Economic and Social Impact of the Opioid Crisis in the US: A State-Level Analysis Using Panel Data

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Abstract

This paper examines the cost of death arising from opioid overdoses, in relation to the supply side of the opioid epidemic being prescription rates. The paper will also examine the hypothesis that there is no change in state revenue in relation to the increasing cost of death from an opioid overdose. Using state wise panel data for the years 2006 to 2018 for the regression models and examining different economic variables such as consumer price index, per capita change in state revenue, unemployment percentage, household income, and labor force participation rate. The research finds that cost of overdoses are increasing with a decrease in prescription rates, and state revenue has not been affected adversely with increasing cost of death from opioid overdoses.

1. Introduction

Opioids, also known as narcotics, are a type of drug which include strong prescription painkillers, such as oxycodone, hydrocodone, fentanyl, and tramadol. Traditionally opioids are made from the opium plant, and recently newer synthetic alternatives have been flooding the market. The opioid crisis in the United States has quickly come into the light for record number users every year to the death tally rising every year along with the number of users, with nearly 450,000 deaths just between 1999 to 2018. Many concerns arise from such a crisis, in addition to the steady human loss from the opioid crisis, many sectors of the economy to have been negatively affected. An estimated 631 billion dollars were lost between the years of 2005 to 2018, these costs include premature mortality, assistance programs, loss in productivity, and loss in education programs. Consequently, resulting in a decrease in quality of life. Statistics from the CDC indicate that nearly 20 million Americans went through "high-impact" chronic pain in 2016. The substantial increase in opioid deaths is on the rise even though the prescription rates for opioids have been in decline from 2006.

People are more likely to suffer from adverse health conditions such as depression, anxiety, difficulties with keeping up with employment and other responsibilities. The number of prescriptions tripled from 76 million to 219 million per year from 1991 to 2011. However, after the clinicians began to reexamine the effectiveness and side effects of opioids in the early 2010s, the number of opioid prescriptions has been declining as a result. This gave birth to a new market of synthetic opioids in the form of illegally manufactured fentanyl. A public health emergency was declared in 2017, by the U.S. Department of Health and Human services (HHS), due to the fact that 130 Americans were dying every day from opioids overdoses. Many hypotheses about the initial opioid crisis, as suggested by Case and Deaton (2015,2017) point towards the role of worsening culture and economic conditions are they causation of the epidemic, overdoses, and suicides. The alternative hypothesis considers the supply factor of the epidemic such as the sharp increase in the rate of prescription rates and access to such strong medications. Since the 1990s, doctors started to respond more aggressively to pain with opioids (Jones et al., 2018), following the belief among physicians that pain is "undertreated" (WHO, 2017; Melzack, 1990). An influential campaign launched by the American Pain Society namely "fifth vital sign", in response to the Joint Commission on Accreditation of Healthcare Organizations (JCAHO) saw their guidelines being revised in 2001, which saw that doctors assess pain along with other vitals at medical visits (Phillips, 2000). The aggressive marketing strategies of Purdue Pharma's OxyContin in 1996 has also been a major cause of the opioid crisis (Van Zee, 2009; Quinones, 2015).

Even though many discussions about these hypotheses have taken place in literature, there is little research done on the individual impact of overdoses that the states have to burden themselves with. Existing researchs have considered lurking causes that may be economic conditions or labor demand shocks (Ruhm, 2019; Betz and Jones, 2018; Charles et al., 2019; Pierce and Schott, forthcoming). Whereas some researches have tried to capture the increased access to opioids, through prescriptions of family members (Khan et al., 2019). Which has led other researchers to predict long-term use and reliance on prescribed opioids (Barnett et al., 2017). This research is relevant in capturing the supply side of the epidemic and connecting it to the cost of the lives lost to the prescription overdoses; however, none of these researches has evaluated the cause relation on Medicare spending and the cost of each life per overdose. Moreover, these studies find little to no effect in explaining the growth in opioid deaths.

In this paper, data is examined to find evidence and relation of cost per overdose relative to prescription rates of opioids. The role of many economic factors is taken into consideration in order to examine the relation of a state's economic performance concerning the lost revenue they have to incur from each overdose. The relation of the rate of prescription is considered an important factor along with all variables because since 2006 the prescription rates have gone down whereas the number of overdoses has actually increased during that time. The research looks over time-series panel data for all states for the years 2006 to 2018. Factors such as household income, percent change in state revenue, and unemployment are considered significant factors in interpreting the results. To access economic impact on state revenue resulting from the lost productivity due to opioid overdoses correlated with decreasing opioid prescription rates. To elaborate further on this question, Section 2 will provide further information on the data and how the cost of overdose per death is calculated, Section 3 defines the models that were utilized to make predictions utilized in R, Section 4 sheds light on these results and findings, and finally, Section 5 provides the concluding remarks.

2. Data

The data used to conduct the research and form the models is the time-series panel data consisting of each state of the United States from the year 2006 to the year 2018, inclusive of 663 observations. These observations include data such as – population, consumer price index (CPI), overdoses, Medicare spending in millions and actual terms, household income, per cent of unemployment, labor force participation rate, high school graduation rate, prescription rate, per capita state revenue, and a dummy variable for post-recession. The forecasts generated were of all these 21 variables for twelve years and are all available at www.kff.org (1). In contrast to the previous research done by the National Institute on Drug Abuse (NIDA), namely medications to treat opioid use disorder, where the research accounts for the cost of opioid treatment rather than the cost of the life involved. This research, in contrast, uses time-series data panel data to generate predictions for the cost per death caused by opioid overdose. Which is achieved by dividing the overdoses by Medicaid spending in millions then multiplied by the population of that particular state. The specified formula is:

(1) Cost per death from overdose = Overdoses ÷ Medicare spending in millions × Population

To judge whether the use of opioids is related to the US population data, correlation check using Pearson-method with listwise-deletion is done along with all other variables involved. The correlation analysis states that all variables are positively correlated, by looking the sign before the numbers and having medium-strength being bigger than 0.3 and having **. Interestingly, overdoses and prescription rates and actual Medicaid spending have a negative correlation but are highly correlated, which means we can run a linear regression model on these variables to learn more about the relation (figure 1 & 2). As expected, Medicare spending, population, state GDP, and overdose cost (ovd_cost) are the variables that have the highest correlation. Other variables such as household income and Medicare spending in millions are also highly correlated. Unsurprisingly, population and Medicare spending have the highest correlation in the data set with a positive 0.884 with ***. Just looking at the correlation is not enough, therefore box plots using the powerful ggplot package in R is implemented. Looking at the boxplots for all the states, we see that not many outliers are present in the data, apart from a handful in states such as North Carolina, Maryland, Pennsylvania, Indiana, New Jersey, Missouri, Arizona, Illinois and Florida. Considering we have 662 observations, consisting of every state of the United States, the outliers present are very few in numbers and not present consistently, which should be expected in a dataset this big. Due to a very few outliers present compared to the 662 observations; we can make useful predictions from this data without worrying about outliers presenting the problem of co-linearity. As the research was conducted using R, many variables such as overdoses, log overdoses, and LFPR had to be converted from a factor variable to a numeric variable. Simply because R software needs all the variables in a numeric form before the regressions can be run. A markdown file containing all codes for the logarithmic transformation, as well as data conversion provides complete information on the code and their interpretation (17). Moreover, as the research looks into the relationship between prescription rates of opioids, the data was available only before the year 2006. Therefore, the initial data that consisted of values from 2000 to 2006 was omitted. The prescription rate data were obtained from the official Centers for Disease Control and Prevention website; cdc.gov (11). It is fair to say that if data for prior years were available, the research would have benefitted from additional understanding of these rates of prescription from physicians. Also, if data was available for which prescribers had the highest percentage of prescription for patients, the research would dwell into the question of the reasoning behind the type of injuries and the type of opioid that was prescribed for that condition. Finally, to fit the logistic regression all the variables had to be manually converted to a log value in R. Log transformation is tricky in R, as it requires to separate the data, taking the log of the entire data set to obtain each point, however usually one variable, this research converts eleven variables to understand the behavior of data transformation better. The straightforward way to do it in R is to format the log (value, base) which returns the log value in the base. In R by default, this function produces a natural logarithm of the value, providing a shortcut variation for base 2 and base 10 respectively. The code and process of transformation are also available in the R markdown file (17).

3. The Models

3.1 Multiple Linear Regression Model

To estimate the impact of the cost of death per overdose caused by opioids. The research primarily relies on the linear regression model, simply because the independent variables can be easily fitted. The goal is to explain the variation between explanatory variables without accompanying response values. Multiple linear regressions are utilized to quantify the strength of the relationship between the response variable and explanatory variables. The model specification is:

$$(2)\quad C_{st} = \beta_0 + \beta_1(\text{overdoses}) + \beta_2(\text{Medicare spending in millions}) + \beta_3(\text{consumer price index}) + \beta_4(\text{population}) + \beta_5(\text{house hold income}) + \beta_6(\text{State GDP}) + \beta_7(\text{unemployment percentage}) + \beta_8(\text{LFPR}) + \beta_9(\text{ high school graduation percentage}) + \beta_{10}(\text{per capita state tax revenue}) + \beta_{11}(\text{prescription rates}) + \varepsilon$$

Where Cst represents the cost of death per opioid overdose in states by year t and ε stands for the error term. Therefore, in the first regression model, we predict the relationship of cost of death per opioid overdose and different variables believed to be important in studying the relationship. The following variables, along with prescription rates, are used as the data collected suggests that prescription rates in the United States have been decreasing onwards since 2006. Other variables such as consumer price index, unemployment percentage, LFPR, and per cent change in state revenue helps us in order to analyze the relation between cost of overdoses with relation to the economic activity in that particular state. The model output presents the residuals, that are essentially the difference between the predicted response values and actual observed response values. Residuals of the model also like R-squared helps us to access the accuracy of the model. The next section of the output the research looks at is the coefficients of the model. In a linear regression, the coefficients are the unknown constants, representing the slope and intercept terms. Finally, the p-value in the model refers to the probability of the observed values being equal or larger than t. Generally, a smaller p-value, less than 5% is a good cut-off point. So, smaller the p-value for the intercepts means we can reject the null hypotheses, which allows concluding relationship between the cost of death per overdose and prescription rates.

3.2 Logarithmic -Transformed Linear Regression Model

For the second model of the research, a logarithmic transformation is done for the dependent variable (cost of death per opioid overdose). A comparison to model 1 reveals that the coefficients will be drastically different and the interpretation will be following the same format apart from the fact that when interpreting the results we will be looking at the percent change of the dependent variable (Cst) in relation to the independent variables. This is done to deal with the non-linear relation between the dependent and independent variables. Variables such as prescription rates, Medicaid spending in millions, unemployment percentage, percentage of insured people, and LFPR display non-linearity, and therefore a logarithmic transformation helps to interpret the results more conveniently. The model specification is:

$$(3)\ Log(C_{st}) = Log(\beta_0)+ \beta_0+\beta_1(overdoses)+ \beta_2(Medicare\ spending\ in\ millions)+ \beta_3(consumer\ price\ index)+ \beta_4(population)+ \beta_5(house\ hold\ income)+ \beta_6(State\ GDP)+ \beta_7(unemployment\ percentage)+\beta_8(LFPR)+ \beta_9(\ high\ school\ graduation\ percentage)+ \beta_{10}(per\ capita\ state\ tax\ revenue)+ \beta_{11}(prescription\ rates)+ \varepsilon$$

To compute the effects on Log (Cst) of another change in the independent variables than an increase of one unit, call this change z, it would be included in the exponent. Therefore, the effect of a z-unit increase in X is obtained by dividing the coefficients output by 1,000,000, to get the average increase or decrease related to the cost of death per opioid overdose. In this particular model, the interpretation would be, for example, one per cent increase in the cost of death from an opioid overdose would result in a (744774.88/1,000,000) = 0.074 decrease in labor force participation rate on average for 50 states, this is done due to our calculations of overdose deaths being divided by Medicare spending in millions, in order to achieve a simple and straightforward interpretation. In the state-level analysis, coefficients are not divided by 1,000,000 as the outputs are between 0 and 1. So, for the state-wise analysis, the dependent variable is log-transformed, and the independent variables are in the original numeric values. The interpretation for the dependent variable transformed, the percent change is calculated after obtaining the coefficient. For example, for a one-unit change increase in log overdose death by opioids overdose will decrease the unemployment rate by .47 per cent in Illinois, 0.02 per cent in Florida, and 0.09 per cent in Maine.

4. Discussion of Results

The research begins with documenting the number of overdoses by each state and calculating the cost of death per overdose in relation to the economic factors of each state as well as referring to the supply side of the opioid crisis by looking at the prescription rates. Then estimations of these variables are investigated nationwide and by state. Alternate explanations are also investigated for the cost relation using a logistic transformation model, to understand the raw values produced from the two transformed models. In the next section, we discuss the results from the linear regression model.

4.1 Results from the linear regression model

The research firstly shows the country-wise results from the regressions indicate that the predictions were consistent with the given research and the predictions about prescription rates and economic activities. The state-wise linear regressions predict that prescription rates increase by 122 with an increase in the cost of overdose by one unit, figure 3 shows the relationship between prescription rates and overdoses to be negatively correlated, therefore proving that cost of overdose rises even when prescription rates are decreasing. Consequently, the consumer price index decreases by 986.56 with a one-unit increase in cost per overdose, and state GDP decreases 1.31 percent, which falls in line with our assumptions. Most variables have a p-value of more than 0.05 which means that they are not highly significant and cannot used to reject the null hypothesis. Apart from state GDP, overdoses, and Medicare spending in real valuation (not in millions). But the R-squared is 0.932 meaning that the model is well fitted, acting as the measure of the linear relationship between our independent and dependent variables. The high number of r - squared can be explained due to adding the high number of variables that increases the r - squared. The most significant finding was perhaps the increase in overdoses by 618.80 on average with a unit increase in cost per overdose. Which in part helps to reject the null, but other economic variables such as household income and per cent change in state revenue show an increasing pattern, meaning that not all variables are significant in rejecting the null hypothesis. Moreover, it is hard to reject or fail to reject that null hypothesis as per capita state tax revenue in fact increases by 1.89 (with a P – value of 0.682) with an increase in one unit of cost of overdose.

Finally, figure 4 shows a clear negative linear relationship between the cost of overdose and prescription rate, which is consistent with the given research.

The state-wise linear model helps the research to understand the effect of the independent variables in terms of each state. Looking over the overdoses as the the independent variable, we can see that Idaho (1018), Kansas (1087), Montana (1156), and Utah (1265) have the highest number of overdoses increase with one unit increase in cost per overdose. Analyzing economic variables such as household income provides a much better coefficient estimate in the state-level regression, rather than the nation-wide regression. States with higher GDP, such as California (-53.02), Michigan (-15.84), and Illinois (-52.4) show the highest losses in household income with an increase in one unit of cost per overdose from opioids. Consequently, states with lower levels of GDP like Alabama (-0.36), Alaska (-0.39), Arkansas (-0.22), and Kansas (-0.36) show the lowest level of change in household income. In terms of prescription rates, states with the highest number of prescription rates such as Alabama (-277.2), Tennessee (2144), Wisconsin (506), Mississippi (-206), and Arkansas (247), show the highest decrease or increase in prescription rates with an increase with a unit increase in cost per opioid overdose, we can see from the positive or the negative sign in front of the estimates. The results are partly contrary to the hypothesis and the data provided by the CDC, keeping in mind that they do not account for the cost of death from the overdose. Therefore, the data and results provided and obtained are pointing towards the fact that the research neither rejects nor fails to reject the null hypothesis.

4.2 Results from the logarithmic transformation linear regression model

The results from the logarithmic transformation model are fairly similar to the linear regression model. The interpretation follows the same method, but in this model instead of looking at the unit change of overdose cost, the percent change in the independent variable is looked at. The linear model does a better job in fitting the independent and dependent variables, than the logistic regression, which is observed with an r – squared of .770 compared to the previous 0.94. Which means that even though the same number of 663 observations are taken into account, the variables are more overfitted than the first model. But looking the p-values we can see that labor force participation rate (LFPR), household income, percent change in state revenue, and overdoses are significant, with p-value less than 0.05. Whereas, all other variables are not considered significant with relatively high p - values. Which means that these variables are not significant in making predictions in the model and therefore would not be used in making predictions. The most significant variable is the log of labor force participation rate, which goes down by 0.074 per cent in the United States, given the total cost of opioid overdose in the United States increase by one per cent. Another significant economic variable namely per capita state tax revenue decreases by .38 perfect (?) with a one percent increase in cost per overdose, and household income decreases by 0.24 percent with a one percent increase in cost per overdose. In this model, overdoses increase by 0.27 per cent as cost per overdose increase by one per cent, as the p-value is less than 0.05 we can assume the predictions are quite accurate. These results are directly in line with our assumptions. To look at the economic impact more deeply a post-recession dummy variable is created for years before 2008 financial recession. Interestingly, post-recession variable shows a decrease of .327 million in tax revenue with a one per cent increase in the cost of an opioid overdose. A similar dummy variable is made for manufacturing states, representing that states with value 1 mainly rely on manufacturing as the prime revenue for state resources. The model shows that manufacturing states lost 0.89 million in tax revenue from 2006 to 2018 when the cost of opioids increase by one per cent. That is in line with the assumptions of the research, but this data is affected by many other economic factors and judgment cannot be made without more data concerned with opioid prescription rate from physicians and exact cause death as well related to opioid addiction.

5. Conclusions

To conclude, this research provides an overview of the cost of death per opioid overdose using outputs from linear regarrisons and linear logarithmic transformation models. Our results account for the supply side of the opioid epidemic by looking at the prescription rates for the years 2006 to 2018 and many economic factors, providing estimates that make it difficult for the research to conclude determining the causation for increasing cost of death caused by opioid overdoses. Therefore, this research fails to conclude that any major economic variables had an impact on the increasing overdoses, or the costs related to these opioid overdoses. But can suggest that the logarithmic regression was more accurate in capturing these results. For the most states measured by the models, assumptions about the prescription rates are in line with our assumptions that prescription rates are decreasing with the cost of per opioid overdose. Meaning that even though the rate of prescriptions has decreased from 2006, the cost per overdose are still on the rise and so are the number of overdoses. Which suggests that the black-market for opioids is playing a major role in these overdose deaths. Most notable economic impacts from this research were the decreasing effect on per capita state revenue, household income, and labor force participation rate. However, this data leads to optimistic results as those factors can rely on many unobserved factors and underlying economic situation to form a causation theory. But most importantly, this research does answer the question, that decreasing prescription rates have no effect on increasing number of overdoses and costs related to these overdoses. This conclusion can be useful for future studies to tackle the underlying problem that starts from the hospitals and physicians that are aggressively prescribing these drugs to their patients and the black-market that has emerged in light of the decreasing prescription rates.

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Figure 1: Correlation relation using litwise - deletion

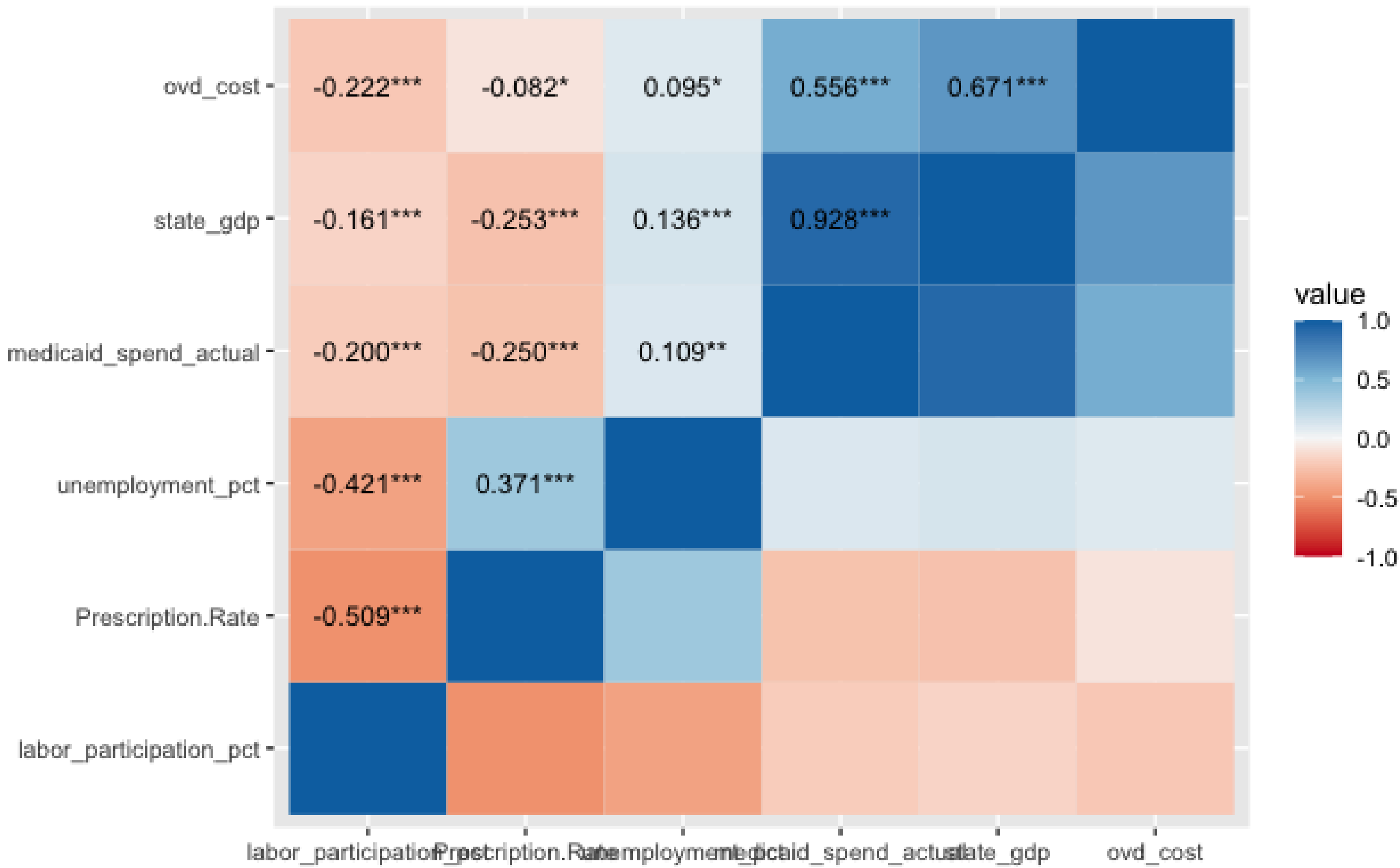

Figure 2: Correlation relation using litwise - deletion

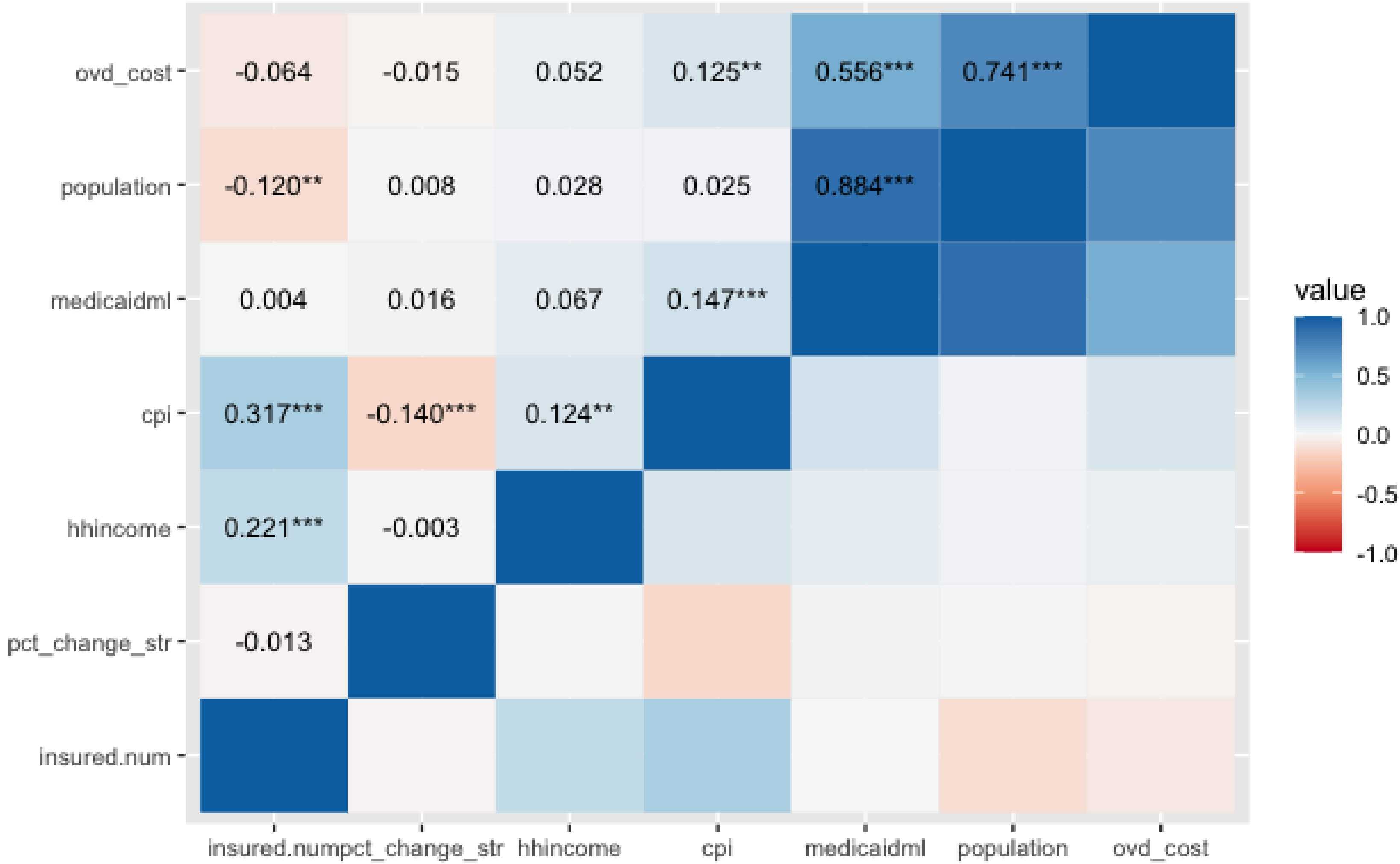

Figure 3: Box plot graph to check for data outlies

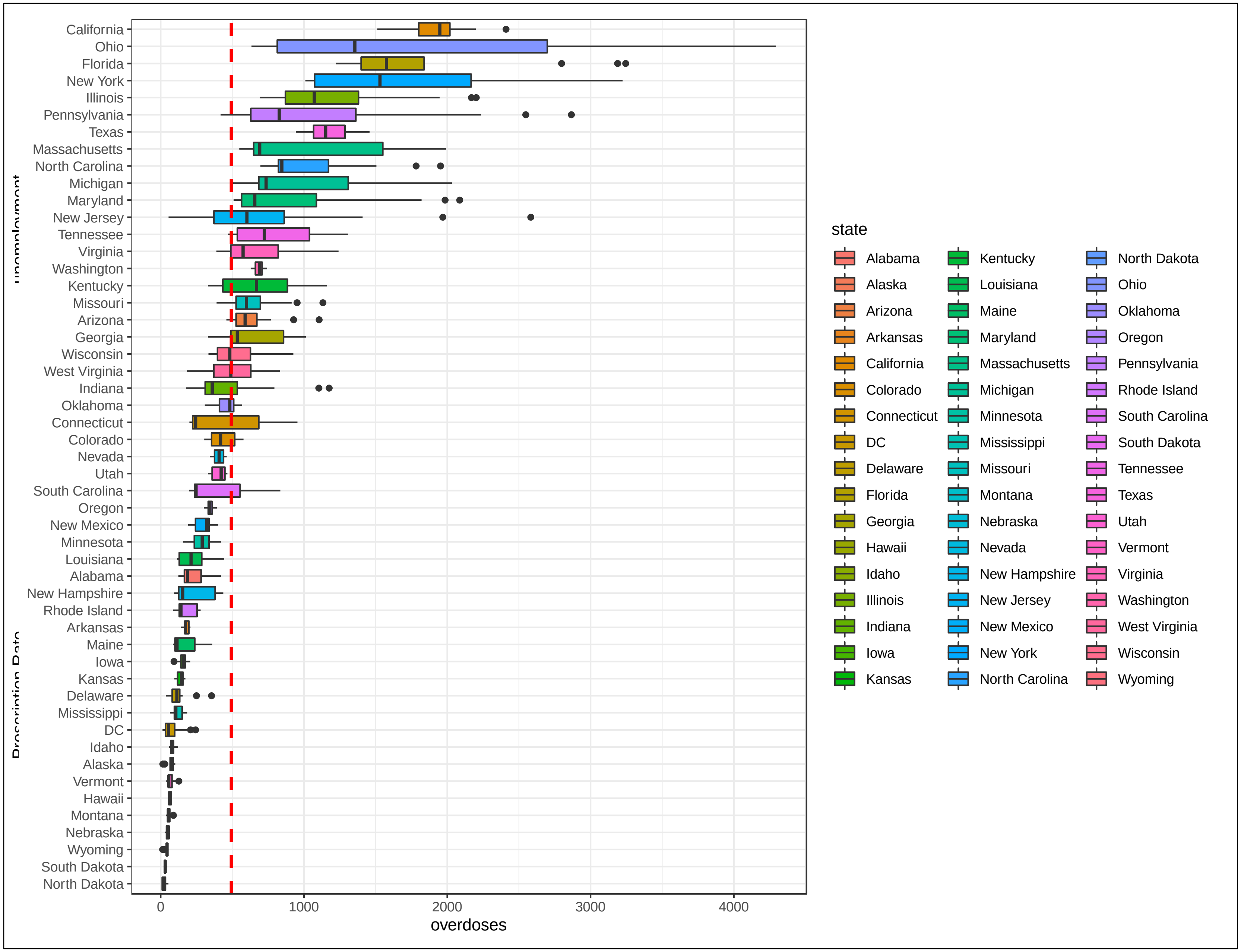

Figure 4 – Log transformed model

	ovd cost		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	3154668.58	13114.65 – 6296222.52	**0.049**
logoverdose	270389.07	238811.04 – 301967.10	**<0.001**
medicaidmlog	-828569.02	-962530.89 – -694607.14	**<0.001**
cpilog	55229.18	-270238.44 – 380696.81	0.739
poplog	40739.41	-113451.85 – 194930.67	0.604
hhincomelog	-249118.27	-415761.17 – -82475.36	**0.003**
gdplog	164769.81	57517.53 – 272022.09	**0.003**
loglfpr	-744774.88	-1088050.02 – -401499.74	**<0.001**
hsgradlog	668705.09	-31363.71 – 1368773.88	0.061
per_cap_strlog	23323.95	-79380.72 – 126028.61	0.656
logpresrate	-385276.83	-468723.25 – -301830.41	**<0.001**
loginsured	-439292.36	-824838.83 – -53745.88	**0.026**
logrealmedicare	646010.87	442306.18 – 849715.55	**<0.001**
Observations	663		
R^2 / R^2 adjusted	0.770 / 0.765		

Figure 5: Results from linear regression

	ovd cost num		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-203.05	-364097.57 – 363691.46	0.999
overdoses	594.83	571.74 – 617.91	**<0.001**
medicaidml	-46.58	-52.85 – -40.31	**<0.001**
cpi	-443.36	-1128.52 – 241.80	0.204
population	0.02	0.01 – 0.04	**0.004**
hhincome	1.44	0.17 – 2.71	**0.026**
state_gdp	0.09	-0.16 – 0.34	0.480
unemployment_pct	2930.47	-1317.28 – 7178.22	0.176
labor_participation_pct	3523.81	807.46 – 6240.16	**0.011**
grad_hs_pct	1504.54	-2406.15 – 5415.23	0.450
per_capita_state_tax_revenue	-12.54	-20.11 – -4.96	**0.001**
Prescription Rate	439.76	-111.32 – 990.83	0.118
insured.num	-3598.60	-5614.04 – -1583.15	**<0.001**
tmcaremcaidmlreal	14.26	10.32 – 18.19	**<0.001**
Observations	663		
R^2 / R^2 adjusted	0.949 / 0.948		