An Empirical Analysis of the Leading Determinants Behind the Opioid Epidemic the 50 States

By: Sydney Levine

Abstract:

This paper investigates the determining factors influencing the opioid epidemic in each of the 50 states of the United States of America. The opioid epidemic is a rising concern throughout the nation and has been associated with economic conditions. The health crisis poses additional threats to the labor market and the overall economy. This study looks at the age adjusted opioid death rate per 100,000 people as the dependent variable and how unemployment rate, the labor force participation rate, ESOOS funding, the number of hospitals, Median household income, the GINI index, adults reporting poor mental health status, individuals reporting past year opioid use disorder and individuals reporting needing but not receiving treatment for illicit drug use in the past year as independent variables. Previous studies imply macroeconomic shocks also increase the overall drug death rate, but this increase is driven by rising opioid deaths. This paper uses a logistic model to appropriately identify which factors have a heighten relationship to the opioid epidemic and vice versa for each of the 50 states. Frequency of overdose by state was estimated by kernel density estimation in order to find a candidate breakpoint for forming the dichotomy. Using 12 as the breakpoint, supported sufficient results; using these determinants the study indicate that ESOOS funding, opioid prescribing rate, the number of hospitals, GINI index, and individuals reporting past year opioid use disorder as statistically significant in predicting opioid mortality.

JEL Classification: E7, I12, I10, J22, J28, R12

Keywords: Opioid, drug-use, United States, labor-force, unemployment rate, mental health

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1.0 Introduction:

In the United States overdose has been considered a major cause of death, specifically, opioids have been attributed to this increasing epidemic. According to the National Institute on Drug Abuse, “Opioids are a class of drugs that include the illegal drug heroin, synthetic opioids such as fentanyl, and pain relievers available legally by prescription, such as oxycodone, hydrocodone, codeine, morphine, and many others” (NIDA, 2020). In the late 1990s pharmaceutical companies promised patients they would not become addicted to opioid pain relievers. Since, there has been an increase in misuse of both prescribed and non-prescribed opioids due to increased prescribing rates. In 2005, Congress addressed its concern regarding the diversion of controlled pharmaceuticals and insisted on spending $60 million from fiscal years 2006 to 2010 to help establish or improve prescription monitoring programs.

The age-adjusted rate of drug overdose deaths tripled between 1999 and 2016 and jumped an additional 10 percent in 2017. To complement this, according to the CDC, sales of prescription opioid medication per capita were 3.5 times higher in 2015 than in 1999. The age-adjusted drug overdose rate for the nation was 21.7 deaths per 100,000 people in 2017. In 2017, there were more than 70,200 drug overdose deaths in the United States, out of these over-dose deaths over 70% can be attributed to opioids. In 2017, the United States Department of Health and Human Services declared the opioid crisis as a public health emergency (CDC).

Research prevails that in May of 2018, the U.S. unemployment rate fell to 3.8 percent, yet the prime working aged population of those aged 25 to 54 years, has fallen from a high of approximately 85 percent in the late 1990s to 81 percent by 2015. Several reports discuss that such drug use is associated with the noticeable decline in the labor force. It is also noted that higher overdose rates and higher prescription rates are correlated with worse employment outcomes. Other research aims to analyze whether economic conditions are associated with increased opioid use and adverse health outcomes. Results vary, as some seem to portray that recessions allow for individuals to spend more time focusing on their health rather than their work. Other studies have since discovered a decrease in manufacturing had a negative effect on unemployment and lead to increased use of opioids and an increased death rate.

Thus, there are various determinants in what is influencing opioid use and associated opioid use mortality. It is crucial to understand the relationship between state economic conditions and the drug-related outcomes as the United States continues to experience a fatal drug epidemic. Studies are aiming to understand perhaps if opioid use influences the economy. In fact, many have tried to quantify the economic impact of the national opioid crisis; the economic burden has been estimated to be $78.5 billion, $28.9 billion representing over one-third of the total amount is due to increased health care and substance abuse treatment costs (Florence, Curtis S et al., 2016). Results conclude that the opioid crisis has affected the economy in several complicated ways as there is a continuous relationship between the health and resiliency of a country's economy and the health of its communities. In addition, many studies tend to observe and analyze either specific states and cities or the entire country altogether.

In this study, the goal is to understand what economic and healthcare associated determinants are most significant in predicting opioid mortality rate, and to identify which states are high or low opioid death rate states. This model differs from previous studies as it will predict the outcome for high and low opioid overdose mortality on the state level. This study will be using a logistic model to predict the probability of opioid mortality due to the highlighted independent variables. Optimizing the generalized least square model, the data is calculated to generate such results.

Data retrieved from the Kaiser Family Foundation and the Bureau of Labor Statistics for the year 2017 will be used to estimate the death rate associated to opioid use. To deviate from similar studies, data will be observed and interpreted for all 50 states. Some of the variables that will be observed in determining opioid associated death are the labor participation rate, ESOOS funding status, unemployment rate, median household income, the number of hospitals, the GINI index, adults reporting poor mental health status, individuals reporting past year opioid use disorder and individuals reporting needing but not receiving treatment for illicit drug use in the past year.

The rest of the paper is organized as follows: Section 2 gives a brief literature review. Section 3 is an overview of associated opioid trends, Section 4 outlines the data used, empirical methodology, and model. Results and predicted values are discussed in Section 5. Section 6 reveals a discussion of results followed by Section 7 covering policy recommendations. Finally, Section 8 looks at the limitations of this study and Section 9 concludes the essence of this study.

2.0 Literature Review

Several papers and additional primary sources were used and interpreted to generate this study. The combination of these various papers explains the rationale for using such a model, data, and justifies interpreted results while highlighting new insights. Jasper Fanning, Thomas Marsh, and Kyle Stiegert provides for the means behind using the logit model. The paper investigated the socioeconomic determinants in determining the likelihood of consuming fast food (Fanning et al, 2005). The logit model was used to estimate the empirical relationship between the probability of an individual consuming fast food based on socioeconomic variables. The paper describes the following model as the probability of purchasing fast food or the "Participation Decision" modeled by (Fanning et al., 2005):

$$P\ (y_i > 0) = e^{BX_i}/(1+e^{BX_i})$$

There has been much investigation of the relationship between macroeconomic conditions and various health behaviors, but less literature observes that between illicit drug use and the economy due to the confinement of data. It has been particularly examined how deaths and emergency room visits related to opioid use and other drugs vary with economic conditions. This paper found as the county unemployment rate increases by one percentage point, the opioid death rate per 100,000 rises by 0.19 (3.6%) and the opioid overdose ED visit rate per 100,000 increases by 0.95 (7.0%). Results also indicated that macroeconomic shocks also increased the overall drug death rate, but this increase is attributed by rising opioid deaths (Hollingsworth et al., 2017).

The study looks at the overall opioid impact at both a national-level and state-level aggravated data for 15 states. The study concludes that the county level does not show an obvious relationship between the economy and drug associated death rates. The study poses that observing this data on a county level, there is more likely to be an error in mortality rates and unemployment rates. In continuation, results from the county level suggest that around half of the macroeconomic effect on drug mortality operates through opioid-related deaths and found a strong significant positive relationship between opioid-related overdose ED visits and unemployment rates (Hollingsworth et al., 2017).

The study also looks to see if the effects of macroeconomic decline on opioid adverse events differ across race and ethnicity groups. The study concludes that white males are most subject to opioid attributed overdose, where a one-point rise in unemployment rate predicts a 3.6 percent mortality increase. The effect on all drug deaths is also dominated by whites with a 4.5 percent increase from a one-point rise in unemployment rate. This prompted the integration of the GINI coefficient in this study as a measure of inequality to see if there is significance between states (Hollingsworth et al., 2017).

On the state-level, the study portrays a one-point increase in unemployment rate is predicted to raise the opioid-related mortality rate by 0.33 per 100,000 people. These estimates suggest that most of the predicted increase in drug deaths is due to opioid-related mortality. Results imply negative economic shocks have larger adverse effects on drug related mortality and ED visits at the state-level. Overall, the study concludes there is strong evidence supporting that opioid-related deaths and ED visits increase in times of economic weakness (Hollingsworth et al., 2017).

A report in 2017 estimates of 20.7 million people aged 12 or older needed substance use treatment, translating to about 1 in 13 people qualifying for treatment. Those qualifying for treatment were considered if they had a substance use disorder in the past year or if they received substance use treatment at a facility in the past year (Bose et al., 2017). In 2017, among the 18.2 million people aged 12 or older who needed to use treatment but did not receive specialty treatment in the past year is about 1 million individuals. This translates to about 2 in 5 people who perceived a need for treatment but did not receive treatment at a facility. There is an economic component here, as 1 out of 3 of these individuals could not afford the cost. This also provides the rationale to investigate the GINI coefficient as a relevant factor. In addition, this is why this study choses to look at the variables indicating individuals reporting past year opioid use disorder and individuals reporting needing but not receiving treatment for illicit drug use in the past year (Bose et al., 2017).

Additional research prevails to understand the effect of local economic factors on the amount of opioid overdose deaths throughout countries in Ohio (Anna M. Gagliardo, 2016).

Ohio is a state with a rather large opioid problem, the paper used two linear regression models to demonstrate there is a significant correlation between both insured rates and poverty rates in respect to opioid overdose deaths. The paper incorporates the used of the unemployment rate, medium household income, poverty rate, insured rate, prescription rate, border status, metropolitan status, and high school graduation rate. The paper identifies the most significant in predicting overdose death rates in 2013 are unemployment rate and poverty rate (Anna M. Gagliardo, 2016).

More literature uses large commercial insurance claims databases to identify demographic, mental health, physical health, and health service utilization variables that distinguish individuals who receive an opioid abuse diagnosis (OUD) within two years of filling an opioid prescription from those who do not receive a diagnosis (non-OUD) within two years. The purpose of this study was to examine the demographics and healthcare related variables that predict the development of opioid abuse or dependence (Cochran et al., 2014).

This study used a series of 18 logistic regression models to fit the data, with variables selected based on several criteria. The first being simple demographics, the second being the clinical setting, and the third all models were tested through a CHAID analysis including both those with and without the interaction variables found. Log likelihood ratio, Wald and Lagrange multiplier "Score test" were used to determine the presence of one of more significant predictor variables. The model fit was evaluated using the Akaike Information Criterion (AIC) model fix index. This model was chosen as it favored sensitivity over parsimony, therefore the choice of the best fitting model was based on the AIC, the overall parsimony, and the predictability of the model to identify opioid disorders (Cochran et al., 2014).

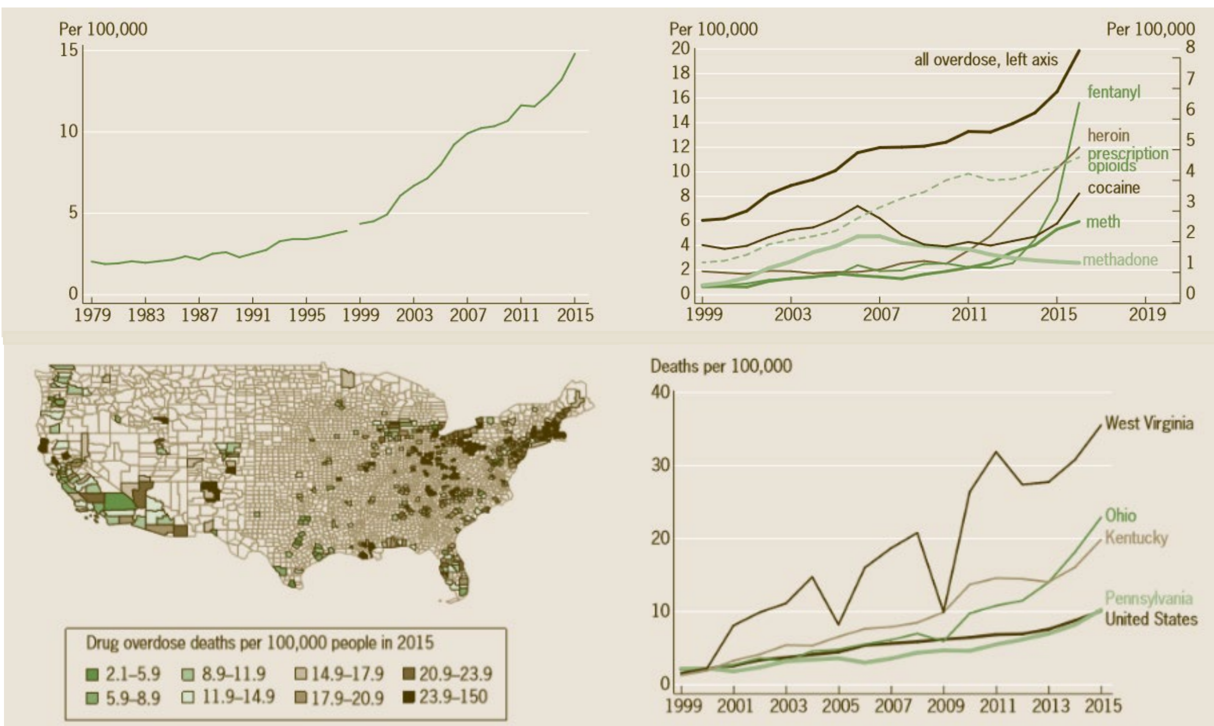
The results provide the best fit for data defined by the AIC values. In addition, the log likelihood ratio test (LR) for the selected model was 12,695 (*df* = 49) ($p < 0.0001$). The remaining models had LR values ranging from 5,785 (*df* = 7) to 13,095 (*df* = 72). To conclude, all of these ratios were also statistically significant ($p < 0.0001$), as well as the results for the Wald and Score tests across all models. Essentially, the study exhibited that those who received a diagnosis were 59.6% more likely to be a male and younger than 37.9 years of age. In addition, the study found those receiving a larger number of days' supply of opioids and having a higher average daily dose was a predictor of opioid use disorder diagnosis. In addition, health service utilization was also significantly greater among OUDs than among non-OUDs. Lastly, OUDs are more likely to be receiving treatment for anxiety, depression, chronic pain, and many other conditions than non-OUDs (Cochran et al., 2014).

Lastly, a paper uses a linear probability model to support their claim that the labor force participation rate has fallen more in U.S. counties where more opioid pain medication is prescribed. This has caused for a depressed labor force and feeds into the opioid crisis itself. The paper explains that men and women not participating in the labor force present the lowest level of emotional well-being and life fulfillment. The study continues to predict that 30 percent of prime aged, not in the labor force men took pain associated opioid medication. Following a conducted survey, 80 percent of those who initially took an opioid medication, claimed to still be taking an opioid in a follow-up survey (Allen Krueger, 2017).

3.0 Opioid Use Trends Across the U.S.A.

Trends in overdose deaths and drug use are used to conceptualize the progression of the opioid market and how it has evolved over time. In figure 1, it is apparent that rising overdose death rate is indicative that the epidemic is indeed getting worse and might have an equivalent impact on the labor force. In 1990 and 2000 the rate increased but continued at a linear pace for the next 10 years. Most of the increase in deaths since 2010 are due to the use of heroin and synthetic opioids. Deaths from fentanyl almost doubled from the previous year rate for years 2014, 2015, and 2016. The fourth district is one of the most affected regions in the country. Data indicates the total overdose deaths from any opioid are occurring at a much higher rate in fourth district states than the United States rate (Aliprantis et al., 2019).

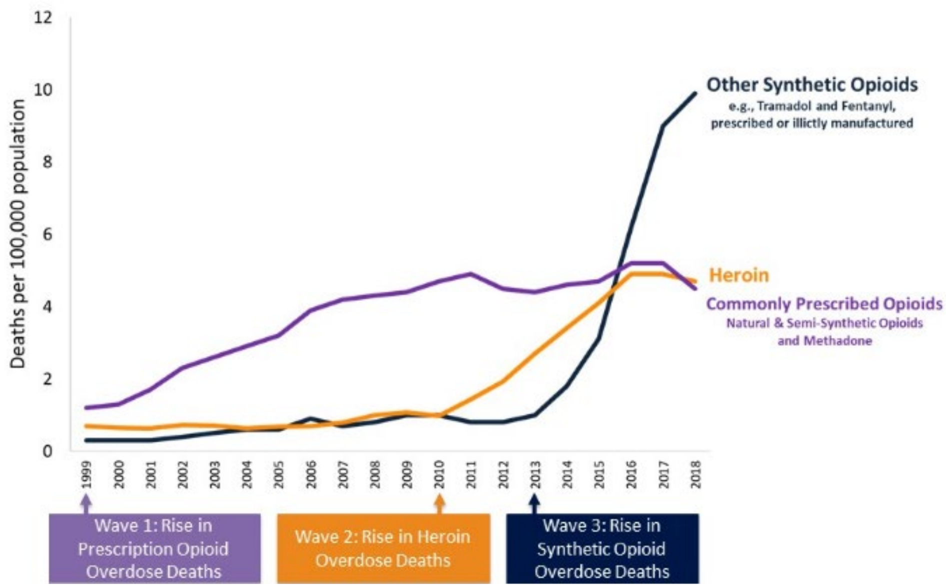
Figure 1. Opioid Overdose Deaths in the United States



Source: Federal reserve Bank of Cleveland; The Opioid Epidemic and the Labor Market

The first wave of the opioid epidemic in the states occurred from 2000 to 2001. As shown in Figure 2, this period was characterized by growing overdose deaths involving the misuse of prescription opioids. During the first wave, prescription opioid prices fell in response to expanded government healthcare coverage and the ever- increasing market share of opioids. There is some evidence that indicates that this price decrease is associated with the increased mortality associated to opioids, which has come to blame pharmaceutical marketing tactics. The second wave, occurring from 2010 to 2016 is characterized by growing overdose deaths involving illicitly manufactured opioids including heroin and fentanyl. Shown in Figure 2, during the second wave, expanding supply capabilities of illicit opioids reduced their prices (11). Figure 2 depicts the third wave beginning in 2013, the leading cause is attributed to significant increases in overdose deaths involving synthetic opioids. As shown in Figure 1, the market for fentanyl, heroin, counterfeit pills, and cocaine continues to expand. From 2017 to 2018, the number of drug overdose deaths decreased by 4 percent, but the number of drug overdose deaths was 4 times higher in 2018 than in 1999 (CDC, 2020).

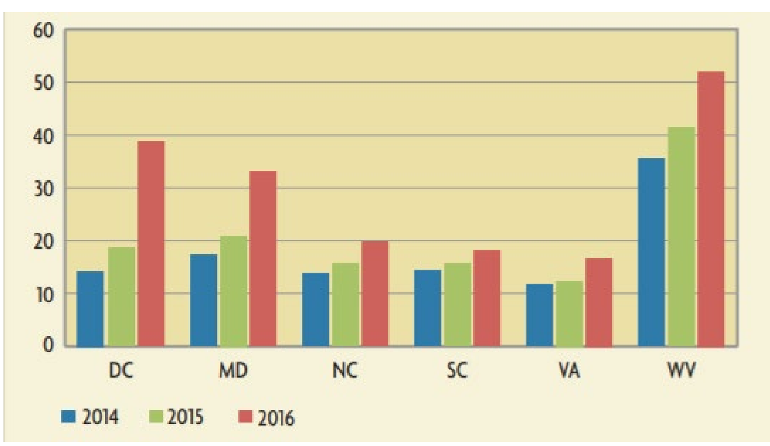
Figure 2. Three Waves of the Rise in Opioid Overdose Deaths



Source: CDC; Center for Disease Control and Prevention

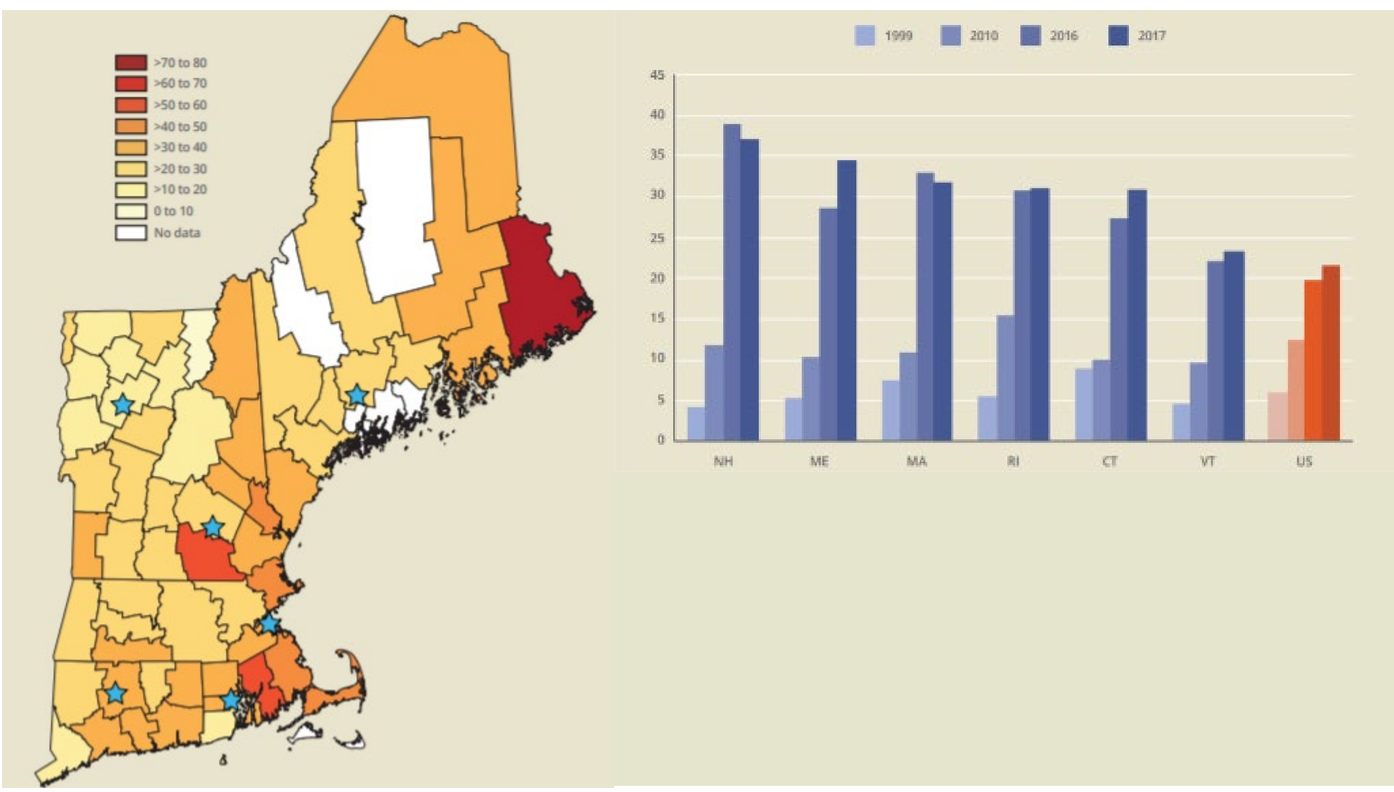
Throughout the Underestimated Cost of the Opioid Crisis, the report summarizes such trends and highlights areas of concern. The opioid drug epidemic is largely affecting the United States and continues to affect the United States as years persist. In 2015, estimates suggest that over 50,000 Americans die from a drug overdose, of which 63 percent or 33,091 were opioid involved. This problem is worsening at an exponential rate. Opioid-involved overdose deaths are doubling over a 10-year period and have quadrupled over a 16-year period. To combat this issue, the Trump Administration and the Opioid Crisis declare this issue as a public health emergency under the Public Health Services Act (HASC, 2017).

Pictured in Figure 3, the fifth federal reserve district, including the district of Columbia, Maryland, North Carolina, South Carolina, Virginia, and especially West Virginia have particularly been hit hard by the increased opioid use and misuse (Waddell, 2018). West Virginia with 52 deaths per 100,000 people had the highest drug overdose death rate in the country in 2016, followed by Ohio at 39.1 deaths. In 2009, West Virginia occupied the highest prescription rate, prescribing 14.9 opioid prescriptions per 100 people. In 2016, West Virginia reduced their prescribing rate to 96 prescriptions per 100 people. Other states such as Alabama prescribed 121 per 100 people, followed by Arkansas at 114.6 per 100 people, Tennessee at 107.5 per 100 people, Mississippi at 105.6 per 100 people, Louisiana at 98.1 per 100 people, Oklahoma at 97.9, and Kentucky at 97.2 per 100 people (Sonya Ravindranath Waddell, 2018).



Lastly, Figure 4. portrays how the opioid epidemic significantly impacts New England. From 2015 through to 2017, more than 10,000 people died from opioid overdoses. Each of the six states of New England in 2017 experienced an overdose death rate that was greater than the national average as shown in Figure 4. The opioid epidemic is costing New England productive workers, especially as those with an opioid use disorder tend to be those aged between 25 and 44. To one's assumption the New England counties with the lowest rates of legal opioid prescribing rates are associated with the lowest rates of overdose. Once again leading to the fact that the supply of opioids is the most critical factor influencing the crisis (Sullivan & Manchester, 2019).

Figure 4. Fatal Drug Overdoese Across New England



Source: Federal Reserve Bank of Boston, 2017.

4.0 Data, Empirical Methodology and Model

4.1 Data

The data used in this paper originates from the Kaiser Family Foundation (KFF) for the year of 2017. The KFF supplied the data for the age-adjusted amount of deaths per 100,000 attributed to opioids (OD), the opioid prescribing rate (OPR), the GDP per state (GDP), the state unemployment rate (UR), the number of hospitals (H), Median household income (MHI), the GINI index (GINI), adults reporting poor mental health status (MENTAL), individuals reporting past year opioid use disorder (DISORDER), and individuals reporting needing but not receiving treatment for illicit drug use in the past year (T). Additionally, the labor force participation rate (LPR) was archived from the Labor Statistics Bureau for the year of 2017. The Center for Disease and Control (CDC) also provides the means for most of this data.

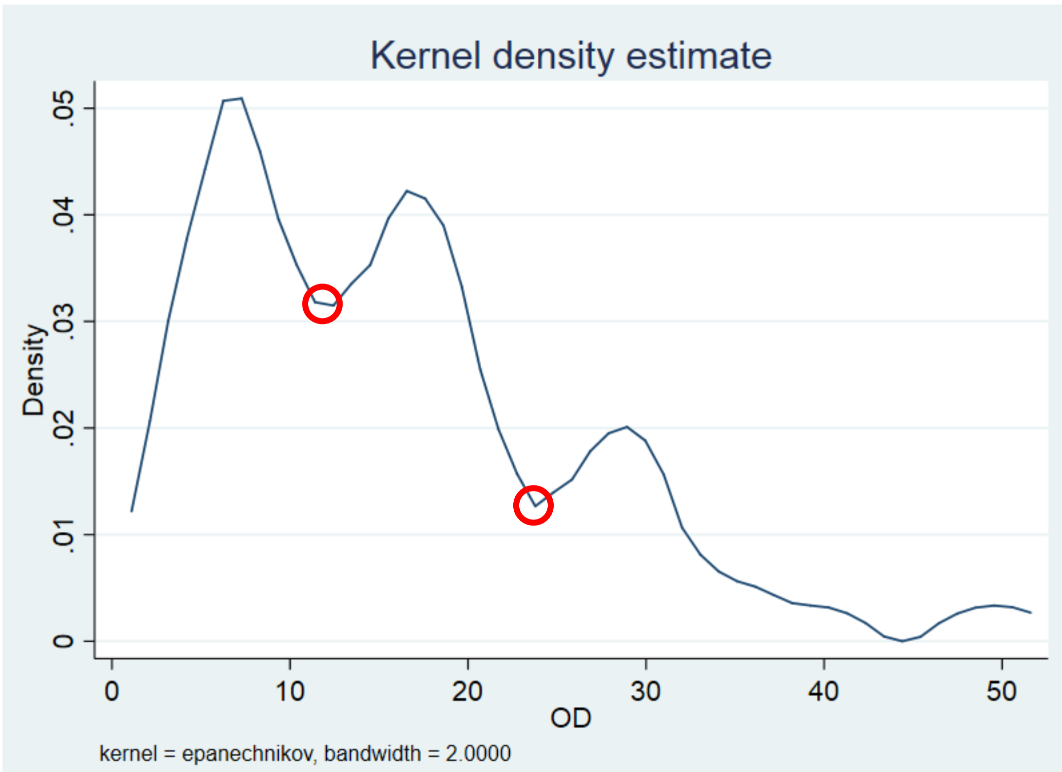
4.2 Empirical Methodology

The following generalized linear model is originally used to frame this study:

$$OD = B_0 + B_1\,LPR + B_2\,ESOOS + B_3\,UR + B_4\,MHI + B_5\,OPR + B_6\,GDP + B_7\,H + B_8\,GINI + B_9\,MENTAL + B_{10}\,DISORDER + B_{11}\,T + \mathcal{E}$$

Frequency of overdose by state (OD) was analyzed by kernel density estimation in order to find candidate breakpoints for forming the dichotomy. The default bandwidth value of 4.0 does not appear to give any clear points of separation, therefore a bandwidth of 2.0 was used. Visualized in Figure 5, using a bandwidth of 2.0, 12 and 24 appear to be reliable candidates. This created the dichotomy, creating two new variables Y12 and Y24. Y12 indicates that states with opioid deaths above 12.0 are high opioid death associated states, and Y24 indicating states with rates over 24 to be considered high opioid associated death states. Y12, has 29 states identifying as high and 21 states identifying as low. Y24 classifies 10 states as being high and 40 states as being low OD states.

Figure 5. Kernel Density Estimate Using a 2.00 Bandwidth



A generalized linear model is used to figure out which model, Y12 or Y24 best predicts high and low opioid death associated states. Shown in Table 1, when setting the breaking point to Y12, ESOOS funding was found to be statistically significant at 0.01 significance level, followed by OPR, GINI, and DISORDER at the 0.05 significance level. As depicted in Table 2, when setting the breaking point to Y24, only disorder was found to be significant at the 0.05 significance level. These results can be improved upon a systematic removal of terms from the full model. The process continues as the Bayesian information criterion (BIC) lowers; hence the model improves.

Table 1. Y12 Breaking- Point Regression Results

	Estimated	Pr(>|z|)
Intercept	-3.149e+01	0.6290
Lfp	-8.711e-02	0.8613
Esoos	7.998e+00	0.0345 *
ur	1.261e+00	0.2351
mhi	-6.710e-05	0.7580
opr	-2.892e-01	0.0609 ·
gdp	-2.350e-04	0.1351
h	-4.27e-02	0.1481
gini	1.239e+02	0.0873·
mental	3.971e+01	0.1299
disorder	5.896+02	0.0815·
t	-4.122e+02	0.1103

Signif. Codes: 0' *** '0.001'**' 0.01'* '0.05'· '0.1' ' ' 1
AIC: 47.575

Table 2. Y24 Breaking- Point Regression Results

	Estimated	Pr(>|z|)
Intercept	--1.028e+02	0.9746
Lfp	3.199e-01	0.5522
Esoos	1.944e+01	0.9952
ur	1.622e+00	0.3764
mhi	9.273e-05	0.6246
opr	2.495e-03	0.9695
gdp	-7.894e-05	0.6893
h	-3.312e-02	0.1004
gini	8.811e+01	0.1641
mental	4.866e+01	0.1904

disorder	7.124e+02	0.0885 ·
t	-3.084e+02	0.3231

Signif. Codes: 0’***‘ 0.001’**‘ 0.01’*‘ 0.05’·‘ 0.1’ ‘ ’ 1

AIC: 45.867

4.3 Model

The two following generalized linear models are both used to predict and interpret this opioid associated data:

1) $Y12 = B_0 + B_1\, ESOOS + B_2\, OPR + B_3\, H + B_4\, GINI + B_5\, DISORDER + \mathcal{E}$
2) $Y24 = B_0 + B_1\, ESOOS + B_2\, H + B_3\, DISORDER + \mathcal{E}$

5.0 RESULTS & PREDICTING FITTED VALUES

5.1 Results

When analyzing Y12 as the dependent variable, as shown in Table 3, this regression yields strong results. Independent variable ESOOS (0.00166) is statistically significant at the 0.001 level. The ESOOS is state funding to help prevent opioid overdose and death. According to the CDC this funding is given to the states that prescribe the most opioids and have large opioid associated death populations (CDC, 2016). Given this knowledge, the results indicate that ESOOS funding is indeed estimated from opioid death state rates. To continue, OPR (0.02807) and the GINI (0.03922) are statistically significant at the 0.01 level. This also corresponds with previous research as the opioid prescribing rate remains to be a significant determinant in predicting opioid abuse, and the GINI coefficient also helping reach this conclusion. Lastly, hospitals (0.05662) and disorder (0.05868) are statistically significant at the 0.05 level, leveraging their ability to predict high opioid death states.

Table 3. Y12 Regression Results with Systematic Removal of Terms from the Full Model

	Estimate	Pr(>|z|)
(Intercept)	-30.33244	0.03469 *
esoos	4.17823	0.00166 **
opr	-0.07626	0.02807 *
h	-0.02002	0.05662 ·
gini	67.54894	0.03922 *
disorder	463.59799	0.05868 ·

Signif. Codes: 0’ *** ‘0.001’**’ 0.01’* ‘0.05’· ‘0.1’ ‘ ’ 1

AIC: 47.421

When analyzing Y24 as the dependent variable, shown in Table 4, yields not as strong as a regression analysis in comparison to Y12. Disorder (0.0453) is seen statistically significant at the 0.01 level. Hospitals (0.0550) are seen statistically significant at the 0.05 level. In comparing the two models, Y12 as the dependent variable yields more and better results than Y24, indicating that Y12 should be the breaking point in predicting high and low opioid death states.

Table 4: Y24 Regression Results with Systematic Removal of Terms from the Full Model

	Estimate	Pr(>|z|)
(Intercept)	-2.098e+01	0.9929
esoos	1.853e+01	0.9937
h	-1.771e+02	0.0550 ·
disorder	3.416e+02	0.0453 *

Signif. Codes: 0’ *** ‘0.001’**’ 0.01’* ‘0.05’· ‘0.1’ ‘ ’ 1

AIC: 36.62

5.2 Predicting Fitted Values

The predicted values aid in determining which model is the best in predicting which states are high and low regarding opioid death rates. The relative accuracy is a measure indicating how much better of prediction is generated in using the logistic regression. Thus, a fitted value analysis was performed:

$$\textit{Relative Accuracy} = \frac{Accuracy - Baseline\ Accuracy}{1 - Baseline\ Accuracy}$$

Given that for the Y12 breaking point, 41 out of the 50 states predicted values are the same, giving the accuracy of 82%. Given that 29 of the 50 states were "high" OD states given the Y12 breaking point yields a baseline accuracy of 58%. Therefore, the relative accuracy of model Y12 is $\frac{.82-.58}{1-.58}$, yielding an accuracy of 57%. To be more precise, there is a 57% improvement in using this model to predict high opioid associated death rates. In calculating such for the Y24 breaking point, 42 out of the 50 states predicted values are the same, giving an accuracy of 84%. Given that the model accounts for 40 of the 50 states as being "high" OD states, generates a baseline accuracy of 80%. Therefore, the relative accuracy of model Y24 is $\frac{.84-.80}{1-.80}$, yielding an accuracy of 20%. Given these results, we opt to use the Y12 model as it predicts high and low opioid death rates 57% better than the baseline. This accounts for over half of the data when using the logistic model.

As we proceed using the Y12 model over the Y24 model, it can be interpreted that the ability to predict the high or low outcome given a state's opioid death rate is a 57% better model than not. When analyzing Table 3, it is imperative to understand these variables and their relationship to the breakpoint of Y12 as the dependent variable. The logistic regression highlights the various relationships between the dependent variable and the independent variables. The ESOOS being highly statistically significant and positively correlated to opioid death rate. Identifying with a disorder is that largest player yet is marginally statistically significant. High opioid prescribing rates seem to not influence the opioid death rate as they are positively correlated. Similarly, the more hospitals present also decreases the opioid death rate.

6.0 Discussion of Results

Using the Y12 model, there are 29 states that are considered to have high rates of opioid associated mortality. These are Alaska, Arizona, Connecticut, Delaware, Florida, Illinois, Indiana, Kentucky, Maine, Maryland, Massachusetts, Michigan, Missouri, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, Ohio, Pennsylvania, Rhode Island , South Carolina, Tennessee, Utah, Vermont, Virginia, West Virginia, and Wisconsin. My results correspond with previous literature as many of these states are already considered to be opioid associated problem states. To continue, empirical evidence supports the notion that ESOOS funding, opioid prescribing rates, the GINI index, the number of hospitals, and the percent of individuals reporting past year opioid use disorder as significant determinants in predicting the outcome of these states. As of 2017, 33 of the 50 states have ESOOS funding, 90 percent or 26 of the 29 states that the Y12 model predicted to be high opioid mortality rated states currently have access to funding. This is crucial as it shows the importance of such a variable and how the model has identified the states that the CDC has also identified as high opioid associated states. All in all, the model is accurate in predicting specific determinants and their predicted outcome.

This data implies which determinants potentially cause those states with high opioid death rates to have such high rates, and why this may be. From an economic perspective, looking into the specific factors influencing the GINI index would give a better indication on demographic profiles, and other assorted data. Other economic factors initially studied such as GDP, unemployment rate, the labor force participation rate, and medium household income have little to no significance in indicating high and low states. This is not to say that these factors are not affected one way or another, but perhaps to not accurately predict a state's susceptibility in being a state with either a high or low opioid death rate.

In addition, this study deviates from other studies that propose that opioid deaths are shown to be largely associated with the prescribing rate. A resolution to this is the fact that this study was based off 2017 data. When reviewing Figure 2 in Section 3.0, explains that in 2013 this stage is characterized by the use of synthetic opioids. To correspond with this, the CDC explains that in 2017, synthetic opioid deaths accounted for 67% of all opioid associated deaths. Further, these reports indicate that increases in synthetic opioid- involved deaths are being driven by fentanyl-involved overdose deaths, and pinpoint the idea that fentanyl is more likely to be illicitly manufactured than pharmaceutical.

7.0 Policy Implication

The opioid epidemic in the United States continues to affect millions around the country and remains as one of the leading causes of death. Considering the age-adjusted rate of drug overdose deaths tripled between 1999 and 2016 and jumped an additional 10 percent in 2017, this should not be a subject treated lightly. Given some of the known determinants in indicating opioid mortality, efforts should be made to minimize opioid associated death rates. Officials should continue to monitor opioid prescribing rates and should monitor their patient's usage. It is also imperative to measure a patient's mental status and perhaps recommend an alternative cure. Given that these drugs are so addictive, follow-up visits after prescribing medication should be conducted. Additionally, it would be useful to develop a tracking device on these drugs to be able to trace their path from its origin through to its end-user. Lastly, continuing to supply ESOOS funding and perhaps expanding this funding will help mitigate the effects of the epidemic.

8.0 Limitations

Although this is a cohesive study generating and predicting accurate results, there are some limitations. First, there may be some discrepancies within the data. It can be difficult to obtain healthcare associated data due to the Health Insurance Portability and Accountability Act of 1996 (HIPAA). Patients are not always honest or may present with a bias when supplying information. Another limit to this study is the fact that it is based on state outcomes rather than a regional, country, or city basis. Looking into this data in a deeper fashion may supply alternative results. Lastly, this study choses to use a bandwidth of 2.0 to generate the dichotomy. This particular bandwidth is appropriate for the sake of this paper but could be further investigated and navigated to generate different results.

9.0 Conclusion

To conclude, using the Y12 generalized linear model to predict which states are to be high opioid associated death states is the better model. Given, the Y12 break-point model has a greater relative accuracy rate of 57%, this model tremendously improved the ability to predict an all or nothing outcome in the 50 states. Therefore, there is a decent idea as to what indicates a state's likelihood of being a high or low state using the Y12 model. Empirical evidence supports the notion that ESOOS funding, opioid prescribing rates, the GINI index, the number of hospitals, and the percent of individuals reporting past year opioid use disorder as significant determinants in predicting states with high opioid death rates.

Bibliography

Alex Hollingsworth & Christopher J. Ruhm & Kosali Simon, 2017. "Macroeconomic conditions and opioid abuse," Journal of Health Economics, .

Aliprantis, Dionissi and Fee, Kyle and Schweitzer, Mark E., Opioids and the Labor Market (November 15, 2019). FRB of Cleveland Working Paper No. 18-07R2. Available at SSRN: https://ssrn.com/abstract=3179068 or http://dx.doi.org/10.2139/ssrn.3179068

Cochran, B. N., Flentje, A., Heck, N. C., Van Den Bos, J., Perlman, D., Torres, J., Valuck, R., & Carter, J. (2014). Factors predicting development of opioid use disorders among individuals who receive an initial opioid prescription: mathematical modeling using a database of commercially-insured individuals. Drug and alcohol dependence, 138, 202–208. https://doi.org/10.1016/j.drugalcdep.2014.02.701

Fanning, Jasper & Marsh, Thomas & Stiegert, Kyle, 2005. "**Determinants of Fast Food Consumption**," Working Papers 201540, University of Wisconsin-Madison, Department of Agricultural and Applied Economics, Food System Research Group.

Florence, Curtis S.; Zhou, Chao; Luo, Feijun; Xu, Likang, 2016. "The Economic Burden of Prescription Opioid Overdose, Abuse, and Dependence in the United States, 2013," Medical Care. 54(10):901–906. Available at doi: 10.1097/MLR.0000000000000625

Gagliardo, Anna M. (2016) "Investigating a Modern Midwestern Crisis: The Economy and Opioid Overdose Death in Ohio," *Undergraduate Economic Review*: Vol. 13 : Iss. 1 , Article 17. Available at: https://digitalcommons.iwu.edu/uer/vol13/iss1/17

Krueger A. B. (2017). Where Have All the Workers Gone? An Inquiry into the Decline of the U.S. Labor Force Participation Rate. *Brookings papers on economic activity*, *2017*(2), 1–87. https://doi.org/10.1353/eca.2017.0012

Mental Health and Substance Use. (2020, February 6). Retrieved from https://www.kff.org/data-collection/mental-health-and-substance-use/

Opioid Overdose Death Rates and All Drug Overdose Death Rates per 100,000 Population (Age-Adjusted). (2020, February 13). Retrieved from https://www.kff.org/other/state-indicator/opioid-overdose-death rates/?currentTimeframe=0&sortModel={"colId":"Location","sort":"asc"}

Riley Sullivan & Joyce Manchester, 2019. "Exploring causes of and responses to the opioid epidemic in New England," New England Public Policy Center Policy Reports 19-2, Federal Reserve Bank of Boston.

Sonya Ravindranath Waddell, 2018. "The Opioid Epidemic, the Fifth District, and the Labor Force," Econ Focus, Federal Reserve Bank of Richmond, issue 2Q, pages 32-35.

Substance Abuse and Mental Health Services Administration. (2018). Key substance use and mental health indicators in the United States: Results from the 2017 National Survey on Drug Use and Health (HHS Publication No. SMA 18-5068, NSDUH Series H-53). Rockville, MD: Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Retrieved from: https://www.samhsa.gov/data/sites/default/files/cbhsq-reports/NSDUHFFR2017/NSDUHFFR2017.htm

The Underestimated Cost of the Opioid Crisis. (2017, December). Retrieved from https://www.hasc.org/post/underestimated-cost-opioid-crisis

Understanding the Epidemic. (2020, March 19). Retrieved from https://www.cdc.gov/drugoverdose/epidemic/index.html

U.S. Opioid Prescribing Rate Maps. (2020, March 5). Retrieved from https://www.cdc.gov/drugoverdose/maps/rxrate-maps.html