**State Treatment Center Counts as Associated with Substance Use Prevalence:**

**Investigating Differences by Profit Status**

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Code available on GitHub:<https://github.com/baileywellen/sud_treatment_profitstatus>

July 25, 2024

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### Funding:

The project described was supported by Grant Number T32DA015035 from the National Institute on Drug Abuse. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institute on Drug Abuse or the National Institutes of Health.

### Candidate Journals:

Health Affairs (<https://www.healthaffairs.org/help-for-authors/journal/new-article-requirements>), Journal of Substance Abuse Treatment (<https://www.sciencedirect.com/journal/journal-of-substance-abuse-treatment>), The Journal of Mental Health Policy and Economics (<http://www.icmpe.org/test1/journal/journal.htm>)

# **Abstract**

This study examines the relationship between the presence of treatment facilities for substance use disorder (SUD) and the prevalence of drug use in the United States. The study considers the profit status of the treatment facilities and examines variability across states and years spanning from 2014 to 2019.

We employ a mixed effects generalized linear model with negative binomial link function using data obtained from the National Survey on Drug Use and Health (NSDUH) and the National Survey on Substance Abuse Treatment Services (NSSATS). The results of our study indicate a strong positive relationship between the prevalence of drug use and the number of for-profit treatment centers. However, we did not uncover a significant association between drug usage and the number of non-profit and government treatment centers. This implies that treatment centers that operate for profit are more adaptable to fluctuations in the demand for substance use disorder treatment.

Control variables such as state population, income, healthcare spending, and demographic parameters were taken into consideration. The study offers valuable insights into how the profit status of treatment facilities is related to the availability of substance use disorder (SUD) treatment and indicates future research on state-level SUD treatment variation, quality considerations, and the SUD treatment industry’s role in addressing this overdose crisis. It also emphasizes the influences of economic and demographic factors in shaping the treatment infrastructure at the state level.

*Keywords: Substance Use Disorder, Treatment Centers, Profit Status, Drug Use Prevalence, Negative Binomial Model, State-Level Analysis*

*Highlights: (bullet pointed list)*

# Introduction

The United States is in a drug overdose crisis, with drug fatalities increasing steadily this century. With the rise in overdose deaths, substance use disorders (SUD) are more recognized and new treatment centers are emerging across the country. This study investigates the relationship between SUD treatment centers and substance use prevalence in the United States focusing on each unique state-year combination from 2014 to 2019. This period was chosen because it coincides with the third wave of the opioid epidemic, marked by a rise in synthetic opioid availability and related deaths starting around 2013. It also follows the implementation of the Affordable Care Act in January 2014, which significantly altered insurance availability, coverage, and access to treatment. Additionally, substance use estimates from the National Survey on Drug Use and Health (NSDUH) end in 2018-2019, and the National Survey on Substance Abuse Treatment Services (NSSATS) estimates for 2020 may be unreliable due to the COVID-19 pandemic and ensuing economic recession, which notably impacted residential treatment facilities and other treatment settings. To the best of our knowledge, this is the first study showing the relationship between SUD treatment centers in the U.S. and the prevalence of substance use.

The rest of this study is organized into 5 sections. Section 1 provides background on the opioid crisis and treatment facilities. Next, we discuss theories, including the theory of healthcare behavior and information asymmetry, as well as the aims of this study. Section 3 provides information on data, methods, and summary statistics. In Section 4, we present the main results and discuss the implications. The last section addresses quality concerns, limitations of the study, future studies based on our study and conclusion.

## Background on the Opioid Crisis

According to the United States Center for Disease Control (CDC), 106,699 people died of a drug overdose in the United States in 2021. Over 75% of those deaths involved an opioid (CDC Injury Center, 2023), defining the “third wave” of the opioid epidemic by the increase in synthetic opioid prevalence (CDC, 2023). Overdose deaths involving cocaine, benzodiazepines, methamphetamine, and antidepressants have also increased from 1999 to 2021 (National Institute on Drug Abuse, 2023). These deaths shorten the lives of people who use drugs (PWUD) and impact their loved ones, employers, and society. Few regions have been left untouched by this crisis; however, several studies identify that drug overdose rates vary widely state-to-state and are constantly evolving. In 2016, West Virginia, New Hampshire, Ohio, Maryland, and Massachusetts saw the highest opioid overdose death rates, while Texas, Kansas, Hawaii, California, and Arkansas saw the lowest opioid death rates (Lyle et al, 2020). Just a few years later in a 2021 report by the CDC, West Virginia, Tennessee, Louisiana, Kentucky, and Delaware had the highest overall age-adjusted drug overdose death rates, while Nebraska, South Dakota, Iowa, Texas, and North Dakota saw the lowest drug overdose death rates (NCHS Pressroom, 2022). As shown by the differences in these estimates, understanding state-level drug use and overdose is difficult. This is partially due to many state-level factors, including legal policies around drug use, healthcare access, state guidelines for treatment (National Alliance for Model State Drug Laws, 2019), Medicaid coverage (Auty, 2022), income, and more, as well as frequent, nonlinear changes in drug use over time (England et al., 2024). It is important to better understand state-level drug use and overdose trends to estimate their impacts on society, the economy, healthcare, and individuals.

## Background on the increase in Substance Use Treatment Facilities

The rise in overdose deaths, substance use disorders, and the struggles of PWUD have made mainstream news. While many news stories report rising overdose deaths, others question the influx of treatment centers. Major news sources, such as CBS and NPR, have published stories criticizing profit-hungry treatment centers. CBS highlights shortcomings including unnecessarily extended treatment, large upfront payments, poor treatment quality, and high-pressure private equity investors (Ryasam, 2023). Similarly, NPR mentions “sales techniques'' and lack of standards, which are especially noticeable since the Affordable Care Act (ACA) (Mann, 2021). Many of these articles chastise the for-profit treatment industry, criticizing their practices as predatory, unjustified, and not evidence-based. One qualitative study called 613 treatment centers pretending to be a PWUD seeking treatment and noted the responses, concluding that for-profit treatment centers charged larger up-front payments and more frequently used recruitment strategies (Beetham, 2021). While many of these studies identify differences in for-profit and non-profit treatment center behaviors, it is unclear how the growing for-profit substance use disorder (SUD) treatment industry is associated with increased drug use and overdose.

## SUD Treatment Changes Post-ACA

We should consider this opioid overdose crisis in light of a changing health policy landscape post-ACA, and remember that SUD treatment has been shown to change after public insurance does. For instance, Hamersa et al investigated youth SUD treatment and found that non-profit and government specialty SUD treatment is most responsive to public insurance changes and that providers are more likely to accept Children’s Health Insurance Program (CHIP) than Medicaid when public insurance becomes more generous (Hamersma, 2021). Moreover, Saloner et al identified that following the ACA's expansion of dependent coverage, there was a decrease in adult treatment utilization, although the percentage of insured individuals receiving treatment increased (Saloner, 2017). Studies investigating the relationship between state parity laws post-ACA and SUD treatment show increases in treatment rates, which vary by insurance type accepted (Wen, 2013) and changes in participation in public markets, price discounts, and quantity of care, which vary by profit type (Maclean, 2018). Other studies have shown that opioid treatment admissions to specialty centers increased in Medicaid expansion states, indicating that Medicaid expansion post-ACA increased access to opioid treatment (Meinhofer, 2018). These studies collectively reveal that the ACA has impacted SUD treatment provision and insurance acceptance in significant ways, but the relationship is not homogenous for all states, populations, profit status, or insurance types.

## Information Asymmetry

In addition to relevant details about ACA policy impacts on SUD treatment provision, the accusations towards SUD treatment centers are concerning given the health economics theory of asymmetric information. Asymmetric information is a common healthcare “market failure” because patients and doctors do not have equal knowledge about medical conditions, potential treatments, costs, and side effects. This causes particular concern when there is evidence of poor quality of care (Folland, 2017); unfortunately, studies show alarmingly high rates of patients not receiving recommended medical care for preventive, acute, and chronic conditions (McGlynn, 2003). Concerns about information asymmetry are amplified in two situations: vulnerable patients and unregulated treatment areas. Existing studies on consumers who are most vulnerable include inpatient psychiatric patients (Shields, 2018) and elderly patients in nursing homes (Chou, 2002), and unregulated emerging treatment areas include brain health technologies (Psychiatric Times, 2021).

SUD treatment falls into both categories – patients who are vulnerable and an industry that is generally under regulated (HMP Global Learning Network, 2016) – making the risks of information asymmetry high. This highlights the importance of understanding SUD treatment market trends and increases urgency to ensure quality of care.

## For-profit and Non-Profit Healthcare Behavior Theory

A final important consideration is for-profit and non-profit healthcare behavior theory. According to Burton Weisbrod’s classic theory of non-profit behavior, the government only interferes to provide a good for which there is unmet demand, and non-profits further only enter the market when the government still does not satisfy demand (Kingma, 1997). An underprovided good is another example of a “market failure”, and one potential cause is externalities – when purchase of a good impacts individuals besides the supplier and consumer (Folland, 2017). Substance use disorders represent a major negative externality, as many costs are absorbed by the community, including drunk driving accidents, emergency response after a drug overdose, decreased productivity among PWUD during active use, and many other unmeasurable externalities such as emotional distress for friends and family of PWUD. Given that negative externalities result in under-provision of a good, and under-provision requires government and non-profits to get involved, it is unsurprising that much of the SUD treatment industry has historically been dominated by non-profit and government entities. However, this trend appears to be changing, as for-profits control more of the SUD treatment industry. Several studies have empirically shown that for-profit hospitals respond more quickly to changing market conditions than do non-profit firms (Hansmann, 2007; Chakvarty, 2005). Based on economic theory and previous profit status healthcare research, we hypothesize that for-profit treatment center counts will be more closely related to drug use prevalence than non-profit or government treatment center counts.

## Study Aims

## This study aims to reveal whether the number of SUD treatment centers is associated with substance use prevalence (a proxy for SUD treatment demand) in the United States during the third wave of the opioid epidemic. The primary goal is to identify this relationship separately in for-profit, non-profit, and government SUD treatment industries. Although it cannot prove causation, the goal of this inquiry is to ascertain whether the number of treatment facilities is associated with trends in substance use. To the authors’ knowledge, there have been no prior scientific studies evaluating whether the count of treatment centers per state is related to substance use prevalence.

# Data and Methods

## Data Sources

The study was performed using two publicly available data sources from the U.S. Substance Abuse and Mental Health Services Administration (SAMHSA) and control variables from other public U.S. datasets. While these data sources both capture survey data about U.S. substance use trends, they differ in sample population, survey questions, and primary goals. Batts et al have succinctly compared and summarized these datasets (Batts et al. 2012).

### NSSATS

The National Survey on Substance Abuse Treatment Services (NSSATS) is a collection of United States SUD treatment centers surveyed annually to understand services provided, beds available, number of patients treated, profit status, state, and more. This data has been collected annually since 1997, with the most recent data uploaded in 2020 (SAMHSA NSSATS 2019).

### NSDUH

Another valuable SAMHSA dataset is the National Survey on Drug Use and Health (NSDUH), which surveys a sample from each state about their experience with substances and SUD/mental health services. Questions include alcohol and drug consumption/frequency, SUD diagnoses, hospitalization for mental health, and more. This data is aggregated over two-year periods before being shared with the public, e.g., 2017-2018 and 2018-2019 statistics are aggregated rather than reporting 2017, 2018, and 2019 individually (Center for Behavioral Health Statistics and Quality, 2021).

### Centers for Medicare and Medicaid Services

State population, state spending on healthcare, and state Medicaid enrollment information comes from the “Center for Medicaid and Medicare Services’ Health Expenditures by State of Residence” data, which is captured every year from 1991 to 2020 (Center for Medicare and Medicaid Services, 2022)**.**

### Kaiser Family Foundation

Health insurance estimates for uninsured population per state-year come from the Kaiser Family Foundation’s “Health Insurance Coverage of the Total Population” dataset. This data is originally sourced from the Census Bureau’s American Community Survey (ACS) and cleaned. We use this data to control for any potential relationship between lack of health insurance coverage and SUD treatment center counts.

### Federal Reserve Bank of St. Louis

The Federal Reserve Bank of St. Louis (FRED) reports unemployment and income data (FRED U.S. Bureau of Labor Statistics, FRED U.S. Census Bureau). The unemployment data come from the U.S. Bureau of Labor Statistics’ Current Population Survey and report the number of unemployed people divided by the size of the civilian workforce in that area. Therefore, we use the unemployment percent in each state-year to control for potential workforce effects on SUD treatment center counts. The income data comes from the U.S. Census Bureau and estimates the median income in each state-year.

### Centers for Disease Control and Prevention

The Centers for Disease Control and Prevention (CDC) releases demographic data about each state and year from the Census Bureau (CDC Wonder, 2021). This includes single-race, ethnicity, and gender population estimates reported as a percent.

## Study Period

The unit of interest is each state-year. Our analysis was limited to the years 2013-2019 for multiple reasons:

1. It is during the third wave of the opioid epidemic, marked by increased synthetic opioid availability and subsequent deaths beginning around 2013.
2. It is post-implementation of the Affordable Care Act (ACA) in January 2014, which marked a shift in insurance availability, insurance coverage, and access to treatment.
3. NSDUH substance use estimates end in 2018–2019, and NSSATS estimates for 2020 may be unstable/outliers due to the COVID-19 pandemic and proceeding economic recession. Qualitative studies have shown that the pandemic had substantial impacts on Californian residential treatment facilities (Pagano, 2021) and likely impacted other states and treatment settings as well.

Therefore, the NSSATS and NSDUH data was filtered to 2013-2019 and aggregated, counting for-profit, non-profit, government-owned, and total treatment centers in each state per year. Treatment demand measures were lagged because administrative barriers limit a treatment center from responding to demand in the same year it emerges. Then, control variables were joined onto the SAMHSA data for each state-year. A Mathematica Policy Research study in 2018 similarly used NSSATS and NSDUH data together to evaluate SUD supply and demand post-ACA, however focused on workforce shortages and measured demand using treatment utilization measures (ASPE, 2018).

## Measures

### Outcome: count of substance use treatment centers in each state-year

The NSSATS OWNERSHP variable was used to split centers into profit types, with 1 (“private for-profit organization”) indicating for-profit treatment centers, 2 (“private non-profit organization”) indicating non-profit treatment centers, and 3 (“State Government”), 4 (“Local, county, or communal government”), 5 (“Tribal government”) and 6 (“Federal government”) grouped under government treatment centers. The data was aggregated to derive a count of each type of treatment center (for-profit, non-profit, government, total) for each state and year.

### Primary Predictors: Substance Use Prevalence in each State-Year

NSDUH changed their measures in 2014, limiting the ability to compare metrics spanning this time period. Therefore, this study analyzed the few substance use metrics that did not change, as other studies have done (Tomko, 2022).

· cocaine use in the past year (COCYR)

· heroin use in the past year (HERYR)

· alcohol use disorder in the past year (ABODALC)

· marijuana use in the past month (MRJMON)

The Benchmarked Small Area Estimate (BSAE) was used for each measure, representing the prevalence rate in the state. COCYR and HERYR BSAE measures were combined via average to consider an overall drug use prevalence metric (defined as (heroin + cocaine) / 2). Adult (persons above 18) prevalence rates were used.

### Control Variables

State population was expected to be correlated with the number of treatment centers because of the need for more treatment centers proportional to the number of people in the state. Financial variables (state spending on healthcare, Medicaid enrollment, uninsurance rates, and income) were hypothesized to represent the state’s investment in healthcare and ability to pay for SUD treatment services. We also hypothesized that state demographics (sex, race, ethnicity) may be related to perceptions of substance use and acceptability of treatment, which could relate to the number of treatment centers. Therefore, we control for population, financial, and demographic variables in each state-year.

## Statistical Analysis

The resultant dataset allowed a balanced panel analysis of the relationship between substance use prevalence and the count of SUD treatment centers per state-year. A generalized linear model (GLM) with mixed effects (family: negative binomial) was chosen to model the count of treatment centers (Figures A1 – A3). The negative binomial link function is a powerful option for modeling count data which is overdispersed (Greene 2007, Salman 2013, Guerrero 2016). Random effects were included to allow different intercepts for each state and year. Results are reported as Incidence Rate Ratios (IRR) by taking the exponent of each coefficient, and are reported along with 95% confidence intervals (CI), standard errors (SE), and p-values. Significance tests used alpha = 0.05. Four separate models were fit with total treatment center count (summing all three profit types), for-profit treatment center count, non-profit treatment center count, and government treatment center count as the outcome.

### Model Definition

The Negative Binomial fixed effects model was estimated using the equation below. This allows us to examine the correlation between substance use disorder and the total number of treatment centers within a state over time.

where represents the count of treatment centers by profit type for state i at year t. The three main explanatory variables are the lag of drug use, alcohol use disorder, and marijuana use for each state and time. The term is a vector of coefficients (associated with the control variables () including population in millions, income, per capita Medicaid enrollment, share of male gender, unemployment rate, per capita health spending, share of uninsured population, share of Latino or Hispanic ethnic group and the share of the white race in each state at year t. and represents state and year fixed effects, which capture any state specific effects (such as state policy) and year effects (such as time-varying investment in SUD), and is the error term.

Endogeneity due to potential reverse causality poses a key challenge in identifying causal estimates of substance use and treatment centers because the relationship between the two variables can be bidirectional. On one hand, the presence of effective treatment centers might lead to decreased substance use, thus lowering substance use rates. On the other hand, higher rates of substance use in a region could lead to the establishment of more treatment centers to address the increased demand for treatment. This simultaneous influence makes it difficult to determine the direction of causality. Therefore, we only establish correlational relationships between substance use and treatment centers.

### Software

R's lme4 package was used to model the GLM relationship and ensure model consistency via multiple estimation methods to assess non-convergence warnings (Bates, 2015). The gtsummary package in R was used for summary statistics and table creation (Sjoberg, 2021). R version 4.3.1 (2023-06-16) was used for all analyses (R Core Team, 2023), and STATA version 18 was used to plot Figure 1 (StataCorp, 2023).

# Results

The number of for-profit treatment centers surveyed by NSSATS increased substantially from 4,631 in 2015 to 6,307 in 2019; non-profit treatment centers increased slightly from 7,479 in 2015 to 7,976 in 2019; and government treatment centers decreased slightly from 1,608 in 2015 to 1,569 in 2019 (Figure 1). These changes varied widely between states (Appendix A1). All three profit types saw a decrease in 2017, which presumably can be attributed to fewer treatment centers responding to the survey that year and not treatment centers closing in 2017 and re-opening in 2018. However, this assumption cannot be confirmed.

The descriptive statistics for all variables used in this study for all 51 jurisdictions from 2015 to 2019 are in Table 1. On average, we find a high number of non-profit treatment centers, followed by for-profit centers, and then government centers. This is evident in Figure 1, which shows a higher share of non-profit centers per total number of treatment centers over time, with for-profit centers increasing since 2015. Moreover, we find an increased prevalence of marijuana use, with an average of 9.43% over the sample period. In Figure 1, we also show an increasing trend in the use of marijuana from 2015 to 2019. This is followed by alcohol use, with a 6.45% average, showing a steady reduction in the trend over the period. Heroin usage was mostly stable over this period, and cocaine usage increased slightly. These trends vary across the states, with the Northeast reporting highest prevalence of drug use and the South and West reporting lowest prevalence, as shown in Appendix Table A2.

In addition to the treatment center data, we also analyzed key demographic and economic variables such as population, income, per capita health spending, and unemployment rates. The average population across the states was 6.37 million. Income levels varied, with an average annual income of $73,283.76. Per capita health spending was substantial, averaging $9,250 over the period. The unemployment rate averaged 4.23%, reflecting a moderate level of unemployment during these years.

## Model Selection

Preliminary collinearity assessment revealed that predictors are not highly correlated (Table A3). The highest correlations were between illicit drug use and health spending showing a correlation of 60.5%, and illicit drug use and marijuana use which has a correlation of 76.2%. Because no covariates were highly correlated, the final model predicted the count of treatment centers (outcome) using fixed effects of lagged drug use prevalence, lagged AUD prevalence, lagged marijuana use prevalence, and controlled for the state’s demographic and economic characteristics, with crossed random effects for both state and year.The model was fit with a panel dataset of 255 observations, for the 50 states and D.C. over five years.

### Main Results

We estimate the correlation between substance use and total number of treatment centers at the state-year level. The result is shown in the second column of Table 2. The results indicate a significantly positive correlation between the lag of drug use on the total number of treatment centers within a state over the sample period, all else being equal. We do not find any significant correlation between AUD and the total number of treatment centers.

In column 4, we also show the results from regressing lagged AUD and drug use on for-profit centers only. The results indicate that previous two years’ drug use prevalence and the previous two years’ AUD prevalence are significantly associated with the number of for-profit treatment centers in each state-year. States’ lagged drug use prevalence was associated with an increase in for-profit treatment centers per state-year, however AUD prevalence was associated with a decrease in the number of for-profit treatment centers per state-year after controlling for other variables. We do not find any significant correlation between lagged AUD, drug use and the number of non-profit or government treatment centers after controlling for key demographic and economic variables. Our results indicate that the correlation between drug and alcohol use and the total number of treatment centers is predominantly driven by for-profit centers rather than non-profit or government facilities.

### State-Level Variation

The five states with the largest for-profit positive random effects were Kentucky (1.21), Colorado (1.17), Maryland (1.16), North Carolina (1.06), and Utah (0.98) (in green in Figure 2). These states had higher for-profit treatment counts than the average country-wide model estimated. On the opposite end, Vermont (-1.78), District of Columbia (-1.55), Wyoming (-1.18), California (-1.12) and Connecticut (-1.11) had the largest negative random effects (in red in Figure 2). These states require a lower intercept on the for-profit treatment count model than the average country-wide for-profit treatment count model. Similar analyses for the non-profit and government centers are available in Figure 2.

### Sensitivity Analysis after model warnings

The lme4 glmer package raised model convergence warnings on the non-profit and government centers, so sensitivity analysis was performed using the allFit function as directed by the lme4 convergence “gold standard” (convergence function – Rdocumentation). This approach ensured that other model estimation methods arrived at similar results despite convergence warnings. The test results are in the appendix, Table A5 and A6, and increase confidence that the models indeed converged appropriately because all methods arrive at similar results. See the convergence and lme4 documentation for more information on the various model estimation methods.

# Discussion

Our findings suggest that the establishment of for-profit treatment centers is closely linked to areas with higher levels of substance use. Similarly, Mojtabai et al. used NSSATS and NSDUH data in a 2019 study and found that treatment facilities in states with higher opioid overdose death rates are more likely to offer medication treatment for opioid use (Mojtabai, 2019). While our study considers all treatment centers (not only opioid treatment) regardless of whether they provide medication, our findings support their conclusion that drug use prevalence in each state is related to SUD treatment characteristics, and further reveals that profit type plays a role.

For-profit centers, with their market-driven business models, are likely to be more responsive to the demand for substance use treatment in regions experiencing higher rates of drug and alcohol use. In contrast, non-profit and government treatment centers show a weaker correlation with substance use levels. These facilities often focus on broader service goals and community health needs rather than profit margins, which could explain their less pronounced association with higher substance use rates. This insight underscores the importance of considering the differing motivations of various types of treatment centers when developing policy and resource allocation strategies. Understanding that for-profit centers are a significant driver of this correlation can inform targeted public health interventions.

We also provide corollary evidence on the correlation between key demographic and economic variables and the total number of treatment centers. We find positive correlation between total population in a state over time on all treatment center profit types. Our results reveal potential evidence that states with higher numbers of people have a higher number of treatment centers relative to states with lesser populations. Additionally, we observe a significantly positive correlation between the share of male population and government treatment centers.

## Investigation into State- and Year- level Variation

The random effects - interpreted as the difference in the estimate for that state from the overall intercept for each state in this model - are interesting. Taking a closer look at for-profit random effects, California stands out. Given that California had the largest increase in for-profit treatment centers during this time and has been criticized harshly for a predatory for-profit SUD treatment industry (Rehab Riviera, 2024), the negative random intercept was unexpected. This may be partially explained by California’s large population and other demographic or economic factors, which were controlled for in the model. Another alternative is that when broadening the scope beyond California’s shocking numbers, the country on average shows more drastic increases in for-profit treatment centers than California given their demographics and population, AUD, and drug use prevalence. State random effects are visualized in Figure 2 and available in Table A4.

## Implications for Treatment Quality

Given the high cost of SUD treatment (SAMHSA, 2009; Peterson, 2021; NCDAS, 2023), increasing urgency of SUD treatment in the wake of high overdose rates, and for-profit healthcare’s proven ability to respond to demand quickly, it makes sense that the U.S. for-profit SUD treatment industry is booming. This intuition is confirmed by the descriptive analyses in this report. However, it is important to understand the implications of such a change, including treatment access and quality. There is a wealth of literature about the distinct behaviors of for-profit and non-profit healthcare providers, and a substantial subset investigating SUD-specific behaviors. Just a few of these studies have revealed that for-profit treatment centers more frequently shorten treatment duration for patients who cannot pay (Nahra, 2009), managed care has different effects on for-profit, non-profit, and public treatment centers (Olmstead, 2005), and for-profit opioid treatment programs less frequently provide comprehensive services such as communicable disease testing and psychiatric services (Bachhuber, 2014). These profit status differences will remain important as the U.S. SUD treatment market evolves, and especially if for-profit treatment center counts continue to rise.

## Limitations

There are several limitations to this study, despite its informative insights. First, aggregating to the state level is required by the granularity of the NSSATS dataset but may mask important trends at city/county levels. Patients may occasionally cross state boundaries for treatment, limiting the power of drug use in the state to predict treatment demand in the state. Independence assumptions required for statistical modeling may also not fully hold at the state-level, because neighboring states may experience similar changes in drug use and potency, cultural expectations and stigma around substance use, and economic shifts.

The NSDUH data also limits the time span to pre-2020, restricts the substances used to those that did not change in 2014, and does not allow a granular look at each year’s substance use reported rates due to 2-year aggregation. NSDUH is a highly trusted survey to gauge drug use in the U.S., but the self-report nature of a stigmatized subject may cause underreporting. Additionally, considering drug use as a measure of market demand for treatment may be imprecise because not all PWUD seek treatment.

Finally, these models are not predictive into the future because there is likely a “ceiling” on the amount of treatment centers in each state, so changes in drug use rates are unlikely to predict count of treatment centers as the number of treatment centers approaches that limit. Ever-evolving federal and state policy further complicate future trajectories of substance use treatment center counts, as do the bidirectional relationship between drug use and treatment centers.

## Future Work

Future research could consider the number of beds as a more detailed measure of supply than the number of treatment centers. Future work could also measure the quality of treatment centers through services offered and meeting standards of care to illuminate whether increased treatment centers meet need with quality care. In addition, the relationship between substance use prevalence and treatment center counts may have changed after the COVID pandemic with changing healthcare practices as well as substance use trends, so this analysis could be continued by contrasting the relationships before and after the COVID pandemic. Finally, a deeper understanding of the relationships between for-profit, non-profit, and government treatment centers in a region and how they may “crowd out” each other (Cohen, 2007) would benefit the broader discussion of how treatment centers respond to market demand.

# Conclusion

These findings are consistent with news headlines suggesting a rising number of for-profit treatment centers. The analysis reveals a positive association between drug use prevalence and number of for-profit treatment centers, and a negative association between alcohol use disorder prevalence and number of for-profit treatment centers in each state-year, after controlling for economic and demographic variables. Consistent with economic theory, this indicates that for-profit treatment centers may be capitalizing on a perceived demand in the SUD treatment market, which non-profit and government treatment centers cannot respond to as rapidly. These findings also raise questions about why the AUD relationship is negative. Importantly, these findings do not indicate causation; more analysis is needed to reveal details about the relationship between drug use and SUD treatment centers, as well as identify other confounders. Nonetheless, there is evidence that profit status matters in the relationship between SUD prevalence and number of treatment centers, and that the 50 United States and D.C. vary widely in their SUD market trends.

# Figures and Tables

| Table 1 - Summary statistics of all variables | | | | |
| --- | --- | --- | --- | --- |
| **Variable (n=255)** | **Mean** | **SD** | **Minimum** | **Maximum** |
| For profit treatment centers | 103.85 | 106.37 | 5 | 780 |
| Government treatment centers | 30.68 | 32.87 | 0 | 209 |
| Non profit treatment centers | 147.78 | 144.83 | 11 | 822 |
| Total treatment centers | 282.31 | 256.87 | 24 | 1797 |
| Lagged Drug Use | 1.18 | 0.36 | 0.58 | 2.59 |
| Lagged AUD | 6.45 | 1.03 | 4.42 | 10.57 |
| Lagged Marijuana Use | 9.43 | 3.4 | 4.72 | 20.04 |
| Population (millions) | 6.37 | 7.22 | 0.58 | 39.44 |
| Percapita Health Spending (thousands) | 9.25 | 1.49 | 6.11 | 13.93 |
| Medicaid Enrollment Percapita | 0.22 | 0.07 | 0.09 | 0.45 |
| Male Gender (%) | 48.87 | 1.01 | 46.72 | 52.62 |
| Hispanic or Latino Ethnicity (%) | 9.81 | 9.18 | 1.16 | 45.92 |
| White Race (%) | 80.59 | 12.81 | 27.47 | 96.12 |
| Uninsured (%) | 8.23 | 3.1 | 2.5 | 18.4 |
| Unemployment (%) | 4.23 | 1.08 | 2.1 | 6.9 |
| Income ($) | $73,283.76 | $12,217.96 | $48,460 | $108,900 |
|  |  |  |  |  |

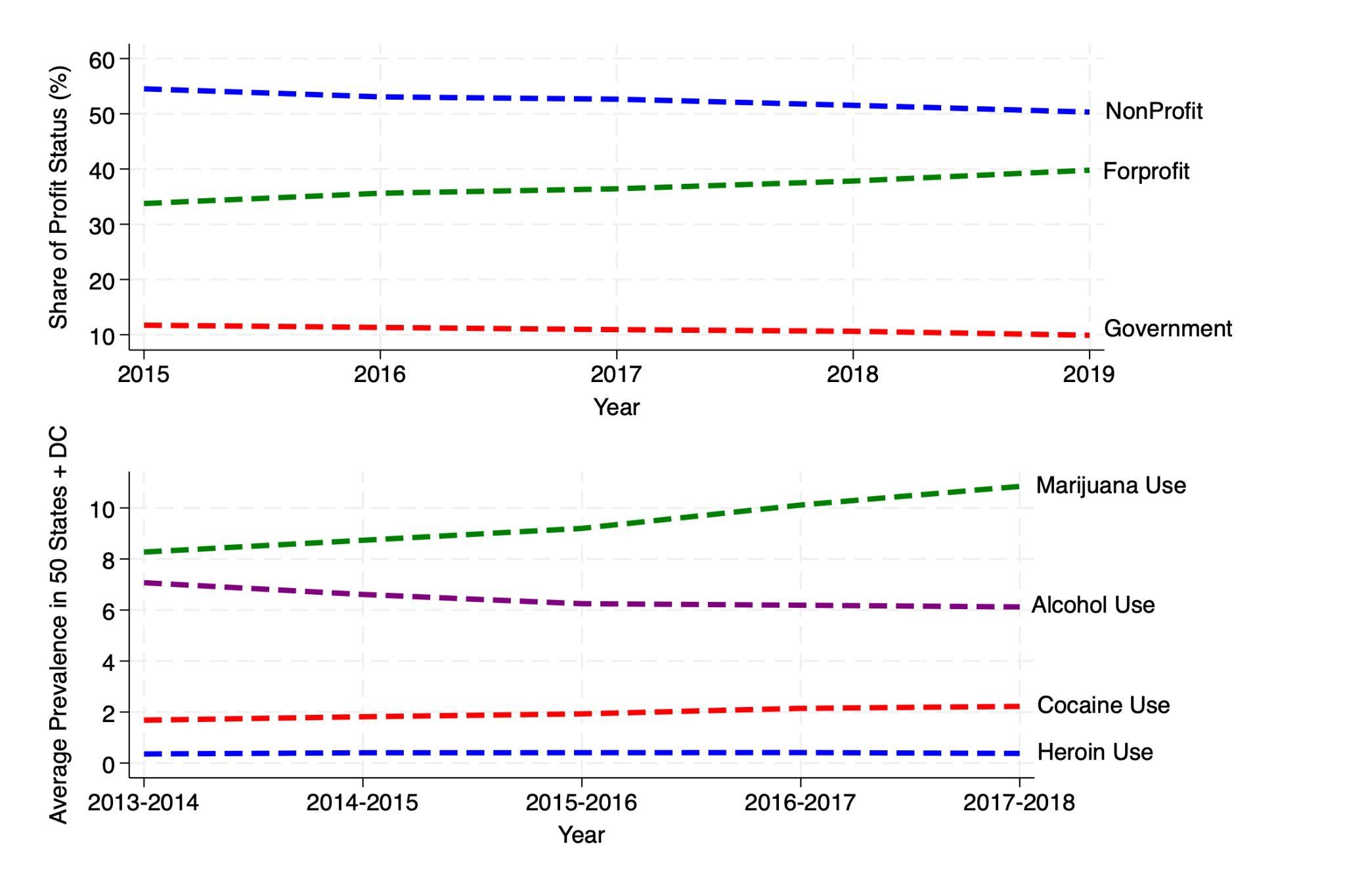


Figure 1 – Share of Treatment Centers and Average Prevalence of Substance Use Over Time

| **Table 2** | **Total** | | **Forprofit** | | **Nonprofit** | | **Government** | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| *Predictors* | *Incidence Rate Ratios* | *std. Error* | *Incidence Rate Ratios* | *std. Error* | *Incidence Rate Ratios* | *std. Error* | *Incidence Rate Ratios* | *std. Error* |
| (Intercept) | 205.72 \*\*\* | 24.02 | 70.11 \*\*\* | 13.25 | 94.23 \*\*\* | 10.30 | 16.90 \*\*\* | 3.43 |
| AUD | 0.98 | 0.01 | 0.95 \* | 0.02 | 1.00 | 0.01 | 1.02 | 0.03 |
| Drug Use | 1.08 | 0.05 | 1.20 \* | 0.10 | 1.02 | 0.05 | 1.00 | 0.10 |
| Marijuana Use | 1.00 | 0.01 | 1.00 | 0.01 | 1.00 | 0.01 | 1.00 | 0.02 |
| Population | 1.86 \*\*\* | 0.17 | 2.07 \*\*\* | 0.27 | 1.66 \*\*\* | 0.15 | 1.84 \*\*\* | 0.22 |
| Income | 1.03 | 0.02 | 1.06 | 0.04 | 1.02 | 0.03 | 0.97 | 0.05 |
| Medicaid Enrollment | 0.97 | 0.03 | 0.93 | 0.06 | 0.99 | 0.04 | 1.00 | 0.07 |
| Gender Male | 0.96 | 0.06 | 0.91 | 0.09 | 0.94 | 0.07 | 1.25 \* | 0.13 |
| Unemployment | 1.00 | 0.02 | 0.99 | 0.03 | 1.02 | 0.02 | 0.98 | 0.04 |
| Health Spending | 0.96 | 0.05 | 0.96 | 0.09 | 1.02 | 0.04 | 0.93 | 0.07 |
| Insurance Uninsured | 0.98 | 0.04 | 0.91 | 0.07 | 1.06 | 0.05 | 1.05 | 0.08 |
| Hispanic Ethnicity | 0.96 | 0.08 | 1.00 | 0.13 | 0.97 | 0.09 | 1.04 | 0.12 |
| White Race | 1.01 | 0.08 | 1.12 | 0.13 | 0.99 | 0.08 | 0.88 | 0.10 |
| **Random Effects** | | | | | | | | |
| σ2 | 0.01 | | 0.02 | | 0.01 | | 0.05 | |
| τ00 | 0.30 State\_Name | | 0.59 State\_Name | | 0.44 State\_Name | | 0.69 State\_Name | |
|  | 0.00 year | | 0.01 year | | 0.00 year | | 0.00 year | |
| ICC | 0.98 | | 0.97 | | 0.98 | | 0.93 | |
| N | 51 State\_Name | | 51 State\_Name | | 51 State\_Name | | 51 State\_Name | |
|  | 5 year | | 5 year | | 5 year | | 5 year | |
| Observations | 255 | | 255 | | 255 | | 255 | |
| Marginal R2 / Conditional R2 | 0.557 / 0.991 | | 0.480 / 0.982 | | 0.373 / 0.986 | | 0.384 / 0.956 | |
| ***\* p<0.05 \*\* p<0.01 \*\*\* p<0.001*** | | | | | | | | |

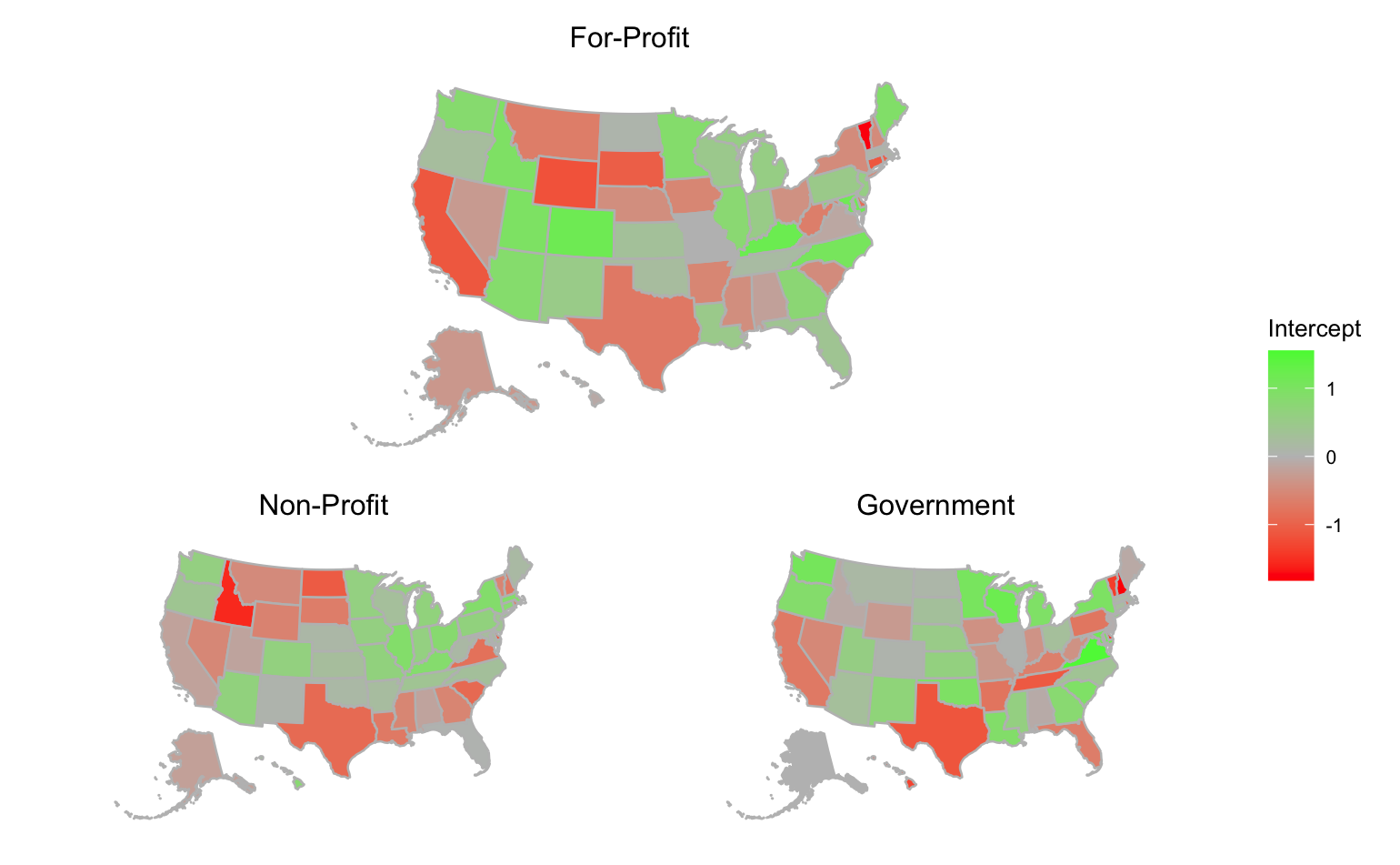


Figure 2 – Random Effects per State in All Three Models

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# Appendix

## Abbreviations

| **Abbreviation** | **Definition** |
| --- | --- |
| ACA | Affordable Care Act |
| AUD | Alcohol Use Disorder |
| GLM | Generalized Linear Model |
| NSDUH | National Survey on Drug Use and Health |
| NSSATS | National Survey of Substance Abuse Treatment Services |
| CMS | Centers for Medicare and Medicaid |
| ACS | American Community Survey |
| PWUD | People who use drugs |
| SAMHSA | Substance Abuse and Mental Health Services Administration |
| SUD | Substance Use Disorder |
| SE | Standard error |

| Table A1 – Number of treatment centers in 2015 in all 50 states and D.C., and the change in treatment centers from 2015 to 2019, according to profit status (sorted decreasing by  the change in count of For-Profit treatment centers) | | | | | | |
| --- | --- | --- | --- | --- | --- | --- |
|  | For-Profit | | Non-Profit | | Government | |
| State | Count 2015 | Change  2019 - 2015 | Count  2015 | Change  2019 - 2015 | Count  2015 | Change  2019 - 2015 |
| California | 402 | 378 | 822 | -14 | 175 | 34 |
| Utah | 95 | 106 | 58 | 17 | 31 | 3 |
| Indiana | 76 | 91 | 176 | 39 | 11 | 0 |
| North Carolina | 222 | 91 | 184 | 17 | 34 | 4 |
| Ohio | 47 | 85 | 298 | 90 | 25 | 9 |
| Kentucky | 144 | 83 | 182 | 35 | 8 | -3 |
| Florida | 321 | 76 | 314 | -19 | 34 | -1 |
| Maryland | 191 | 70 | 132 | -2 | 59 | -19 |
| Massachusetts | 66 | 69 | 240 | 49 | 15 | -1 |
| Texas | 195 | 62 | 200 | -4 | 47 | 12 |
| Arizona | 130 | 61 | 176 | 49 | 35 | -5 |
| Pennsylvania | 202 | 56 | 311 | 18 | 10 | 3 |
| Tennessee | 64 | 50 | 157 | 38 | 6 | -2 |
| Georgia | 157 | 42 | 88 | 5 | 77 | -11 |
| Minnesota | 144 | 41 | 163 | 10 | 45 | 0 |
| Virginia | 60 | 36 | 60 | -6 | 110 | -6 |
| New Jersey | 146 | 28 | 210 | -32 | 21 | -3 |
| Arkansas | 11 | 26 | 60 | 63 | 5 | 2 |
| Illinois | 263 | 24 | 366 | 83 | 25 | 14 |
| Montana | 9 | 21 | 39 | 5 | 18 | -4 |
| New Hampshire | 22 | 17 | 34 | 6 | 2 | -1 |
| Alabama | 37 | 15 | 88 | -2 | 14 | 1 |
| Mississippi | 16 | 14 | 45 | 9 | 38 | -12 |
| Iowa | 23 | 13 | 118 | 27 | 10 | -4 |
| Michigan | 153 | 13 | 255 | -11 | 55 | 2 |
| Oregon | 61 | 13 | 138 | -13 | 38 | -3 |
| West Virginia | 15 | 13 | 83 | -2 | 5 | 2 |
| Louisiana | 57 | 12 | 55 | -20 | 47 | -5 |
| Wisconsin | 104 | 12 | 122 | -17 | 62 | -7 |
| New York | 143 | 11 | 642 | 22 | 116 | -9 |
| North Dakota | 30 | 11 | 17 | 6 | 17 | 4 |
| Nevada | 27 | 10 | 39 | 16 | 13 | 1 |
| Hawaii | 21 | 8 | 142 | -9 | 6 | -1 |
| South Carolina | 29 | 8 | 39 | 5 | 41 | -1 |
| Delaware | 12 | 7 | 24 | 0 | 2 | -1 |
| Rhode Island | 13 | 6 | 32 | 5 | 2 | 1 |
| Colorado | 220 | 5 | 159 | 0 | 24 | 0 |
| Vermont | 5 | 5 | 38 | -1 | 1 | 0 |
| Alaska | 13 | 3 | 54 | -2 | 21 | 7 |
| Missouri | 60 | 3 | 193 | 16 | 12 | -3 |
| Nebraska | 29 | 3 | 80 | 1 | 23 | -5 |
| Washington | 175 | 3 | 170 | 44 | 73 | -13 |
| New Mexico | 51 | 2 | 72 | 9 | 36 | -4 |
| Connecticut | 17 | 1 | 185 | 5 | 13 | -1 |
| Idaho | 101 | 0 | 16 | -5 | 15 | -3 |
| Wyoming | 8 | 0 | 36 | 1 | 15 | -3 |
| District of Columbia | 7 | -1 | 25 | -7 | 1 | 1 |
| Maine | 100 | -1 | 98 | -19 | 10 | -2 |
| South Dakota | 11 | -2 | 37 | -4 | 22 | -5 |
| Oklahoma | 54 | -10 | 104 | 6 | 50 | 4 |
| Kansas | 72 | -14 | 103 | -10 | 33 | -5 |
| **Average** | **90.80** | **32.86** | **146.65** | **9.75** | **31.53** | **-0.765** |
| **Sum** | **4631** | **1676** | **7479** | **497** | **1608** | **-39** |

| Table A2 - Cocaine, Heroin, Drug Use Combined (Cocaine + Heroin), AUD, and Marijuana Use Prevalence from the NSDUH data per state in 2013-2014. (sorted decreasing by drug use prevalence) | | | | | |
| --- | --- | --- | --- | --- | --- |
| State\_Name | Drug Use 2013-14 | Cocaine 2013-14 | Heroin 2013-14 | AUD 2013-14 | Marijuana 2013-14 |
| District of Columbia | 2.089 | 3.643 | 0.534 | 10.196 | 12.715 |
| New Hampshire | 1.598 | 2.636 | 0.560 | 7.982 | 11.665 |
| Delaware | 1.597 | 1.978 | 1.216 | 6.529 | 8.226 |
| Colorado | 1.522 | 2.738 | 0.305 | 7.927 | 15.170 |
| Connecticut | 1.467 | 2.332 | 0.603 | 7.179 | 8.559 |
| Vermont | 1.439 | 2.375 | 0.503 | 7.488 | 13.401 |
| Massachusetts | 1.434 | 2.497 | 0.371 | 7.003 | 12.013 |
| New York | 1.419 | 2.431 | 0.406 | 6.971 | 8.596 |
| Arizona | 1.359 | 2.384 | 0.335 | 8.063 | 8.850 |
| New Mexico | 1.314 | 2.303 | 0.326 | 7.367 | 9.726 |
| Oregon | 1.240 | 2.116 | 0.364 | 7.312 | 12.591 |
| California | 1.237 | 2.269 | 0.204 | 7.068 | 9.253 |
| Rhode Island | 1.218 | 2.128 | 0.309 | 8.146 | 12.942 |
| Alaska | 1.211 | 1.653 | 0.769 | 7.249 | 12.160 |
| Washington | 1.210 | 2.041 | 0.380 | 6.928 | 13.064 |
| Florida | 1.210 | 2.090 | 0.330 | 6.306 | 7.589 |
| Wisconsin | 1.109 | 1.935 | 0.283 | 8.190 | 6.386 |
| Kentucky | 1.108 | 1.673 | 0.542 | 5.857 | 6.863 |
| Pennsylvania | 1.074 | 1.624 | 0.524 | 7.012 | 7.308 |
| Illinois | 1.071 | 1.845 | 0.297 | 6.578 | 7.735 |
| Louisiana | 1.029 | 1.747 | 0.311 | 6.401 | 6.175 |
| Virginia | 1.016 | 1.679 | 0.354 | 7.504 | 6.957 |
| Maine | 1.004 | 1.488 | 0.520 | 5.970 | 12.914 |
| Nevada | 0.975 | 1.699 | 0.251 | 7.169 | 7.743 |
| Ohio | 0.966 | 1.485 | 0.446 | 7.074 | 7.023 |
| Maryland | 0.961 | 1.441 | 0.480 | 7.060 | 8.605 |
| New Jersey | 0.946 | 1.412 | 0.481 | 6.816 | 6.294 |
| North Carolina | 0.936 | 1.534 | 0.338 | 6.508 | 6.724 |
| Hawaii | 0.889 | 1.649 | 0.130 | 7.193 | 7.924 |
| Georgia | 0.871 | 1.553 | 0.190 | 6.613 | 7.957 |
| Kansas | 0.849 | 1.460 | 0.239 | 7.921 | 6.393 |
| North Dakota | 0.847 | 1.353 | 0.341 | 8.150 | 5.791 |
| Wyoming | 0.842 | 1.271 | 0.413 | 7.949 | 6.329 |
| Indiana | 0.824 | 1.290 | 0.358 | 7.097 | 7.638 |
| Texas | 0.793 | 1.409 | 0.176 | 6.952 | 5.919 |
| Minnesota | 0.784 | 1.309 | 0.259 | 6.723 | 7.335 |
| Nebraska | 0.771 | 1.234 | 0.308 | 8.030 | 5.812 |
| Iowa | 0.769 | 1.358 | 0.180 | 6.593 | 5.002 |
| Montana | 0.769 | 1.291 | 0.247 | 8.042 | 10.200 |
| Alabama | 0.768 | 1.309 | 0.228 | 6.065 | 5.629 |
| West Virginia | 0.756 | 1.246 | 0.265 | 6.595 | 6.366 |
| South Carolina | 0.755 | 1.205 | 0.304 | 6.235 | 6.614 |
| Utah | 0.749 | 1.186 | 0.312 | 5.861 | 5.608 |
| Missouri | 0.742 | 1.211 | 0.273 | 6.754 | 8.136 |
| Tennessee | 0.727 | 1.165 | 0.289 | 5.682 | 5.527 |
| Michigan | 0.724 | 1.120 | 0.329 | 6.493 | 10.404 |
| Idaho | 0.638 | 1.024 | 0.252 | 7.066 | 6.337 |
| Mississippi | 0.625 | 1.051 | 0.198 | 6.189 | 5.874 |
| Oklahoma | 0.613 | 1.026 | 0.199 | 6.838 | 6.299 |
| Arkansas | 0.593 | 0.985 | 0.202 | 5.511 | 6.754 |
| South Dakota | 0.578 | 0.959 | 0.196 | 8.135 | 4.758 |
| **Average** | **1.020** | **1.683** | **0.357** | **7.069** | **8.272** |

Figure A1- Distribution of for-profit treatment counts in each state-year

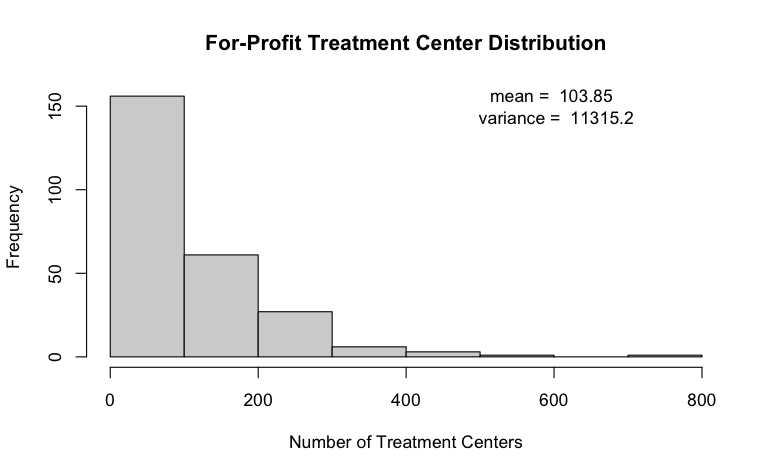


Figure A2 distribution of non-profit treatment counts in each state-year

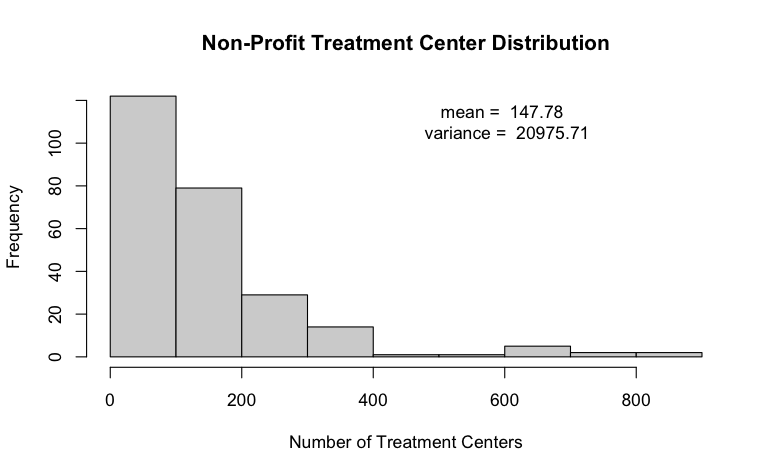
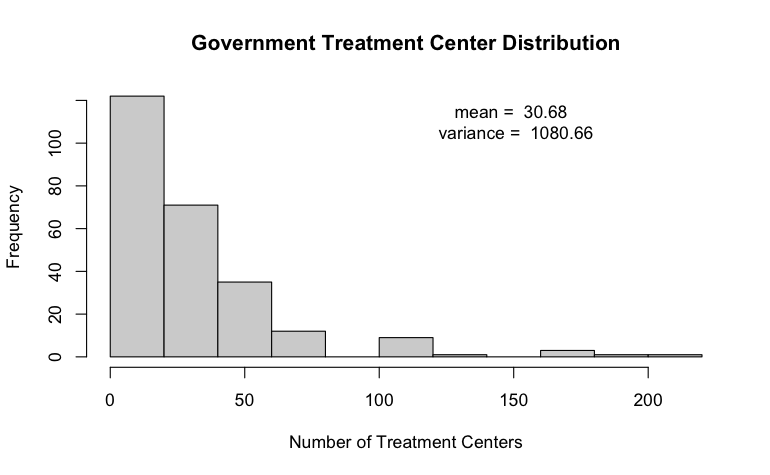


Figure A3 - distribution of government treatment counts in each state-year



| **Table A3 - Correlation coefficients on control variables and demand variables** | | | | | | | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** |
| **1** | 1.000 | -0.163 | 0.043 | 0.001 | -0.212 | -0.121 | -0.181 | 0.542 | -0.132 | 0.209 | 0.153 | 0.024 |
| **2** | -0.163 | 1.000 | 0.324 | 0.605 | 0.314 | 0.467 | -0.114 | -0.256 | -0.053 | -0.491 | -0.045 | 0.438 |
| **3** | 0.043 | 0.324 | 1.000 | 0.412 | 0.123 | 0.350 | -0.376 | 0.199 | -0.291 | -0.372 | 0.492 | -0.116 |
| **4** | 0.001 | 0.605 | 0.412 | 1.000 | 0.377 | 0.762 | -0.193 | 0.152 | -0.130 | -0.428 | 0.001 | 0.554 |
| **5** | -0.212 | 0.314 | 0.123 | 0.377 | 1.000 | 0.404 | 0.165 | -0.002 | 0.079 | -0.283 | 0.123 | 0.263 |
| **6** | -0.121 | 0.467 | 0.350 | 0.762 | 0.404 | 1.000 | 0.054 | 0.072 | 0.058 | -0.328 | -0.045 | 0.435 |
| **7** | -0.181 | -0.114 | -0.376 | -0.193 | 0.165 | 0.054 | 1.000 | 0.058 | 0.294 | 0.254 | -0.185 | 0.127 |
| **8** | 0.542 | -0.256 | 0.199 | 0.152 | -0.002 | 0.072 | 0.058 | 1.000 | -0.080 | 0.295 | 0.230 | 0.074 |
| **9** | -0.132 | -0.053 | -0.291 | -0.130 | 0.079 | 0.058 | 0.294 | -0.080 | 1.000 | -0.030 | -0.252 | -0.156 |
| **10** | 0.209 | -0.491 | -0.372 | -0.428 | -0.283 | -0.328 | 0.254 | 0.295 | -0.030 | 1.000 | 0.170 | -0.420 |
| **11** | 0.153 | -0.045 | 0.492 | 0.001 | 0.123 | -0.045 | -0.185 | 0.230 | -0.252 | 0.170 | 1.000 | -0.327 |
| **12** | 0.024 | 0.438 | -0.116 | 0.554 | 0.263 | 0.435 | 0.127 | 0.074 | -0.156 | -0.420 | -0.327 | 1.000 |

| **Table A3 Key** | |
| --- | --- |
| 1 | Population in Millions |
| 2 | Percapita Health Spending |
| 3 | Percapita Medicaid Enrollment |
| 4 | Lagged Drug Use |
| 5 | Lagged AUD |
| 6 | Lagged Marijuana Use |
| 7 | Male |
| 8 | Hispanic |
| 9 | White Race |
| 10 | Uninsured |
| 11 | Unemployment |
| 12 | Income |

| **Table A4 - State level random effects (sorted increasing)** | | | | |
| --- | --- | --- | --- | --- |
| State\_Name | Forprofit\_Intercept | NonProfit\_Intercept | Government\_Intercept | Total\_Intercept |
| District of Columbia | -1.55298 | -1.32035 | -1.33976 | -1.38309 |
| Delaware | -0.84325 | -1.16131 | -1.51929 | -1.13931 |
| Vermont | -1.76173 | -0.56538 | -1.39063 | -0.99901 |
| Rhode Island | -1.03349 | -0.72748 | -1.00016 | -0.90855 |
| Texas | -0.7195 | -0.89664 | -1.14762 | -0.90614 |
| New Hampshire | -0.48721 | -0.72857 | -1.81757 | -0.76028 |
| California | -1.11733 | -0.18478 | -0.71487 | -0.72678 |
| Wyoming | -1.18175 | -0.59613 | -0.2858 | -0.71562 |
| South Dakota | -1.03593 | -0.66351 | 0.288743 | -0.61925 |
| Montana | -0.66891 | -0.49084 | 0.160991 | -0.50311 |
| South Carolina | -0.47833 | -0.90692 | 0.943985 | -0.50293 |
| Nevada | -0.28387 | -0.53326 | -0.51899 | -0.48674 |
| North Dakota | 0.077222 | -1.06675 | 0.09494 | -0.48152 |
| Mississippi | -0.45731 | -0.55731 | 0.607161 | -0.3977 |
| Alabama | -0.21073 | -0.16932 | -0.08052 | -0.30199 |
| West Virginia | -0.64807 | 0.153807 | -0.39587 | -0.18118 |
| Arkansas | -0.55677 | 0.216794 | -0.77434 | -0.15796 |
| Virginia | -0.1257 | -0.81677 | 1.502669 | -0.11917 |
| Louisiana | 0.485455 | -0.71567 | 0.909022 | -0.08173 |
| Nebraska | -0.45539 | 0.133754 | 0.513582 | -0.07613 |
| Alaska | -0.32851 | -0.22126 | 8.39E-05 | -0.05104 |
| Idaho | 0.969193 | -1.55444 | -0.09998 | -0.03341 |
| Florida | 0.37951 | 0.014894 | -0.66582 | 0.046743 |
| Iowa | -0.56118 | 0.601546 | -0.40541 | 0.066003 |
| Georgia | 0.766056 | -0.56683 | 0.801484 | 0.093638 |
| Tennessee | 0.192873 | 0.371471 | -1.09192 | 0.108254 |
| Kansas | 0.296889 | 0.259076 | 0.62589 | 0.205411 |
| Oklahoma | 0.224591 | 0.14621 | 0.970014 | 0.257371 |
| Hawaii | -0.08597 | 0.782351 | -1.32264 | 0.277147 |
| Missouri | 0.006862 | 0.653453 | -0.33786 | 0.284826 |
| Ohio | -0.41417 | 0.828359 | 0.271995 | 0.295055 |
| Connecticut | -1.11604 | 0.773687 | 0.188596 | 0.299637 |
| Oregon | 0.24716 | 0.399827 | 0.878053 | 0.318466 |
| New Mexico | 0.506328 | 0.051915 | 0.697022 | 0.345902 |
| Wisconsin | 0.473449 | 0.268336 | 1.212432 | 0.348051 |
| New Jersey | 0.562231 | 0.390579 | -0.03163 | 0.359603 |
| Utah | 0.981405 | -0.16344 | 0.576879 | 0.383884 |
| Indiana | 0.523508 | 0.609199 | -0.38278 | 0.402926 |
| Pennsylvania | 0.493083 | 0.659598 | -0.75284 | 0.405355 |
| New York | -0.48787 | 0.883648 | 0.976651 | 0.406129 |
| Maine | 0.914522 | 0.173637 | -0.09636 | 0.406877 |
| North Carolina | 1.065257 | 0.284861 | 0.3629 | 0.504546 |
| Michigan | 0.566638 | 0.667197 | 0.950022 | 0.507764 |
| Massachusetts | 0.08494 | 0.892974 | 0.112335 | 0.513563 |
| Maryland | 1.162078 | 0.231573 | 1.145442 | 0.625707 |
| Arizona | 0.862624 | 0.654128 | 0.277233 | 0.631053 |
| Washington | 0.84201 | 0.608061 | 1.083485 | 0.635 |
| Minnesota | 0.880089 | 0.611243 | 1.046012 | 0.635239 |
| Illinois | 0.786923 | 0.889626 | 0.016541 | 0.665431 |
| Colorado | 1.183351 | 0.626022 | 0.059029 | 0.734893 |
| Kentucky | 1.213866 | 0.861473 | -0.64434 | 0.802665 |

| **Table A5 – AllFit results from nonprofit model** | | | | | | | | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
| bobyqa | 4.547 | 0.001 | 0.015 | 0.004 | 0.505 | 0.023 | -0.011 | -0.065 | 0.019 | 0.017 | 0.057 | -0.026 | -0.009 |
| Nelder\_Mead | 4.548 | 0.001 | 0.018 | 0.004 | 0.510 | 0.019 | -0.007 | -0.058 | 0.021 | 0.020 | 0.065 | -0.023 | -0.004 |
| nlminbwrap | 4.546 | 0.001 | 0.015 | 0.004 | 0.505 | 0.023 | -0.011 | -0.065 | 0.019 | 0.017 | 0.057 | -0.026 | -0.009 |
| nloptwrap.NLOPT\_LN\_NELDERMEAD | 4.545 | 0.001 | 0.015 | 0.004 | 0.505 | 0.023 | -0.011 | -0.065 | 0.019 | 0.017 | 0.057 | -0.026 | -0.009 |
| nloptwrap.NLOPT\_LN\_BOBYQA | 4.546 | 0.001 | 0.015 | 0.004 | 0.505 | 0.023 | -0.011 | -0.065 | 0.019 | 0.017 | 0.057 | -0.026 | -0.009 |

| **Table A6 – AllFit results for Government model** | | | | | | | | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
| bobyqa | 2.828 | 0.018 | 0.000 | -0.002 | 0.612 | -0.029 | 0.002 | 0.225 | -0.020 | -0.069 | 0.054 | 0.035 | -0.128 |
| Nelder\_Mead | 2.827 | 0.018 | 0.000 | -0.002 | 0.612 | -0.029 | 0.002 | 0.225 | -0.020 | -0.069 | 0.054 | 0.035 | -0.128 |
| nlminbwrap | 2.827 | 0.018 | 0.000 | -0.002 | 0.612 | -0.029 | 0.002 | 0.225 | -0.020 | -0.069 | 0.035 | 0.035 | -0.128 |
| nloptwrap.NLOPT\_LN\_NELDERMEAD | 2.826 | 0.018 | 0.000 | -0.002 | 0.611 | -0.028 | 0.002 | 0.225 | -0.020 | -0.069 | 0.054 | 0.035 | -0.128 |
| nloptwrap.NLOPT\_LN\_BOBYQA | 2.827 | 0.018 | -0.000 | -0.002 | 0.611 | -0.029 | 0.002 | 0.225 | -0.020 | -0.069 | 0.035 | 0.035 | -0.128 |

| Table A5 and A6 Key | |
| --- | --- |
| 1 | Method |
| 2 | Intercept |
| 3 | AUD |
| 4 | Drug Use |
| 5 | Marijuana Use |
| 6 | Population |
| 7 | Income |
| 8 | Medicaid |
| 9 | Male |
| 10 | Unemployment |
| 11 | Health Spending |
| 12 | Uninsured |
| 13 | Hispanic Ethnicity |
| 14 | White Race |