individual characteristics (demographic variables and drug use), treatment modality, and treatment completion status was related to subsequent readmission.

Results: Close to 40% of patients were readmitted at least once during the six-year follow-up period. Figure 8 shows the frequency of readmissions. Fifty percent of readmissions occurred within 203 days. Only 3.3% of the sample was readmitted more than once. Table 9 shows the results of logistic regression models predicting any readmission over the six-year follow-up period. In the adjusted model, it can be seen that being readmitted was significantly associated with being female, being White as compared to Black, being unemployed, having more than one drug problem, having more than one prior treatment admission, noncompletion of treatment (either because of being referred, noncompliance, or administrative discharge), being referred to treatment because of a DWI offense, and attending a residential treatment center.

Figure 8. Frequency of Readmission to Drug Treatment at Any Time during a Six-year Follow-up Period among a Statewide Sample of Patients Attending Drug Treatment in Maryland (n = 11, 876).

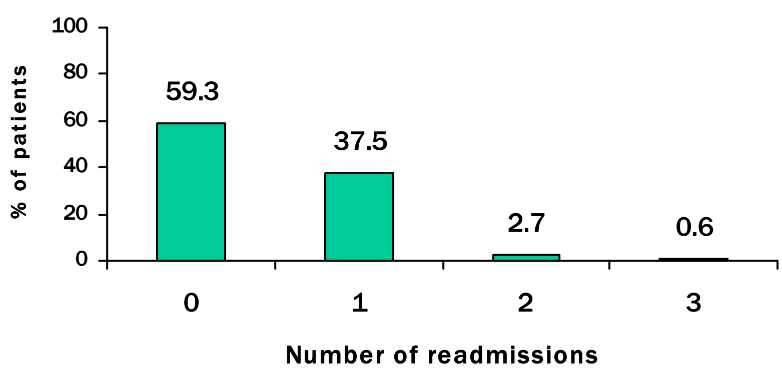


Table 9. Regression Models Predicting at Least One Readmission Over a Six-year Follow-up Period following Admission to Drug Treatment during FY 1996 in Maryland (n = 11,876).

	Readmitted (n = 4939)		Not Readmitted (n = 7037)		Unadjusted		Adjusted	
VARIABLES	N	%	N	%	OR	95% C.I.	OR	95% C.I.
Sex								
Male	2,951	68.2	5,635	74.6	1.00	—	1.00	—
Female	1,375	31.8	1,915	25.4	1.37*	1.26-1.49	1.26*	1.15-1.37
Race								
Black	2,242	51.8	3,845	50.9	1.00	—	1.00	—
White	2,031	46.9	3,423	45.3	1.02	.94-1.10	1.15*	1.06-1.25
Other	53	1.2	282	3.7	.32*	.24-.43	.45	.33-.61
Marital Status								
Married	568	13.1	1,173	15.5	1.00	—	1.00	—
Never Married	2,634	60.9	4,454	59.0	1.22*	1.09-1.37	1.07	.95-1.20
Divorced/Separated/ Widowed	1,124	26.0	1,923	25.5	1.21*	1.07-1.37	1.02	.89-1.16
Highest Education Completed	11.46	1.86	11.57	2.00	.97*	.95-.99	.98	.96-1.00
Employment at Discharge								
Employed	1,563	36.1	3,393	44.9	1.00	—	1.00	—
Unemployed	2,483	57.4	3,578	47.4	1.51*	1.39-1.63	1.15*	1.05-1.26
Not Seeking Employment	280	6.5	579	7.7	1.05	.90-1.23	.94	.80-1.10
Drug Problem								
Alcohol Use Only	829	19.2	2,070	27.4	.63*	.57-.69		
Marijuana Use Only	116	2.7	280	3.7	.72*	.57-.89		
Heroin Use Only	213	4.9	291	3.9	1.29*	1.08-1.55		
Cocaine Use Only	266	6.1	465	6.2	1.00	.85-1.17		
Multiple Drug Use	2,883	66.6	4,404	58.3	1.43*	1.32-1.54		
Number of Problem Drugs								
One	1,443	33.4	3,144	41.6	1.00	—	1.00	—
Two	1,466	33.9	2,419	32.0	1.32*	1.21-1.44	1.12	1.02-1.23
Three	1,417	32.8	1,987	26.3	1.55*	1.42-1.70	1.22*	1.11-1.35
Number of Arrests at Admission	1.07	1.28	1.00	1.22	1.05*	1.01-1.08	1.02	.99-1.06
Number of Prior Admissions	1.38	1.56	.99	1.35	1.20*	1.17-1.23	1.16*	1.13-1.20
Reason for Discharge								
Completion	1,163	26.9	2,991	39.6	1.00	—	1.00	—
Noncompletion	2,522	58.3	3,730	49.4	1.74*	1.60-1.89	1.65*	1.49-1.83
Refer/Change	641	14.8	829	11.0	1.99*	1.76-2.25	1.77*	1.55-2.03
Length of Stay	57.86	61.8	79.69	77.68	1.00	.99-1.00	1.00	1.00-1.00
Source of Referral								
Other Referral	1,034	23.9	1,694	22.4	1.00	—	1.00	—
Self/Voluntary	1,091	25.2	1,692	22.4	1.06	.95-1.18	.99	.88-1.11
DWI	526	12.2	1,183	15.7	.73*	.64-.83	1.34*	1.15-1.56
Court-Related	1,675	38.7	2,981	39.5	.92	.84-1.01	1.10	.98-1.23
Treatment Modality								
Outpatient	2,568	59.4	5,016	66.4	1.00	—	1.00	—
Intensive Outpatient	446	10.3	671	8.9	1.30*	1.14-1.48	.96	.84-1.11
Residential	1,312	30.3	1,863	24.7	1.37*	1.26-1.50	1.17*	1.03-1.33

* denotes a statistically significant odds ratio

9. Patient Homogeneity and Treatment Completion Among "Alcohol-only" Patients in Maryland

Purpose: This study tested the hypothesis that clients presenting with alcohol problems only are more likely to complete their treatment in clinics where there is a high proportion of similar clients.

Sample: 4,699 patients who presented for treatment with an alcohol problem only (no other substances) and who were discharged during FY 1997. Patients attended 48 Maryland outpatient drug-free programs receiving public funds.

Methods: Completion of treatment plan collected at discharge was the main dependent variable. The primary independent variable was the proportion of alcohol-only admissions in the program (< 1/3, 1/3 – 2/3, >2/3) that the patient was attending. Logistic regression models were developed that adjusted standard errors to account for clustering within the clinics (used STATA 7.0). Adjustments were made for sex, race, age, marital status, education level, employment status, alcohol problem severity, age of first intoxication, and source of referral to treatment.

Results: Figure 9 below shows the completion rate for patients who attended programs with different levels of patient homogeneity. It can be seen that, of those patients who attended programs in which more than 2/3 of the patients had only alcohol problems, 87% completed treatment. The completion rate of patients who attended programs with a lower percentage (less than 1/3) of alcohol-only patients was 49%. Evidence from this research suggests that alcohol-only patients entering drug treatment clinics are more likely to complete treatment when the programs they attend are more homogenous with regard to other alcohol-only patients. Given the known relationship between the importance of treatment retention for long-term benefit of drug treatment, this finding has significant implications for alcohol treatment providers. Table 11 shows the results of the adjusted multivariate logistic regression model. Holding constant all other factors, patients attending clinics with a high proportion of alcohol-only patients were almost five times as likely to complete treatment.

Figure 9. Comparison of Completion Rates for Patients Attending Programs with Different Levels of Homogeneity (i.e., the proportion of other alcohol-only patients in the treatment program).

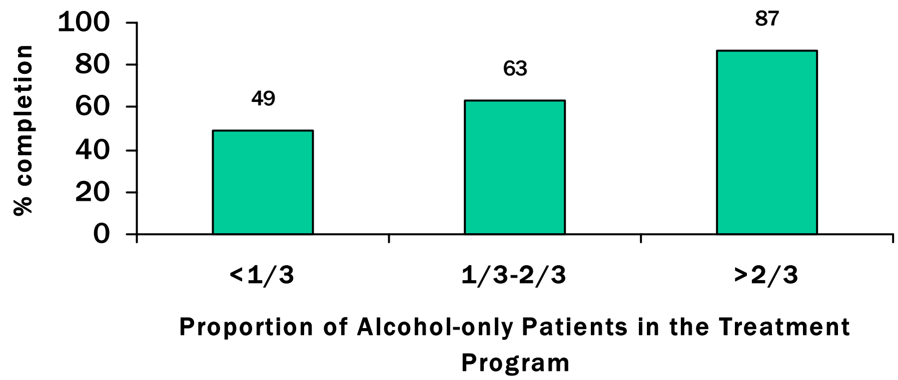


Table 11. Results of a Multivariate Logistic Regression Model for the Association between Homogeneity in Patient Mix and Treatment Completion (n = 4,699).

VARIABLES	OR	95% C.I.
Homogeneity in Patient Mix		
Attended program with <1/3 alcohol-only patients	1.0	—
Attended program with 1/3—2/3 alcohol-only patients	1.3	0.93-1.72
Attended program with >2/3 alcohol-only patients	4.9*	3.23-7.31
Sex		
Female	1.0	—
Male	1.0	0.87-1.22
Race		
Black	1.0	—
White	1.2*	1.01-1.53
Age at Discharge	1.0	1.01-1.03
Marital Status		
Never Married	1.0	—
Married	1.1	0.87-1.32
Divorced/Separated	0.8	0.69-0.93
Widowed/Unknown	1.0	0.61-1.52
Educational Level		
Less than High School	1.0	—
High School/GED	1.2	0.99-1.46
More than High School	1.3*	1.09-1.58
Employment Status		
No	1.0	—
Yes	1.4*	1.20-1.64
Severity of Alcohol Problem		
Mild/Moderate	1.0	—
Severe	0.7*	0.58-0.78
Age of first Intoxication 18 or older	1.2*	1.04-1.36
Source of Referral to Treatment		
DWI	1.0	—
Other Criminal Justice	0.4*	0.35-0.54
Self	0.4*	0.25-0.63
Other Voluntary	0.3*	0.25-0.43

10. The Impact of Distance Traveled on Treatment Completion in Baltimore City

Purpose: Potential barriers to successful treatment completion include having to travel long distances or not having access to public transportation. Few studies have empirically investigated this question. This study examined the association between the approximate distance traveled to outpatient drug treatment programs and treatment retention, which was measured by both treatment completion and length of stay.

Sample: 1,735 Baltimore City patients who attended outpatient programs who were admitted and discharged in FY 1998.

Methods: CIRMIS records were used to obtain demographic, residential zip code, and drug use information on patients. Addresses of the treatment facilities were obtained from ADAA. Population centroids of each zip code were obtained from the United States Census. A distance variable was calculated for each patient that was the distance between the treatment center and the population centroid of the zip code. Length of stay was calculated as the number of days between the admission and discharge dates.

Logistic regression models were developed to examine the strength of the association between distance traveled to the treatment center and treatment completion. Covariates included the type of drug problem, sex, race, educational level, marital status, and health insurance coverage status. Ordinary least squares regression models were developed to examine the relationship between distance traveled and length of stay.

Results: Table 12 shows the results of the adjusted multivariate logistic regression model predicting completion of treatment on the basis of an array of individual level characteristics and approximate distance traveled to the treatment center. Holding constant all other factors, patients traveling less than one mile to treatment were 50% more likely to complete treatment.

Table 12. Results of Logistic Regression Models to Predict Completion of Treatment on the Basis of Approximate Distance Traveled to the Treatment Center in a Sample of Patients Attending Outpatient Drug Treatment in Baltimore City (n = 1,735)

Variables	Adjusted O.R.	95% C.I.
Age	1.02	1.01 - 1.03
Race		
White/Other	1.00	—
Black	0.94	0.69 - 1.27
Sex		
Male	1.00	—
Female	1.49*	1.15 - 1.92
Education		
Not a high school graduate	1.00	—
High school graduate	1.34*	1.06 - 1.69
Marital Status		
Not Married	1.00	—
Married	1.10	0.78 - 1.56
Insurance Coverage		
None	1.00	—
Some	1.21	0.92 - 1.60
Drug Cluster		
Alcohol Only	1.00	—
Heroin & Alcohol	0.46*	0.32 - 0.64
Heroin & Cocaine	0.49*	0.34 - 0.71
Marijuana & Alcohol	0.65*	0.45 - 0.94
Cocaine & Alcohol	0.59*	0.41 - 0.84
Approximate Distance Traveled to Treatment Center		
<1 mile	1.00	—
1 - 2 miles	0.52*	0.37 - 0.74
2 - 4 miles	0.66*	0.47 - 0.93
>4 miles	0.58*	0.40 - 0.84

* denotes statistically significant odds ratio

VI. Discussion and Conclusion

A. Implications of Findings for Treatment Programs and Policies

As discussed earlier, the overarching goal of the Maryland TOPPS-II project was to assess the feasibility of using administrative data linking methods to conduct studies on long-term drug treatment outcomes. This method proved to be extremely successful. Section VA details some of the methodological and administrative challenges that were overcome, as well as other lessons learned from the project. It was not possible to link some types of data to SAMIS drug treatment data, but when datasets could be linked the resulting dataset provided a rich source of information.

Because the utilization of administrative data overcomes many of the limitations inherent in primary data collection (e.g., attrition bias, limited sample sizes), it should be encouraged as a method of measuring drug treatment outcomes in Maryland. The strengths, weaknesses, and research potential of administrative data have been reviewed elsewhere (Alterman et al., 2001). While limitations exist, these data provide an efficient and effective means of answering questions posed by policymakers, researchers, and service providers. With the appropriate manipulation, administrative data can provide a rich source of information on a population of patients often neglected in other studies (McCarty et al., 1998).

In addition to demonstrating feasibility, the TOPPS-II project provided local evidence to support earlier studies showing that completion of drug treatment is effective in increasing the likelihood of employment and reducing the chances of re-arrest and readmission.

B. Data Utilization

Utilization of Data Generated through TOPPS-II

The data generated through TOPPS-II have been utilized in two main ways. First, the preliminary results have been useful in presentations to legislators and other policymakers to convince them of the need for sustained funding of drug treatment as well as the need for performance measurement outcome systems. Second, some of the results from the TOPPS-II project have already been sent to scientific journals for publication consideration and other studies are being prepared for publication. In this way, the results of the TOPPS-II project will not only help Maryland, but will add to the growing body of literature supporting the effectiveness of drug treatment.

Projected Sustained Systems Change as a Result of TOPPS-II Participation

As discussed earlier, there is a need for continued performance measurement of drug treatment in Maryland. Efforts have already begun to systematically automate the SAMIS system. Studies similar to those implemented in TOPPS-II have been proposed to utilize SAMIS data to measure long-term outcomes. Moreover, such a system will allow Maryland to answer more complex questions such as what kinds of treatment appear to be most effective for various subgroups of patients entering drug treatment.

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