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INVESTIGATING THE EFFECTS OF SAN FRANCISCO'S TREATMENT ON DEMAND INITIATIVE ON A PUBLICLY-FUNDED SUBSTANCE ABUSE TREATMENT SYSTEM: A TIME SERIES ANALYSIS

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Abstract

This study investigated effects of San Francisco's Treatment on Demand Initiative, which was designed to increase substance abuse treatment capacity, on the host treatment system. Secondary data on substance abuse treatment admissions, from 1995 through 2000, were obtained from the Department of Public Health, Community Substance Abuse Services, San Francisco, California. Data on 73,988 admissions were retained and grouped by week of admission. Time series analysis was used to assess the effects of time and treatment on demand (independent variables) on weekly number of admissions, sociodemographic characteristics and types of treatment received (dependent variables). As a function of treatment on demand, the number of weekly new admissions significantly increased. Standard outpatient treatment and comprehensive care admissions constituted greater proportions of admissions after treatment on demand. Persons with a primary heroin, cocaine or alcohol problem constituted greater proportions of admissions, and first-time treatment clients constituted a smaller proportion of admissions. Findings suggest that a capacity expansion initiative can increase system wide admissions and redistribute admissions among modalities towards more comprehensive care treatments.

Keywords

substance abuse treatment; time series analysis; treatment on demand

Research supports the effectiveness and cost-effectiveness of substance abuse treatment (Ettner et al. 2006; Gerstein et al. 1994), but also shows that the need for treatment far exceeds supply (SAMHSA 2007). The need to expand treatment capacity has received increasing attention in recent years, through efforts to increase the national treatment budget, the provision of SAMSHA grants for targeted capacity expansion, and the revision of state

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sentencing laws to provide treatment rather than jail for nonviolent drug possession offenders (Hser et al. 2003; Arizona State Legislature 1997). Local initiatives that seek to provide “treatment on demand” in San Francisco, CA or “treatment on request” in Baltimore, MD offer one approach to expanding treatment capacity (Sorensen et al. 2007; Drug Strategies 2000).

While expanding capacity is a key objective for publicly-funded substance abuse treatment, little is known about the effects of capacity expansion policies on the host treatment system. Efforts to redesign treatment systems have focused on managed care principles (Deck et al. 2000; Chang et al. 1998), centralized intake and referral procedures (Stephens, Scott & Muck 2003) and linkages between primary care, mental health, and criminal justice systems (Fletcher et al. 2009; Friedmann et al. 2000). More recent efforts to improve substance abuse treatment have focused on, for example, developing strategies for screening, brief intervention and referral to treatment (Desy & Perhats 2008; Bernstein et al. 2005), performance monitoring (Hoffman et al. 2008), and interventions to better address the chronic nature of addictions (Scott, Dennis & Foss 2005; McKay et al. 2004). Little comparable research has been conducted on efforts to expand treatment capacity (e.g., Hser et al. 2007). This may be because few large-scale initiatives have been implemented at the community level. The San Francisco Treatment on Demand Initiative provides an opportunity to assess the impact of capacity expansion on a local treatment system.

TREATMENT ON DEMAND IN SAN FRANCISCO

In November 1996 the San Francisco Board of Supervisors approved a resolution to provide substance abuse treatment on demand (San Francisco Board of Supervisors 1996). The resolution recognized that only 12,000 of the estimated 45,000 San Franciscans who needed treatment were receiving it, and that untreated substance abuse was costing the city an estimated $1.7 billion per year (San Francisco Department of Public Health 1997). The Treatment on Demand Resolution also made a commitment to increase substance abuse treatment funding until capacity met demand. Over the next five years, local government funding for treatment increased by 132%, from $11,070,472 (FY 95–96) to $25,687,307 (FY 99-00). However, in FY 00–01, this trend stopped, and the treatment budget decreased by 6.3% ($1,608,029). Consequently, the present study is focused on FY 95–96 to FY 99-00 as the five-year period when funding increased in accordance with the Treatment on Demand Resolution.

A previous report found that increased treatment on demand funding was associated with a 15% increase in the annual number of treatment admissions and with a change in the way admissions were distributed across types of treatment (Guydish et al. 2000). However, that report did not assess whether changes resulted from the Treatment on Demand Initiative or from preexisting time trends. Time series analysis is a tool for distinguishing time and intervention effects, and has been used in substance abuse treatment to study, for example, methadone maintenance and alcoholism treatments (Holder & Parker 1992; Brecht, Hser & Anglin 1990-91), drunk driver legislation (Mann et al. 2002), policies regulating substance availability (Falcato et al. 2001; Chiu, Perez & Parker 1997), and the impact of methamphetamine precursor regulation on methamphetamine treatment admissions (Cunningham & Liu 2008).

The current study applies time series analysis to assess the independent effect of treatment on demand on San Francisco’s substance abuse treatment system. The report first describes annual changes in the number of new treatment admissions for the five-year study period. Second, it describes annual proportional changes in the types of treatment provided and the sociodemographic characteristics of new admissions. Third, it uses time series analysis to

assess whether observed changes in the number of weekly admissions were effects of treatment on demand or of preexisting time trends. Finally, it applies time series analysis to assess the relationship of treatment on demand to types of treatment provided and sociodemographic characteristics of new weekly admissions.

METHODS

Data Source

Data were extracted from administrative datasets maintained by the San Francisco Department of Public Health Community Substance Abuse Services (CSAS). CSAS is responsible for distributing funds to the city's publicly-funded substance abuse treatment programs, and it collects admission, discharge, and service utilization data. CSAS data were obtained for all treatment system admissions between FY 95–96 and FY 99-00 (n = 153,750). Data were excluded for admissions into methadone programs that did not receive CSAS funding (n = 25,468), drunk driver programs that were self-pay rather than county supported (n = 6,776), and modalities that provided ancillary, referral or short-term stabilization services, but not substance abuse treatment. These programs offered services for supportive housing (n = 77), ancillary medical needs (n = 61), short-term stabilization (n = 36,218), and central intake (n = 11,162), an optional entry point into the treatment system that provided assessment and referral (Guydish et al. 2001). For each of the remaining 73,988 admissions, data included sociodemographics, primary substance abuse problem, treatment program attended, admission and discharge dates, and dates that services were received.

Measures

Number of new treatment admissions—New treatment admission was defined as entrance into any CSAS-funded treatment program and was measured by completion of a client intake form. Admissions were not linked to client identifiers, and a single individual could have multiple admissions. Each admission was counted one time only, on the date the intake occurred.

Sociodemographics—Variables included age, gender, race, drug use (primary substance problem, prior treatment experience), and criminal involvement (recently arrested, current legal status). Age data were collected using a continuous measure, and were then categorized as young adults (18 to 25), adults (26 to 64), and seniors (65 and older) to focus on the age groups targeted by the Treatment on Demand Initiative. Race data were collected using a 22-attribute variable, which was recoded for analytic purposes into six categories (African-American, Asian/Pacific Islander, Latino, Native American/Alaskan Native, White, and "other").

Primary substance use problem was measured using an 18-attribute variable, which was collapsed into six categories: alcohol, cocaine, heroin, marijuana, amphetamines and other drugs (e.g., PCP, other opiates). Prior treatment and recent (past two years) arrests were collected through continuous measures, and then dichotomized as any vs. no prior treatment, and any vs. no arrest in past two years. Data on current legal status were collected through a six-attribute variable reflecting incarceration, or involvement in diversion, probation, or parole. These data were dichotomized as any vs. no current involvement in the criminal justice system.

Types of treatments received—Each service delivery unit in the San Francisco treatment system is assigned a unique reporting number, which includes designation of the treatment modality. This number was reported on the client intake form, and was used to

connect each admission with the treatment modality received. The treatment modality variable consisted of seven attributes: residential treatment, day treatment, standard outpatient, intensive outpatient, methadone maintenance, methadone detoxification, and residential detoxification.

We also measured type of treatment received by a dichotomous level of care variable (detoxification-only vs. comprehensive care), to supplement and streamline the modality measure. We defined detoxification-only as admission into a short-term program that provides residential detoxification or methadone detoxification services. Comprehensive care was defined as admission into a longer-term program that provides more comprehensive services, i.e. residential treatment, day treatment, outpatient, intensive outpatient, or methadone maintenance.

Treatment on demand—"Treatment on demand" was entered into each analytic model as the intervention variable. Ideally, this would have been a continuous variable reflecting the amount of treatment on demand monies spent per month. However, CSAS did not keep monthly expenditure records for the first two years of the study period and a monthly spending variable could not be created. Instead, we used annual increases in treatment on demand funding. Because a distinct "Treatment on Demand" line-item was not consistently reported in budget documents, we used the County General Fund line-item, adjusted for inflation, to indicate treatment on demand funding. The County General Fund includes all monies provided by the City and County of San Francisco for substance abuse treatment, and changes in this line-item during the study period reflect changes in treatment on demand funds (Guydish et al. 2000).

Control variables—To control for external influences, the analytic model included four meteorological, economic and population indicators: local rainfall, local unemployment rate, NASDAQ composite index at close of day, and San Francisco population (Bureau of Labor Statistics 2002; NASDAQ 2002; University of California, San Diego 2002; United States Census Bureau 2000). All variables were entered weekly; average weekly unemployment rates were computed from monthly unemployment rates, and average weekly population values were computed from annual population figures.

Statistical Analysis

To describe the treatment system before and during treatment on demand, all admissions for FY 95–96 to FY 99-00 were examined, grouped by fiscal year (July 1 through June 30). All demographic, drug use, criminal involvement, and types of treatment measures were expressed as a percent of total annual admissions.

To analyze the effect of treatment on demand on system changes, data were grouped into weeks by date of admission. All weeks in FY 95-00 were included and all measures were expressed as a percent of total weekly admissions. Standard linear regression analyses were inappropriate for these data, since they exhibited autocorrelation such that adjacent observations were dependent on each other, which results in biased estimates of the relationship between variables (e.g., number of treatment admissions in one week may affect the number of treatment admissions the next week). Instead, analyses used auto-regressive integrated moving average (ARIMA) modeling techniques, developed to address this characteristic of time series data.

Analyses were conducted with the R statistical package, which provides ARIMA procedures for fitting time series data (R Development Core Team 2005; Durbin & Koopman 2001; Gardner, Harvey & Phillips 1980). Each outcome time series was tested for stationarity using a Phillips-Peron Unit Root Test to ensure constant mean and variance over the time

series (Banerjee et al. 1993). If a time series proved to be nonstationary the series was linearly detrended, resulting in stationarity (Warner 1998). Each time series was then seasonally decomposed to identify seasonal periodicity (Cleveland et al. 1990). The Yule-Walker method was used to estimate the order in which adjacent observations were dependent on each other (Brockwell & Davis 1991). The order of autocorrelation and period of seasonality were passed as input parameters into the ARIMA procedure. The final ARIMA procedure resulted in a linear regression model with coefficients controlling for autocorrelation and seasonal effects, as well as estimated coefficients for the treatment on demand variable and the four external regresses (rainfall, unemployment, NASDAQ composite index, and population). Last, a Box-Pierce test verified the normality of the model residuals distribution; a normal distribution indicated that the model was controlling for the autocorrelation effect (Box & Pierce 1970). Overall, set time series models were run, one for each dependent measure. Each model included the covariates treatment on demand, time, and the meteorological, economic and population control variables.

RESULTS

Descriptive Results: Annual Trends in Treatment Admissions

Figure 1 shows the number of weekly new treatment admissions (labeled in the left vertical axis) as a jagged line plotted over time (horizontal axis). A second line, resembling steps, reflects the annual increases in Treatment on Demand funding (right vertical axis). On visual inspection, admissions appeared stable during the first 18 months of treatment on demand (July 1997 through December 1998) and peaked between January and June 1999. This suggests that it took 18 months from the initial allocation of treatment on demand funds for an observable increase in admissions to occur.

Treatment on demand funding, total admissions and how admissions were distributed across modalities are shown, by year, in Table 1. The annual number of new treatment admissions increased 53% from 12,638 admissions in fiscal year (FY) 95–96 to 19,298 admissions in FY 99-00. Over this same time there were substantial increases (more than five percentage points) in the proportion of new admissions entering standard outpatient treatment (30% vs. 39%) and intensive outpatient treatment (0% vs. 9%), and a substantial decrease in the percent entering residential detoxification (42% vs. 26%). There was also an increase in the percent of total admissions entering comprehensive care (51% vs. 66%).

Sociodemographic characteristics of the treatment admission population were also compared across the five year period (data not shown). Only minor fluctuations were seen over time for age, gender, race/ethnicity, and the proportion that had been arrested in the past two years. However, from FY 95–96 to FY 99-00, substantial increases were observed in the proportion of admissions who were entering treatment for the first time (44% vs. 49%), involved in the criminal justice system (22% vs. 27%), and entering treatment for a primary heroin problem (32% vs. 38%). Decreases were observed in the proportion of admissions entering treatment with a primary cocaine problem (29% vs. 22%).

Time Series Results: Effects of Treatment on Demand Funding on Admissions

Number of new admissions—Table 2 shows the results of time series analysis assessing the independent effects of treatment on demand funding and time on total number of new weekly admissions. Treatment on demand was independently associated with an increase in weekly number of new treatment admissions ($p = .0002$), while time was not ($p = .9422$).

Types of treatment provided—With treatment on demand funding, also shown in Table 2, there was a significant increase in the proportion of all admissions that entered standard

outpatient treatment (p = .0496) and comprehensive care treatment (p = .0432). For time, there was a significant increase in the proportion of all admissions that entered standard outpatient treatment, residential treatment, and comprehensive care treatment, and a significant decrease in the proportions that entered methadone maintenance and methadone detoxification.

Demographic characteristics of persons admitted to treatment—Time series analyses were also used to assess the independent effects of treatment on demand funding and time on the demographic characteristics of persons admitted to treatment (data not shown). These included age (in two groupings: 18 to 25 and 26 to 64), race/ethnicity, gender, and primary drug problem. Other demographic characteristics assessed were whether this was the first time in treatment, whether the person had been arrested in the past two years, and whether they were currently involved in the criminal justice system.

Treatment on demand was significantly associated with an increase in the percent of admissions for persons with a primary alcohol problem (coefficient = 1.52E-08, SE = 1.38E-09, $p < .0001$), primary cocaine problem (coefficient = 8.77E-09, SE = 1.81E-09, $p < .0001$), and primary heroin problem (coefficient = 1.17E-08, SE = 3.95E-09, $p = .0031$). Treatment on demand funding was also associated with a significant decrease in the proportion of admissions entering treatment for the first time (coefficient = −4.26E-08, SE = 5.67E-09, $p < .0001$).

Time was associated with significant increases in the percent of admissions made by 18- to 25-year-olds, women, Asian/Pacific Islanders, Latinos, Native Americans, people of “other race/ethnicity,” entering treatment for the first time, entering treatment with a primary marijuana problem, and involvement in the criminal justice system. Time was also associated with significant decreases in the percent of admissions for persons over age 25, Whites, and people entering treatment with a primary alcohol, primary amphetamine, and primary heroin problem.

DISCUSSION

This study assessed the relationship between the San Francisco Treatment on Demand Initiative and changes observed in the treatment system. Treatment on demand was associated with an increase in the number of weekly admissions, with increased utilization of outpatient treatment and comprehensive care, and with changes in the sociodemographics of admissions, including a decrease in first-time treatment clients.

The increase in new admissions was associated with treatment on demand independent of preexisting time trends. Some delay in translating new funds into new services can be expected in any system, and the 18-month lag observed in Figure 1 may reflect such delays. For example, McLellan and colleagues (1998) reported on a clinical case management intervention in eight treatment programs, where full implementation of the intervention took 26 months. The San Francisco Treatment on Demand Initiative involved a process of identifying needs, establishing priorities, requesting proposals, evaluating proposals, and awarding contracts. The translation of those contracts into client services was sometimes delayed when the expansion involved developing new programs or renovating existing program sites, and where zoning laws or neighborhood opposition slowed program expansion (Guydish et al. 2000). At the same time, the peaking of admissions in 1999 may not reflect the delayed effects of funds allocated 18 months earlier, but the effects of sustained funding increases. Our data cannot assess these hypotheses, but they do provide some guidelines for other treatment systems interested in capacity expansion. The Treatment on Demand Initiative sought to expand capacity through increased local funding and a

community planning process, and our findings suggest a relationship between this approach and a lagged increase in new admissions.

Treatment on demand was associated with a proportional increase in the utilization of comprehensive care treatments, particularly standard outpatient treatment, and a concomitant decrease in the utilization of front-end treatments. This suggests that treatment on demand facilitated a shift away from modalities that specialized in short term and detoxification services, and increased access into modalities that provided longer-term treatment. Front-end programs are important in the treatment system, as they provide detoxification and referral, and engage drug users who may not be ready to enroll in more demanding treatments (Mattick & Hall 1996). The shift described here is encouraging, as the aim of most front-end programs is to facilitate entrance into comprehensive care programs and not to independently impact outcomes. Lack of treatment capacity often thwarts this aim, and substance users can get trapped in the “revolving door” of front-end treatments (McCarty et al. 2000). These results suggest that treatment on demand may have enabled more ready access to comprehensive treatments.

Treatment on demand was also associated with changes in the sociodemographics of new admissions. Admissions for a primary heroin, cocaine and alcohol problem proportionately increased in association with treatment on demand, suggesting that the initiative effectively reached users of these particularly addictive substances. However, first-time treatment clients decreased as a percent of all admissions, suggesting that treatment on demand may have been more effective in supporting treatment reentry than in supporting treatment initiation. Treatment reentry is of interest because a high proportion of persons entering substance abuse treatment require multiple treatment episodes to achieve and maintain sobriety (Dennis et al. 2005; Weisner et al. 2003; Hser et al. 2001). Nonetheless, treatment initiation follows addiction by approximately seven years, during which time a host of problems accrue (Anglin, Hser & Grella 1997), so that plans to expand capacity may consider strategies to attract treatment novices.

Analyses relied on administrative data that were not collected for the specific purposes of this study, and were not subject to scientific oversight and quality control. We sought to minimize data quality limitations by data cleaning and crosschecking, by consultation with Department of Public Health data analysis staff, and by eliminating questionable variables from analysis. Second, this investigation of treatment on demand effects was confined to the relatively small set of variables available. No data were available on monthly treatment expenditures, which limited the sensitivity of our “treatment on demand” variable, and no data were available on treatment outcomes. Finally, although time series models distinguished between time and intervention effects, and included several control variables, other events not reflected in the model may have occurred at the same time and may have influenced treatment admissions (e.g. changes in drug prices or cuts in federal funding).

San Francisco’s Treatment on Demand Initiative provided an opportunity to examine the effects of a capacity-expansion policy on one host treatment system. In this study treatment on demand was associated with increases in the number of new admissions, the percent of new admissions who were primary heroin, cocaine and alcohol users, and the percent of new admissions who entered a comprehensive care treatment modality. Findings suggest that a capacity expansion initiative can increase system wide admissions and redistribute admissions among modalities towards more comprehensive care treatments.

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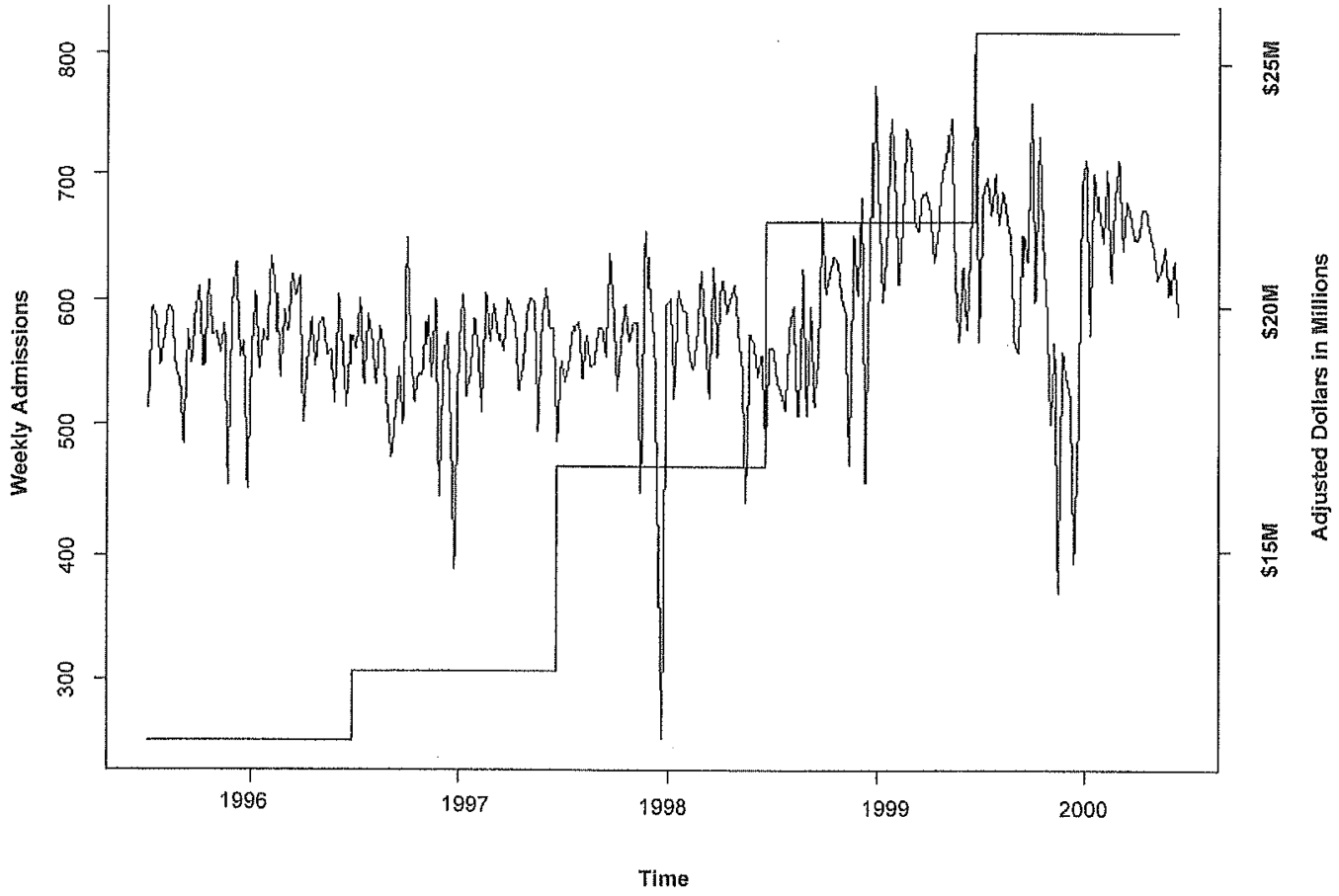

FIGURE 1.
Annual Local Government Funding and Weekly New Admissions into San Francisco's Substance Abuse Treatment System, July 1995 to June 2000

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TABLE 1

Annual Treatment on Demand Funding, Total New Admissions, and Types of Treatment Provided, FY 95–96 to FY 99-00

	FY 95–96		FY 96–97		FY 97–98		FY 98–99		FY 99-00	
Treatment on Demand Funding	11,070,472		12,494,251		16,708,146		21,759,525		25,687,307	
Total Admissions	12,638		12,489		13,225		16,338		19,298	
	n	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
Modality										
Day Treatment	512	4	511	4	650	5	663	4	792	4
Methadone Detoxification	855	7	756	6	1110	8	1346	8	1486	8
Methadone Maintenance	713	6	776	6	782	6	775	5	966	5
Standard OP	3818	30	3792	30	4195	32	6018	37	7592	39
Intensive OP	0	0	0	0	0	0	57	0	1725	9
Residential	1386	11	1612	13	1525	12	1666	10	1639	8
Residential Detoxification	5354	42	5042	40	4963	38	5813	36	5098	26
Comprehensive	6429	51	6691	54	7152	54	9179	56	12714	66

TABLE 2

Time Series Analysis of Effects of Treatment on Demand Funding and Time on Total Weekly New Admissions and Types of Treatment Provided, FY 95–96 to FY 99-00

	Treatment on Demand				Time				
Dependent Variable	**Regression Coefficient**	**SE**	**z-stat**	***p*-value**	**Regression Coefficient**	**SE**	**z-stat**	***p*-value**	**AIC***
Total new admissions Modality (%)	1.09E-05	2.92E-06	3.74	0.0002	−1.63E+00	2.24E+01	−0.07	0.9422	*3997.95*
Day Treatment	3.57E-10	7.14E-09	0.05	0.9601	−2.74E-05	1.95E-05	−1.41	0.1594	*−1321.95*
Methadone									
Detoxification	2.20E-09	3.19E-09	0.69	0.4911	−1.24E-04	4.41E-05	−2.81	0.0049	*−1228.75*
Methadone Maintenance	2.44E-09	5.74E-09	0.43	0.6703	−2.95E-04	7.17E-05	−4.12	< 0.0001	*−1092.03*
Standard Outpatient	6.45E-09	3.28E-09	1.96	0.0496	1.54E-03	2.38E-04	6.50	< 0.0001	*−679.15*
Residential	−3.49E-09	2.42E-08	−0.14	0.8856	4.12E-04	2.01E-05	20.51	< 0.0001	*−1097.18*
Residential Detoxification	−1.82E-10	7.58E-10	−0.24	0.8106	8.61E-05	7.96E-05	1.08	0.2797	*−976.31*
Comprehensive Care	1.06E-08	5.24E-09	2.02	0.0432	1.97E-03	2.05E-04	9.58	< 0.0001	*−515.75*

* The Akaike Information Criterion (AIC) is a measure of goodness of fit of the model, balancing for the number of parameters in the model against the sample size.