2021

The Price to Save Lives: Funding for Treatment Centers in America's Opioid Crisis

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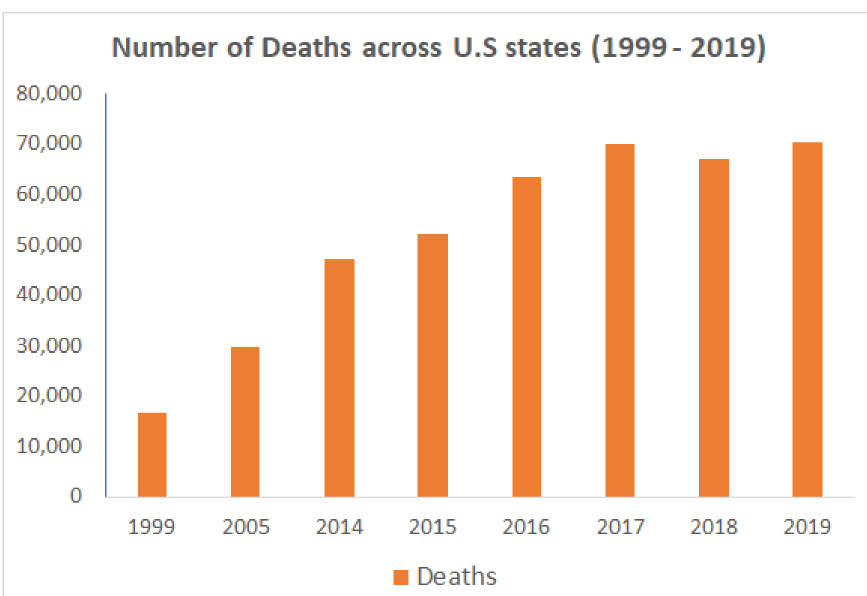
Abstract

Nearly 841,000 people have died since 1999 from a drug overdose (CDC Wonder 2020). The misuse of and addiction to opioids—including prescription pain relievers, heroin, and synthetic opioids such as fentanyl—is a serious national crisis that affects public health as well as social and economic welfare. By the time public health officials realized the dangers that came with addiction to these drugs, an estimated 10.8 million people had misused prescription drugs by 2018 alone (HHS 2020). It is with this startling statistic that since then the United States has struggled to contain this crisis through various means. The most successful method of dealing with the crisis is through public health programs called Medical Assisted Treatment (MAT), which are provided through treatment centers across the United States. Considering the large amount of funding that is being spent on combating the crisis, especially seen with the recent $26 billion settlement with Johnson & Johnson and distributors McKesson, AmerisourceBergen, and Cardinal Health, it is more important than ever to understand and gauge the effectiveness of these programs done through treatment centers and see if funding is being spent in the right places. That is what I work towards with my research, seeing how best to put state and federal funding into combating the opioid crisis.

Background

The opioid crisis is a multifaceted issue that affects millions of people in the United States and continues to grow at an alarming rate. An opioid can be any type of drug that circulates in licit or illicit markets like prescription drugs, synthetic opiates or heroin. There has been a significant amount of evidence that the origins of the crisis can be placed in the introduction and marketing of Oxycontin during the late 1990's, and the lack of regulation in the healthcare industry that led to an massive increase in the availability of these drugs in the public sector (Alpert et al. 2019, Vadivelu et al. 2018). The result of this is that between 1999 and 2010, opioid prescriptions increased by 300% (Kunins et al., 2013). Over this time period the increase in mortality rates has taken a significant toll on the United States, from 2000 to 2014 nearly half a million persons in the United States have died from drug overdoses (Rudd et al. 2016). The number of deaths each year had been steadily rising since the 1990's up until 2018, in which the death rate dropped to 68,557 from 2017's 70,237 (Goodnough, Katz, and Sanger-Katz 2019). This graph pulls from respective state data on mortality rates, and portrays quite clearly the toll this crisis has placed on American lives



Note: Using the data from Drug Overdose Mortality by State 2021 (https://www.cdc.gov/nchs/pressroom/sosmap/drug_poisoning_mortality/drug_poisoning.htm),

As far as treatment for those suffering from opioid addiction, there have been a few consistent methods that have been utilized to get people back on track. Along with utilizing Naloxone to revitalize an overdosed person in an emergency scenario, another useful combative tool is what's called Medical-Assisted-Treatment programs (MAT) which use medication along with counseling to solve addiction problems (Pitt, Humphreys, and Brandeau 2018). Both of these methods are utilized in situations in which an opioid user is combating their addiction, one preemptive tool that tries to slow the opioid trade is what is called Prescription Drug Monitoring Programs. These are state-run electronic databases used to track the prescribing and dispensing of controlled prescription drugs to patients ("National Threat Assessment" 2017). They are designed to monitor this information for suspected CPD abuse or diversion, and emerging evidence has shown that PDMP's are effective at significantly lowering opioid misuse in broad application on state levels (Buchmueller and Carey, n.d.). It is because of the magnitude of total deaths so far and the continued misuse of opioids that so many researchers have placed a great deal of study into this issue. In order to reduce future morbidity and mortality rates, a systemic look at how federal and state funding is being utilized to combat the opioid crisis needs to be taken into consideration.

In order to find out this multifaceted question surrounding federal and state funding towards the opioid crisis, I started first with finding what previous budgetary plans had been put out over the years. This was provided from organizations like the National Institute of Drug Abuse that specifically detailed what funding from the national government would be spent towards with respect to programs and treatment on the federal level. Coupled with the recent news of the $26 Billion settlement which will be finalized in September, finding out where federal funding was being allocated was not as difficult a task as I initially thought. One aspect of my research that I still needed to look at was the state level of funding for the opioid crisis, which would be harder to find information on as each state has a different way of reporting where funding is being spent on combating the opioid crisis. I found databases that individual states did as part of their private research, such as with Indiana and the county level aggregate cost equation that researchers from the University of Indiana created (Brewer and Freeman, 2018). Through extensive research I found an aspect of state funding that directly correlates with the usage of treatment programs in the states, and that was the access to medicaid which appears in datasets for those admitted to treatment centers. It was from this point that my topic came through with the dataset I found, and will be expanded upon later in this paper.

Literature Review/Federal and State Funding

This crisis requires a systematic analysis of how federal and state funding is being allocated to properly solve it. My research adds to an already existing literature of scholarly articles that analyzes the impact of federal and state funding on the overall crisis. The question that these researchers look at is how best to measure the economic burden that combating the opioid crisis brings about (Florence et al. 2016). Emerging studies have charted different methods to accomplishing this task, with a great deal focusing on how aggregate costs are accumulated in states. One example from the Indiana Business Review allocates damages to counties in Indiana through direct costs (first response, long-term treatment), indirect costs through lost GSP in labor markets, and present value of all lost future productivity of past opioid-related casualties (Brewer and Freeman, n.d.). Different researchers have looked at datasets that all contribute to a greater narrative, such as the CDC mortality data and the National

Vital Statistics System for opioid overdoses and deaths (Hollingsworth, Ruhm, and Simon 2017, Florence et al. 2016). Analysis stems from strategies for how opioid funding can be best used in specific treatment programs, and the findings that they attain are best recommended strategies such as increasing opioid grant funding on state targeted response (STR) programs (High et al. 2019). The findings that different researchers have found all look at case examples of states that have been the most effective at reducing opioid deaths, such as with Vermont which actually expanded Medicaid before the ACA officially took effect, and about 80 percent of patients in medication-assisted treatment in the state are covered by Medicaid (Knopf 2017).

Data

When taking a look at how researchers have gathered data to provide analysis on the opioid crisis, it is important to consider both what databases they have pulled from and how they adjusted their variables to make their own conclusions about the topic. There are a great deal of datasets available that can be utilized in unique ways that fall under the topic of the opioid crisis and it can be challenging to find which one suits a specific research question. One of the largest publicly available websites that hosts databases that feature opioid statistics are the ones provided by the Substance Abuse and Mental Health Data Archive (SAMHDA). The multitude of datasets provided surrounding the overall drug abuse topic gives researchers the option to create a wide range of analysis through regressions and data tables on the crisis over the years. A few cases examples will be looked at using one dataset from SAMHDA, the Treatment Episode Data Set-Admissions (TEDS-A), which reports characteristics of clients admitted to specialty substance use treatment programs licensed or funded by public agencies in U.S. states, Washington, DC and Puerto Rico (Batts et al. 2016).

The TEDS-A dataset provides demographic, clinical, and substance use characteristics of admissions to alcohol or drug treatment in facilities that report to state administrative data systems (SAMHDA 2018). Through these systems states send data that includes general demographic information, primary along with secondary and tertiary substances upon admission, source of referral for treatment, record of previous treatment episodes and whether or not medication assisted therapy (MAT) programs were utilized. This specific dataset covers only the year of 2018, with 1,935,541 different cases of people being admitted to substance abuse treatment that year. This dataset is ideal for my research as it provides the greatest amount of variables surrounding the tracking method for the amount of people in each state who were admitted to substance abuse treatment, and the versatile dataset will prove useful in forming my research on state and federal funding onto the total admissions in each state.

Literature Surrounding Dataset

This TEDS-A dataset has a wide range of variables that allows researchers to emphasize their specific points, and trends among these papers with respect to the data will now be looked at. One of the most prevalent trends in grouping how this data will be used with respect to the crisis is to look at the different categories of opioid users that have entered these substance use treatment programs. One paper that utilizes this as their main point titled *Medications for opioid use disorder among American Indians and Alaska natives: Availability and use across a national sample* looks at the access that American Indians and Alaskan natives have to medications used to treat opioid disorders. The way that this source uses the TEDS-A dataset is by cross referencing it with another dataset from SAMHDA called National Survey of Substance Abuse Treatment Services (N-SSATS), which is an annual census of characteristics of public and private substance use treatment facilities in the U.S., including information on types of medications offered (Batts et al. 2016). Using these two datasets, the researchers looked at the availability of medication for opioid use disorder in facilities through the N-SSATS dataset and the client level through the TEDS-A dataset among American Indian and Alaskan natives (Krawczyk et al. 2021). With this the researchers conducted multivariate regression analysis among different race groups to see the access the American Indian and Alaskan natives had to these medications when compared to other groups. This form of data collection shows the importance of picking a specific topic and honing in on how it will answer the research question, and will be important to consider for what I will add with my research.

Another article that does a similar form of data analysis is *Medicaid Expansion Increased Medications For Opioid Use Disorder Among Adults Referred By Criminal Justice Agencies*, the main difference being that the researchers pulled TEDS-A datasets from the past ten years. The main independent variables are the sources of treatment referral, and was grouped by criminal justice referrals and noncriminal/justice referrals which makes sense as the researchers want to chart the availability of opioid use disorder medication before and after Medicaid. To reinforce this the main dependent variable are the receipts of medication for opioid use disorder, and assessed age, race/ethnicity, employment status, sex, educational attainment, service setting, and region by referral source (Khatri, Howell, and Winkelman 2021). This study would also stratify their regression analysis in a similar manner to the previous article, with race/ethnicity being the largest group to do this. One limitation of the TEDS-A dataset is because the unit of analysis within TEDS-A is a treatment admission, not an individual; some individuals may be represented more than once (Khatri, Howell, and Winkelman 2021). The way that this article looks at data over time will be important to consider going forward with my research.

Another article that utilizes this dataset is *The role of health insurance on treatment for opioid use disorders: Evidence from the Affordable Care Act Medicaid expansion*, which analyzes the utility of the Medicaid act in treating opioid use disorder. This source uses general administrative data including TEDS-A from 2007 to 2016, specifically looking at how Medicaid coverage of opioid use disorder treatment has increased from this time period. To look at how health care coverage has changed over this time, control variables are pain clinic laws and PDMP to see how supply reduction has changed over time. One limitation of the TEDS-A dataset as mentioned in this article is the lack of information from certain years as it is a supplemental dataset, and missing values throughout the dataset (Meinhofer and Witman 2018). Taking this dataset and applying it to the implementation of public policy is an aspect of econometric research that relates heavily to my research question, and understanding how I can do that for when my dataset will be important.

An article that takes a look at the TEDS-A dataset in a new comparative manner is *Disparities in Opioid Use Disorder Treatment Admissions in the United States*. The way that this dataset was used was by identifying the group of individuals who have received treatment for opioid use disorder and comparing the changes between the city of Cincinnati and other major cities. Logistic regression models were performed to assess the differences for treatment wait time and type of planned treatment. From this three different models were created that showed the covariates of the outcomes (Mallow, Mercado, and Topmiller 2020). Similarly to the previous article, one of the limitations of this dataset is the fact that the information provided is dependent on the public fund, and as such some states are missing information and it is all self-reported information. It is important to consider the limitations of the dataset, so when I utilize it I will be cognizant of the weaknesses and give proper analysis of why these limitations exist.

Description of Data

Of all the variables present in the TEDS-A dataset, the dependent variable I consider for analysis is METHUSE. This variable identifies whether or not a patient who had been admitted to a treatment facility used opioid medications such as methadone, buprenorphine, and/or naltrexone (SAMHDA 2018). Of the 1,935,541 admission cases, 296,778 were marked as having utilized opioid medications. I include a set of independent variables that define the usage of opioid medications and the relationship it has with co-existing mental and substance use disorders; individual (patients) characteristics capturing race, ethnicity, income, employment, education and marital status, and types of health insurance. The information in the datasets has breakdowns based on the US census divisions and regions which I hope to observe differential effects of both state and federal fundings across divisions.

Many variables in this dataset have missing observations for unknown reasons and they take a value of 9 which I don't include in the dataset for analysis. Along with this, one of the independent variables that indicates if any client had any co-existing mental and substance use disorders (PSYPROB) was modified to a binary variable. If they have none the PSYPROB variable takes the value of 0. I created a number of binary variables for variables of interest to use for the regression analysis.

These independent variables, which can also be called predictor variables as they are all being put in comparison to one dependent variable, will be utilized to show some form of numerical change that is focused on METHUSE and is different for each variable. The total number of observations varies for almost all variables as some are missing. MARSTAT and EDUC are variables to control for marital status and education level of individuals. I use these variables to define, as they are grouped by different sections that will allow for direct comparison between these values and those who were not married or had no education. After I had eliminated the invalid numbers from each of the variables in this dataset, I set about making new binary variables from all the different independent variables that will be utilized to dig deeper into specific key groups that respond higher to METHUSE than if we just left the dataset as is. Certain modifications that I made to these variables were done for the sake of better aggregating the grouping of values, such as with the AGE variable. I changed how it was grouped in the dataset from having values 1-12 be every 4 years of age to groups of teenagers (12-21) and then ten year gaps in each binary variable. This is one example of the choices I made to this dataset, and other modifications I created were done in a similar vein as this in that I chose to create better clarification for specific groups that will impact METHUSE. All the new variables that I will be using for my regression analysis are in the table below, the values for the mean add up to 1.0 as they each are binary and are in direct correlation with one another and a variable in the original dataset.

Table 1: Descriptive Statistics for Original Dataset

Variable	Obs	Mean	Std. Dev.	Min	Max
Primary Pay Source of funding or payment:					
SELFPAYINS	854,133	0.065231	0.2469333	0	1
PRIVATEINS	854,133	0.05065	0.2192825	0	1
MEDICARE	854,133	0.020473	0.1416131	0	1
MEDICAID	854,133	0.566507	0.4955574	0	1
GOVPAYMENTS	854,133	0.226327	0.4184532	0	1

NOCHARGE	854,133	0.02348	0.1514222	0	1
OTHERPRIMPAY	854,133	0.047332	0.2123486	0	1
Type of Health Insurance:					
PRIVATEINS	951,904	0.077166	0.2668554	0	1
MEDICAID	951,904	0.555035	0.4969622	0	1
MEDICARE	951,904	0.077442	0.267291	0	1
NOHLTHINS	951,904	0.290357	0.4539273	0	1
Division:					
USTERRITOR~S	1,935,541	0.001524	0.0390036	0	1
NEW ENGLAND	1,935,541	0.093026	0.2904685	0	1
MIDDLE ATLANTIC	1,935,541	0.20393	0.4029177	0	1
ESTNRTHCENTRAL	1,935,541	0.115516	0.3196431	0	1
WSTNRTHCENTRAL	1,935,541	0.086795	0.2815343	0	1
SOUTH ATLANTIC	1,935,541	0.195571	0.3966394	0	1
ESTSTHCENTRAL	1,935,541	0.034075	0.1814212	0	1
WSTSTHCENTRAL	1,935,541	0.041478	0.1993938	0	1
MOUNTAIN	1,935,541	0.142166	0.3492203	0	1
PACIFIC	1,935,541	0.085921	0.280247	0	1
Race:					
ALASKA NATIVE	1,859,620	0.001928	0.0438645	0	1
AMERICAN IN~N	1,859,620	0.026955	0.1619519	0	1
BLACK	1,859,620	0.195004	0.3962042	0	1
WHITE	1,859,620	0.673462	0.4689466	0	1

PACIFICISL~R	1,859,620	0.000123	0.0110721	0	1
ASIAN	1,859,620	0.006156	0.0782155	0	1
OTHERSINGL~E	1,859,620	0.072204	0.2588246	0	1
TWOORMORER~S	1,859,620	0.020466	0.1415862	0	1
NATIVEHAWA~N	1,859,620	0.003703	0.0607432	0	1
Ethnic:					
PUERTORICAN	1,856,174	0.035981	0.1862415	0	1
MEXICAN	1,856,174	0.037171	0.1891809	0	1
CUBAN	1,856,174	0.034306	0.1820142	0	1
NOT HISPANIC	1,856,174	0.861648	0.3452695	0	1
GENERAL HIS~C	1,856,174	0.030895	0.1730326	0	1
Marital Status:					
NEVER MARRIED	1,508,148	0.677985	0.4672488	0	1
MARRIED	1,508,148	0.125797	0.3316209	0	1
SEPERATED	1,508,148	0.055477	0.2289096	0	1
DIVORCED/WIDOWED	1,508,148	0.14074	0.3477534	0	1
Education:					
BELOW GRADE8	1,716,995	0.058012	0.233767	0	1
GRADES 9-11	1,716,995	0.211143	0.40812	0	1
GRADE12 OR GED	1,716,995	0.481402	0.4996541	0	1
COLLEGEUPT~S	1,716,995	0.183211	0.3868398	0	1
COLLEGEGRA~E	1,716,995	0.066231	0.2486862	0	1
Employment:					

FULL TIME	1,709,433	0.184812	0.3881452	0	1
PART TIME	1,709,433	0.07261	0.2594954	0	1
UNEMPLOYED	1,709,433	0.372776	0.4835433	0	1
NOT IN LABOR FORCE	1,709,433	0.369802	0.4827511	0	1
Source of Income:					
WAGES	1,183,287	0.292067	0.4547131	0	1
PUBLICASSI~E	1,183,287	0.084999	0.2788801	0	1
RETIREMENT~Y	1,183,287	0.075372	0.2639912	0	1
OTHERPRIMINC	1,183,287	0.174006	0.3791148	0	1
NOPRIMINC	1,183,287	0.373556	0.483748	0	1
Age group:					
AGE 12-20	1,935,541	0.060916	0.2391758	0	1
AGE 21-29	1,935,541	0.256324	0.436603	0	1
AGE 30-39	1,935,541	0.3084	0.4618326	0	1
AGE 40-49	1,935,541	0.18192	0.3857784	0	1
AGE 50 and older	1,935,541	0.192441	0.3942175	0	1

From this descriptive table, there are a few key variables that have noticeable details. By looking at the mean values for these variables and identifying where large groups are present narrative details surrounding who is admitted to these treatment facilities will come about. Two of the most noticeable details are with the large number of admissions of people who were on medicaid, seen in both the HLTHINS and PRIMPAY primary variables. Seen with both MEDICAIDPRIMARYPAY and MEDICAIDHLTHINS, the mean values are a significant percentage of the total amount (0.566507 = 56.6% for HLTHINS, 0.555035 = 55.5% for

PRIMPAY). This is not something that I expected when looking at the descriptive statistics, and considering that medicaid is a state and federal program focused on providing health coverage for those with low income, the purpose of medicaid fits directly with my research topic and provides me with the largest pool of data. Another stark percentage value that sticks out was the racial distribution, with the largest percentage being white (0.673462 = 67.3%) which speaks to what groups are most able to get into the proper treatment for their opioid use disorder. Another high percentage are those who never married (0.677985 = 67.7%) and those who only graduated from high school (0.481402 = 48.1%), these two percentages combined with the other high percentages show the general grouping of a person that requires treatment at an admission facility. The newly named created variables are shown in table 2 below, and a short description of each one is shown along with it.

Table 2: Variable Names and Descriptions

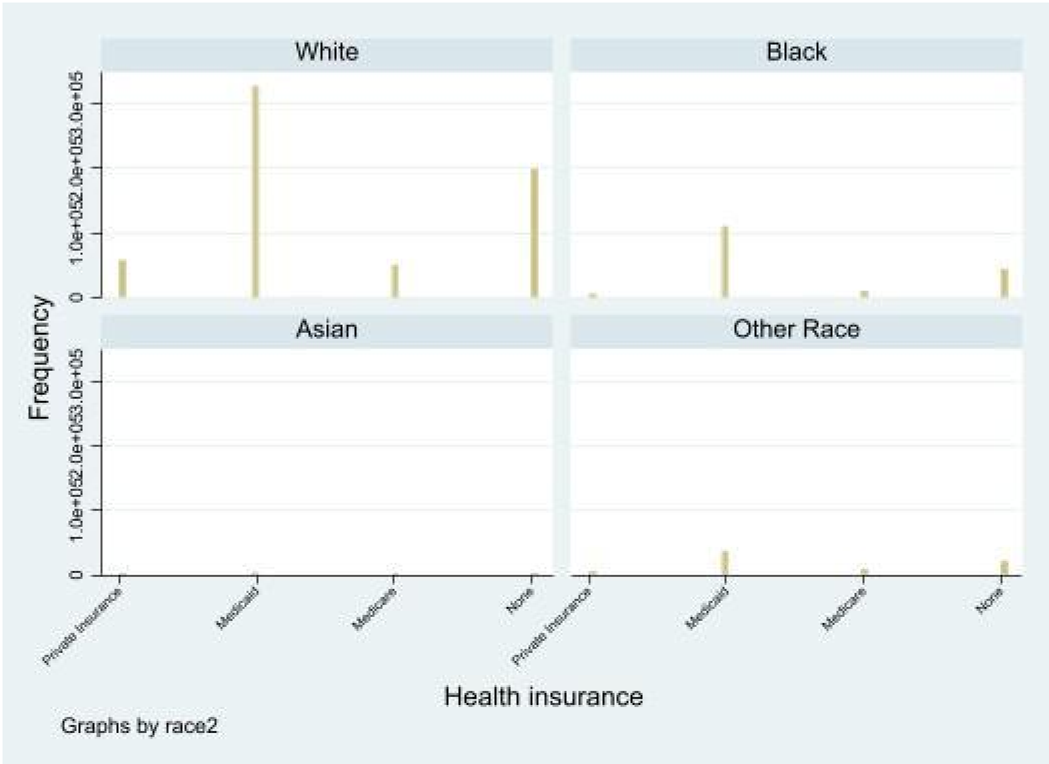
Variable	Description
Reported Opiates:	Opiates reported at admission
Reported Methadone:	Non-prescription Methadone reported at admission
Mental/Substance Disorders:	Co-occurring mental and substance use disorders
Type of Health Insurance:	Client's health insurance at admission

Medicaid Health Insurance	
Medicare Health Insurance	
No Health Insurance	
Census Division:	Groupings of states that are subdivisions of the 4 Census regions
New England	
Middle Atlantic	
East North Central	
West North Central	
South Atlantic	
East South Central	
West South Central	
Mountain	
Pacific	
Race:	Client’s race
White	
Black	

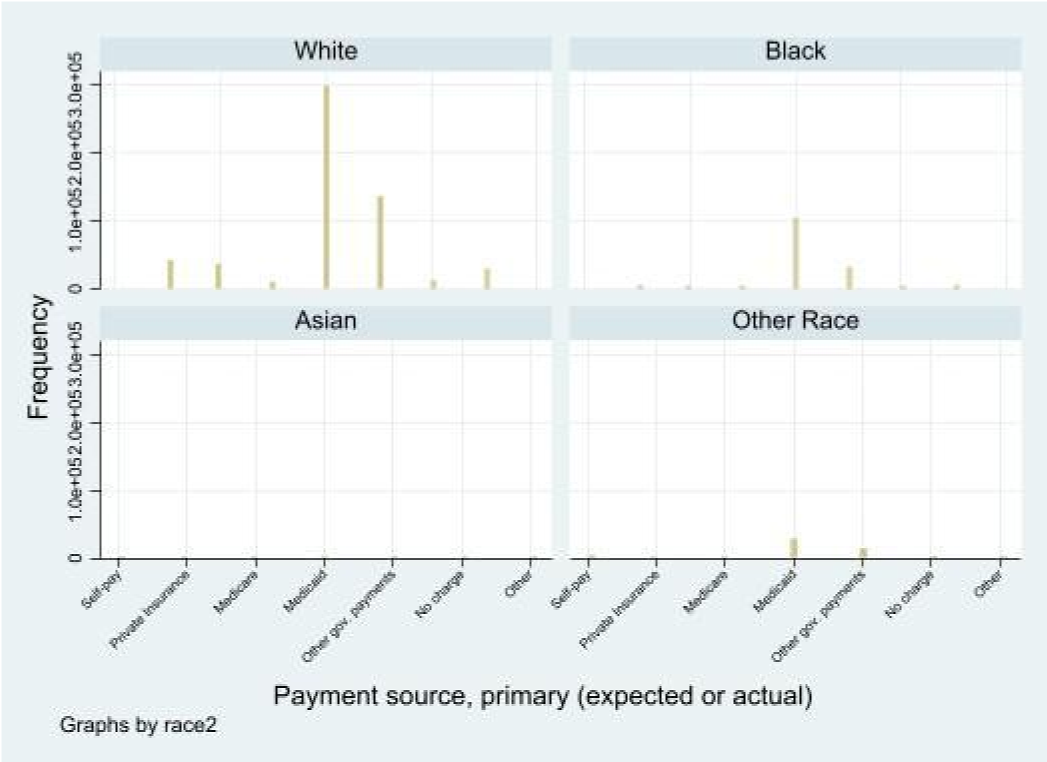
Other Race	
Marital Status:	Client's marital status
Never Married	
Now Married	
Divorced/Widowed	
Education:	Client's education
Grades 9 to 11	
Grade 12/GED	
College up to 3 Years	
College Graduate	
Employment:	Client's employment
Full time	
Unemployed	
Not in Labor Force	
Source of Primary Income:	Client's primary source of income
Wages	

Public Assistance	
Other Primary Income	
No Primary Income	
Age group:	Client’s age
Age 21 to 29	
Age 30 to 39	
Age 40 to 49	
Age 50 to Older	
Female	

With all of this detail surrounding the variables, it was time to create a comparable format that unites data with the narratives above. The way that this will be accomplished is by showcasing histographic models comparing a modified race variable with the HLTHINS and PRIMPAY variables. The new race variable that was created groups the total races in the dataset from 9 groups to just 4, this is done in order to better compare in a histogram. The four racial groups in the race2 variable are white, black, asian, and other racial groups which are the 4 numbers in the titles of each smaller graph. The 4 groups of HLTHINS are having private insurance, medicaid and medicare, and no health insurance available.



The biggest conclusion from this graph is that white (1) and black (2) groups have the highest frequency for getting access to health insurance and the largest group is the medicaid (2) and no health insurance (4). The implication that white people have the most readily available access to health insurance, specifically one that is backed up by federal and state funding is an interesting spin on my research topic.



Similarly with the HLTHINS histogram, predominantly white and black groups have the highest association with medicaid as a source of payment for entering these treatment facilities. One of the main interesting facts about this graph is the other government payments section, which is surprisingly the second highest percentage for both white and black groups and the other race groups. Looking at these different racial groups in isolation from the others would be necessary to better understand how these groups relate to other key variables, which will be accomplished through running a probit regression analysis with one of these racial groups being the control variable by being excluded from the regression.

<u>Method of Analysis</u>

I chose the probit model for estimation as the independent variable METHUSE is a binary variable. The probit function is able to create a nonlinear relationship from the binary variable, and is thus able to be properly used in this dataset. In order to properly represent this dataset, a variety of new variables had to be created that broke up the different categorical variables into separate binary variables. This allows for greater look at specialized factors in different areas, such as looking at each of the different racial groups individually and how they each relate to the dependent variable. From these variables, a final regression model utilizing the probit function was created, all variables are modeled with the use of medication assisted therapy.

Table 3: Probit estimates of relationship between use of medication assisted therapy and variables of admitted patients

Variable	Coefficient	Standard Error
Reported Opiates	0.481513	0.006591***
Reported Methadone	0.672559	0.034965***
Mental/Substance Disorders	0.017739	0.004969***
Types of Health Insurance:		
Medicaid Health Insurance	0.316267	0.010013***
Medicare Health Insurance	0.022816	0.01263
No Health Insurance	-0.09308	0.010461***
Census Division:		
New England	0.30657	0.041684***
Middle Atlantic	0.59608	0.041733***
East North Central	-0.71771	0.043699***
West North Central	-0.91948	0.042636***

South Atlantic	0.213773	0.042026***
East South Central	-0.42389	0.0427***
West South Central	-0.93966	0.047088***
Mountain	-0.42546	0.04224***
Pacific	-0.40725	0.046513***
Race:		
White	0.318489	0.027667***
Black	0.054451	0.028204***
Other Race	0.121324	0.029148***
Marital Status:		
Never Married	0.043552	0.011395***
Now Married	0.105531	0.012769***
Divorced/Widowed	-0.04145	0.012603**
Education:		
Grades 9 to 11	0.100116	0.010754***
Grade 12/GED	0.020665	0.00936*
College up to 3 Years	-0.01365	0.010565
College Graduate	-0.1256	0.012734***
Employment:		
Full time	-0.09102	0.010331***
Unemployed	-0.07944	0.011603***
Not in Labor Force	-0.16357	0.011655***
Primary Income:		
Wages	-0.27562	0.011543***
Public Assistance	-0.08037	0.010364***

Other Primary Income	-0.22351	0.010037***
No Primary Income	-0.31179	0.008718***
Age:		
Age 21 to 29	0.615782	0.017135***
Age 30 to 39	0.750545	0.017066***
Age 40 to 49	0.718954	0.017589***
Age 50 to Older	0.745786	0.017851***
Female	0.185893	0.005127***
Constant Value	-2.23847	0.060631***

Discussion of results

Several important factors that stick out in this regression analysis are the ones that relate to what I discussed in the introduction section. Starting with the access a person had to medicaid in a treatment center, there is a higher probability that person would actively utilize an MAT program. The data shows a positive relationship with medicaid and MAT programs, with the positive coefficient for medicaid health insurance leading to a numerical increase in MAT programs (0.316267). Looking at the census divisions, it is interesting to see the positive relation that New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont) Middle Atlantic (New Jersey, New York, and Pennsylvania) and South Atlantic (Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, and West Virginia). These regions and the increased access to MAT programs as seen in the dataset (0.30657, 0.59608, 0.213773) showcases what regions have greater percentage access to these programs for people who need it as opposed to other regions. A case could be made for these regions utilizing their funding more effectively than other regions of the United

States. Looking at the race binary variables, considering both the previous histograms with the conclusion that the white variable had the highest access to medicaid, it makes sense that the white coefficient has the highest percentage for receiving access to MAT treatment (0.318489) than the other races (0.054451 for black, 0.121324 for other races). These results suggest that region along with racial identity decide whether or not a person gets access to proper treatment for addiction through MAT programs, and this predictor is prevalent across other variables like age and primary source of income. It seems that in order to allow for better treatment in the United States, making sure that funding is provided to different regions than the ones discussed here and allowing marginalized populations receive access to medicaid will lead to greater access to treatment programs.

Conclusion

To sum up everything that has been brought up so far, funding meant for combating the opioid crisis will need to make revisions that highlight disparities brought up in the data of this research. Making sure that funding from the federal government is utilized with accountability on the states is another important aspect that needs to be brought to the forefront even as funding continues to be doled out to the states. The findings of this research allows for a greater look into how discrepancies among different factors impact how people receive access to medical treatment, and makes clear that the road for reforming the American healthcare field is an important stepping stone to solving the opioid crisis.

APPENDIX

List of variables used in analysis

Variable	Obs	Mean	Std. Dev.	Min	Max
METHUSE	1,793,132	0.165508	0.3716387	0	1
METHFLG	1,935,541	0.003458	0.0587026	0	1
OPSYNFLG	1,935,541	0.122163	0.3274738	0	1
PSYPROB	1,620,475	0.411036	0.4920218	0	1
HLTHINS	951,904	2.580989	0.9891858	1	4
PRIMPAY	854,133	4.097816	1.243714	1	7
RACE	1,859,620	4.942947	1.002045	1	9
ETHNIC	1,856,174	3.814305	0.7093849	1	5
MARSTAT	1,508,148	1.658972	1.086335	1	4
EDUC	1,716,995	2.988506	0.944033	1	5
EMPLOY	1,709,433	2.927568	1.084627	1	4
PRIMINC	1,183,287	3.251985	1.690563	1	5
DETNLF	563,807	4.123024	1.170725	1	5
AGE	1,935,541	6.927559	2.445001	1	12

METHUSE= Whether the use of opioid medications such as methadone, buprenorphine, and/or naltrexone is part of the client's treatment plan.

METHFLG= Flag records if non-prescription methadone was reported as the primary, secondary, or tertiary substance at the time of admission.

OPSYNFLG= Flag records if other opiates or synthetics were reported as the primary, secondary, or tertiary substance at the time of admission.

PSYPROB= Indicates whether the client has co-occurring mental and substance use disorders.

HLTHINS= This field specifies the client's health insurance at admission. The insurance may or may not cover behavioral health treatment.

PRIMPAY= This field identifies the primary source of payment for this treatment episode anticipated at the time of admission.

RACE= This field identifies the client's race

ETHNIC= This field identifies the client's ethnicity

MARSTAT= This field identifies the client's marital status

EDUC= This field identifies the client's education level

EMPLOY= This field identifies the client's employment status

PRIMINC= This field identifies the client's principal source of financial support

DETNLF= Provides more detailed information about those clients who are coded as '04 Not in labor force' in Employment Status

AGE= This field identifies the client's age

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