Estimate the Impact of Opioid Control Policies (For Nick)

Beibei Du, Wafiakmal Miftah, Suzanna Thompson, Alisa Tian

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Motivation

A nationwide opioid epidemic has reached unprecedented levels in the United States for a long time. Opioids, served as both prescription painkillers and illegal drugs, have become a major threat to public health and global health. Overdose of opioids can lead to overdose and death.

One potential solution to encounter this crisis is to implement policies that reduce the availability of these drugs. In order to evaluate the effectiveness of such policies, we plan to select three states and compare them to controlled states. By analyzing the data, we aim to determine whether the implementation of policies has had a positive effect on reducing the opioid crisis. Addressing the opioid crisis is crucial for protecting the public health in the United States and can serve as an example for other countries. Once again, opioids are highly addictive and potentially fatal if intake overdoses. Therefore, a policy control protects public health to minimize the death risk from an overdose of opioids. The number of overdose deaths and prescription information of opioids after policy change is something we want to find out in this project.

For this project, we are trying to address the problem of rising opioid usage and its connection with death by drugs in the United States. We have two specific questions: What effect did the opioid policies in Texas, Washington, and Florida have on the number of opioid deaths and overall drug deaths in those states? In other words, how do opioid deaths and overall drug deaths differ in Texas, Washington, and Florida from our chosen control states?

To evaluate the effectiveness of policy interventions in addressing the opioid crisis, we will implement research designs to answer above two research questions. Our focus will be on the United States, but our results may have broader implications and be applicable to other regions once the data is ready. Additionally, we will use opioids as a case study for drug overdose, but our research design may be replicated for other drugs as well. Our goal is to study the mortality rate before and after policy intervention to determine whether the policies are effective.

Specifically, we hope to see a drop in both mortality and opioid prescription rates after policy intervention.

Motivation for Research Design

The research design methods that we are using are pre-post comparison and difference-in-difference regression. Since this problem can't be randomly assigned and policies are different from each state, we want to compare the Opioids per Capita before and after the policy to see if there's any decreasing trend after the policy change (our initial assumption) and other potential variables. However, this research design can't wipe out the possibility of other confounding variables. Thus, difference-in-difference regression will play an imperative role in encountering the issues. Instead, we compare the chosen states with other states that don't have the policy change. We will observe the trend after the policy intervention and see if it will decrease the death rate/opioids per capita.

Pre-Post Analysis

Our first methodology is a **pre-post analysis**. We compare the change of mortality rate and prescription rate before and after the policy implementation.

We are interested in the effect of opioid policy change for the state directly with the comparison (before and after the policy intervention). This is a very simple way to see if there's a difference before and after the policy intervention. However, there are many other potential confounding variables causing the change in the trend of death rate or Opioids per Capita. For example, the death rate drops could be due to other reasons such as the development of the medical system across time. Thus, this is a baseline analysis we will take a look at in the first step.

Difference in Difference analysis

Simply using the pre-post analysis is not enough to make our results more reliable and persuasive. For example, we are interested in analyzing the effect of policy change on mortality rate in Washington (around 2012), and comparing the mortality rate in Washington before and after 2012 (the policy implementation). Suppose, one type of hallucinogens is banned nationwide in the same year, which will possibly lead to a decrease in overdose death. However, we do not know whether this is caused by the policy change or this hallucinogen ban. Thus, we need our second approach – difference-in-difference analysis. The difference is that we are comparing the state with another state that does not have the policy intervention, but with a similar trend before the policy intervention. Thus our focus will shift to the trend after the policy intervention. We expect to see the overdose mortality rate and prescription rate drops after the policy change.

Details of the Data

1. Opioids Prescription/shipment data (Washington Post):

   In this dataset, it holds most of the information of the opioids prescription across the years in all states in the United States. This dataset is about 100GB and we select the 3 states and their controlled states to preprocess. The unit of observation for this dataset is at the county-level. We sum the all data of all counties in a state and take that into our analyses.

2. Mortality Rate data (CDC Wonder):

   In this dataset, we have state, county, year, opioid-related cause of death, and the number of deaths per county and state. For this data, we query the CDC Wonder database and select all entries where the cause of death is the category 'Drug-induced causes,' which includes unintentional overdose, suicidal overdose, homicidal overdose, and undetermined overdose. The unit of observation for this data is at the county-level.

   For both the Prescription and Shipment Data and the Mortality Rate Data, we found inconsistencies at the county level. In that, there were missing counties in excess of a thousand, country-wide. This is because deaths are not reported per county if they do not exceed ten. To combat this, we imputed the quantity of death per county with five, which we understand to be an adequate average. We select five as our imputed value because we have no way of knowing if the actual count of deaths is actually zero or if it's one, two, three, etc. Because our analysis' focus is understanding what effect a policy had on opioid deaths, we chose 5 to be a liberal count of deaths. In that, it's more likely that we're overestimating the quantity of deaths because it's likely that there are counties that actually report zero deaths. Consequently, our understanding of the policy's effect is conservative and we're not overestimating the effect of the policies. We believe a value of five that will capture the real values of zero will reconcile the real death counts that are between five and ten.

   To select our comparison states, we use an additional four datasets and we reuse the death rate dataset. We use an income dataset, which has average income per state per year. We also use an educational ranking dataset. The educational ranking dataset has each state's ranking for education. For our purposes, the pure ranking is enough for evaluation and our understanding of 'closenses.' We use a population dataset that has population per year, per state. Because we're selecting states on the whole for comparison and the policy implementations are state-wide, our unit of observation for the state selection is on the state level.

Selecting States

For our analysis, we are comparing the opioid prescription rates and the opioid death rate for each policy state, Texas, Washington, and Florida, to suitable comparison states respectively. Our methodology for selecting states for comparison is a conditional closeness calculation. Closeness is computed by taking an average of four similarity scores. We're choosing to define similarity as a function of four socioeconomic and demographic factors, which are education, income, population, rate of opioid shipments, and rate of opioid-related deaths. We are including general socioeconomic variables, education, income, and population, in order to account for any confounding variables that would affect the opioid-related death rate. It's known that a lack of education and an impoverished lifestyle are predictors for opioid abuse (Socioeconomic risk factors for fatal opioid overdoses in the United States: Findings from the Mortality Disparities in American Communities Study (MDAC), Altekruse, et. al), so we chose them in our analysis in order to understand if a reduction of opioid shipments and an increase of policies will have an effect or if there's a deeper problem in the state with educating the population and maintaining their welfare. In that, this will give us an understanding for future work wherein we can compare shipments and death rates to states that have a better educated and richer population. The similarity score is calculated by dividing each candidate state by the current policy-state. As an example, we compute this as an income similarity score for Arkansas and Florida:

$Similarity_{Income,\ AR\ vs\ FL} \ = \ \text{Income}_{\text{Arkansas}} \div \ \text{Income}_{\text{Florida}}$

So, for this example, an output close to 100% is interpreted to mean that the average income in Arkansas is sufficiently similar to the average income in Florida. Our bounds for being sufficiently similar are:

$80\% \ \leq \ \text{Similarity Score} \ \leq 120\%$

We choose this 20% swing to be sufficiently similar because we are seeking at least three control states per policy state. If the bound is slightly larger, the number of comparison states grows beyond what we believe to be a reasonable list. In that, for two of our control states, a slightly larger bound captures over half of the states in the US. A smaller bound gives a list of control states that is less than three for Florida. We considered making a custom bound for each state to account for Florida's list situation, however that would involve us creating a bound on the number of control states. We did not believe this was an adequate approach for our analysis as a state like Washington, which had very many similar states within these bounds, would be limited in the number of control states it is assigned.

Once the similarity score is calculated for income, population, education, and rate of drug-related deaths, the four scores are averaged to create a combined similarity metric. The bounds for being sufficiently similar in the combined similarity metric are:

$80\% \ \leq$ Combined Similarity Score $\leq 120\%$

After we've compiled the list of states that fall within the bounds, we then compare each state's quantity of implemented opioid-crisis related policies. For this comparison, we use How States Are Tackling the Opioid Crisis by Shalini Wickramatilake, et. al. In their paper, they use questionnaire data from state alcohol and drug agency directors and designated senior agency managers to understand what policies are implemented in each state. In their Table 1, they diagram what states have implemented what policies. The polices they're investigating are Education on Risks of Opioids, Education on Prescribing of Opioids, Good Samaritan Law, Funding for MAT, Access to Naloxone, PDMP Reporting Required, Pain Clinic Regulation, and Prescriber Guidelines. Each education category is also separated by subcategories. For our purposes, we are only using the 'General Population' subcategory within the Education on Risks of Opioids Category, and all three subcategories, 'Physicians and Other Prescribers,' 'Patients and Families,' 'Pharmacists,' within the Education on Prescribing of Opioids category.

For context, the Good Samaritan Law legally protects individuals who attempt to help a person in crisis. In our case, if a person is experiencing an opioid overdose and a bystander attempts to help, but instead hurts the situation, then the bystander has legal protection from being sued by the person who was overdosing. Funding for MAT (medically assisted treatment) "Aims to decrease opioid misuse and opioid-related overdose deaths by offering financial and technical assistance to state, local, and tribal government entities." Access to Naloxone gives funding to local agencies to keep Naloxone on hand, which is a nasal spray used to treat narcotic overdoses. PDMP (prescription drug monitoring programs) are databases used to track the distribution of prescription drugs.

We use the information from their paper to create a final, conditional metric for evaluating candidate states. We count the quantity of policies that are missing from each state. The questionnaire is from 2015 and all of the policy implementations of our three policy states were before 2015. So, we decide to count the number of missing policies to ensure a stable timeline for the other policies that candidate states may or may not have implemented. In that, we can safely assume that policies that were missing in 2015, were also missing in 2007 (Texas), 2010 (Florida), and 2012 (Washington).

So, from our list of candidate states for each policy state, we limit to states that only have more missing policies than the respective comparison states. In turn, we're comparing each Florida, Texas, and Washington to states that have similar demographic and socio-economic statuses while having a lesser response to the opioid crisis. Below is a table showing each treatment state and a list of their respective control states.

Treatment State	Control States
Texas	Arkansas, California, Georgia, Missouri, New York, Wyoming
Washington	Hawaii, Iowa, Kansas, Maine, Massachusetts, Minnesota, Montana, Nebraska, North Dakota, Oregon, South Dakota, Virginia, and Wyoming
Florida	California, Nevada, New York

Table 1. *Summary of Treatment and Control States*

It is worth noting that for Texas, we are not using population in its combined similarity metric calculation because its population is much larger than other states and creates a weighting-effect on the metric towards population.

Summary Statistics

This table shows the summary statistics for the mortality rate. The mortality rate is converted to death per 100,000 population. For Florida, the mean mortality rate per capita dropped from 12.46 to 11.43 after the policy implementation. For control states, however, we observe an increase in the mortality rate from 16.29 to 17.34, which indicates a positive impact of the policy in Florida. For the other states: Washington, the mean of mortality rate also decreased after the policy change. On the contrary, for Texas, the mortality rate increased from 58.60 to 60.38 after 2007, suggesting there is little influence of the opioid policy change in Texas.

Descriptive Statistics for Mortality Rate

	Before or after policy change	mean	min	25%	50%	75%	max	Standard deviation
Florida (2010)	Before	12.46	0.20	2.31	6.82	17.13	76.76	14.51
	After	11.43	0.18	1.85	6.32	16.15	60.96	13.32
Control States	Before	16.29	0.05	1.78	5.01	10.24	620.34	50.36
	After	17.34	0.04	1.79	5.05	10.40	645.16	55.98
Washington (2012)	Before	24.28	0.26	4.25	8.36	24.27	226.96	41.79
	After	22.66	0.21	3.87	7.03	22.61	226.24	41.27
Control States	Before	64.52	0.33	14.47	36.58	79.22	772.79	80.22
	After	66.60	0.30	14.05	35.46	81.76	821.01	85.64
Texas (2007)	Before	58.60	0.13	10.63	27.12	67.88	649.35	85.22
	After	60.38	0.10	9.69	25.66	68.59	771.60	92.80
Control States	Before	28.26	0.05	6.58	19.62	37.62	413.90	33.85
	After	28.20	0.04	6.14	18.53	36.70	466.85	36.21

Table 2. *Summary of Treatment and Control States for Mortality Rate*

According to the summary statistics in table 3, it appears that the minimum, 25th percentile, median, 75th percentile, and maximum values for Florida are higher after the policy change in 2010. However, when we refer to the plot of the prescription data for Florida in Figure 5, we can see that in 2010 the prescription data is significantly higher than the data from before 2010, such as 2009. Y Additionally, the trend after the policy change appears to be decreasing. Therefore, the summary statistics for the prescription data do not provide a conclusive understanding of the trend after the policy change. In the case of the control states for Florida, the summary statistics do not show significant differences before and after the policy change. For each of these states, the prescription data appears to increase. What we know is that the MGE rate increases, which is not what we expected. We assume that there are some reasons causing the drastic increase of MGE rate for Florida from 2009 to 2010.

On the other hand, for Washington, the summary statistics for prescription data which the policy change was implemented in 2012 appears to show an increase after the policy change. This is also opposite of what was expected as well. In the control states for Washington, the summary statistics also show an increase after the policy change.

In conclusion, we can see that both Florida and Washington and their controlling States, the summary statistics seem to increase after policy change. We can't conclude trends after the policy change based on the summary statistics. We aren't taking each year's data into the summary statistics thus we can't know the trend before and after policy change.

Descriptive Statistics for Prescription Data								
	Before or after policy change	mean	min	25%	50%	75%	max	Standard deviation
Florida (2010)	Before	1.85e+05	0	7.66e+03	4.55e+04	1.72e+05	2.5e+06	3.91e+05
	After	2.24e+05	0	9.63e+03	5.85e+04	2.18e+05	3.03e+06	4.24e+05
Control States	Before	1.16e+05	0	1.31e+04	3.18e+04	1.25e+05	1.77e+06	2.15e+05
	After	1.46e+05	0	1.65e+04	3.78e+04	1.55e+05	1.85e+06	2.64e+05
Washing ton (2012)	Before	63713.63	761.06	7111.88	19808.06	54483.7	627939.38	119902.91
	After	63538.50	786.1	7893.08	21411.38	60598.07	646956.45	115531.98
Control States	Before	13596.78	0	770.37	2755.96	8884.10	382503.20	37661.51
	After	15323.35	0	957.79	2265.76	10441.89	392790.30	40660.86

Table 3. *Summary of Treatment and Control States for Prescription & Shipment data*

Analysis

With our selected states, we analyze them against their respective policy states. To do this, we first take an average of all of the selected states within their groups. So, for Florida, we average the death rate and prescription and shipment rate in county level. We take the average to account for any inconsistencies between states and to have just one metric for comparison.

After averaging the rates, we create the pre-post plots and the difference-in-difference plots. The pre-post plots show us a fitted line of our averages only looking at each policy state. This gives us a method to analyze what effect the policy had locally in the state. The difference-in-difference plots show us our comparison state average, which operates as a control, and our policy state before and after the policy implementation.

Interpretation

Washington: Mortality Rate

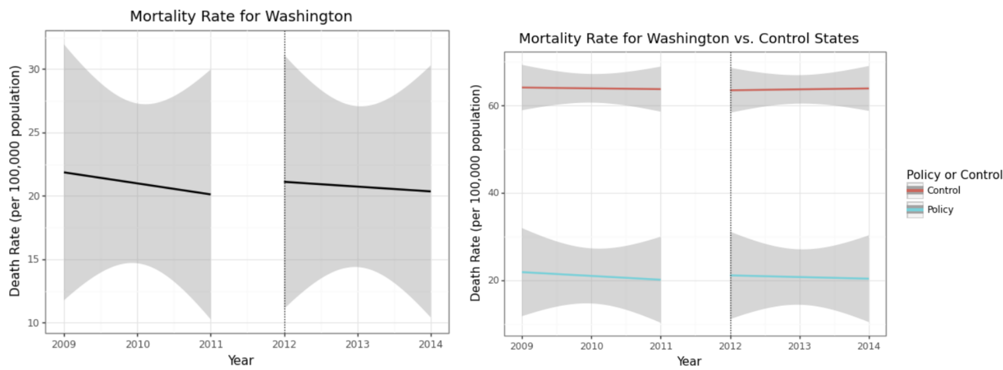

Figure 1. *Diff-in-Diff Model and Pre-Post Model for Mortality Rate in Washington*

This figure shows the pre-post graph for the death rate related to drug use per 100,000 people in Washington and the difference-in-difference graph for control states (Hawaii, Iowa, Kansas, Maine, Massachusetts, Minnesota, Montana, Nebraska, North Dakota, Oregon, South Dakota, Virginia, Wyoming). Washington showed a stagnant trend in the death rate before 2012, when the opioid policy was implemented. The pre-post graph showed that after implementing the policy, the death rate decreased and showed a downward trend, but not as steep as before. Meanwhile, the difference-in-difference analysis showed that the death rate in the control states was stagnant after policy implementation in 2012. This slightly decreasing graph for Washington hints that the opioid policy had a positive impact in decreasing drug-related death in Washington.

Washington: Prescription & Shipment Rate

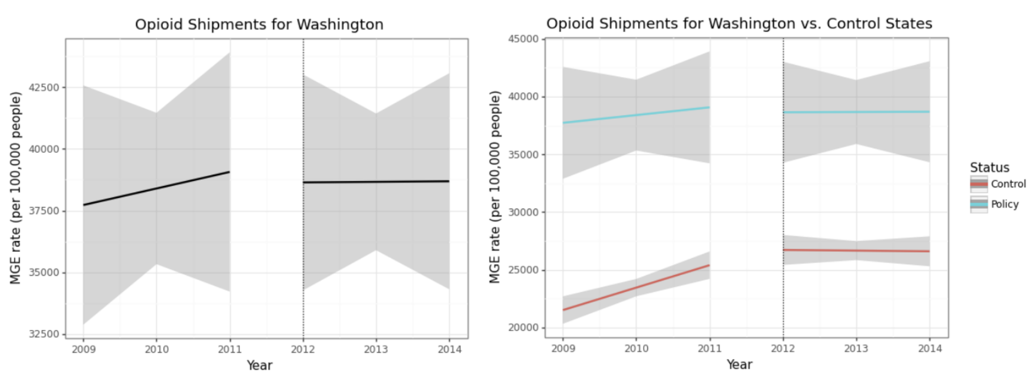

Figure 2. *Diff-in-Diff Model and Pre-Post Model for Prescription Rate in Washington*

Figure 2 shows the pre-post graph for opioid shipment in Morphine Gram Equivalent in Washington and the difference-in-difference graph for control states (Hawaii, Iowa, Kansas, Maine, Massachusetts, Minnesota, Montana, Nebraska, North Dakota, Oregon, South Dakota, Virginia, Wyoming). Washington showed an upward trend of opioid shipment per 100,000 people before 2012, when the opioid policy was implemented. The pre-post graph also showed the shipment rate in a stagnant trend after implementing the policy. Meanwhile, the difference-in-difference analysis showed that the opioid shipment in the control states stagnated after policy implementation in 2012. This decreasing graph for Washington hints that the opioid policy had a slightly positive impact on decreasing opioid shipments in Washington.

Texas: Mortality Rate

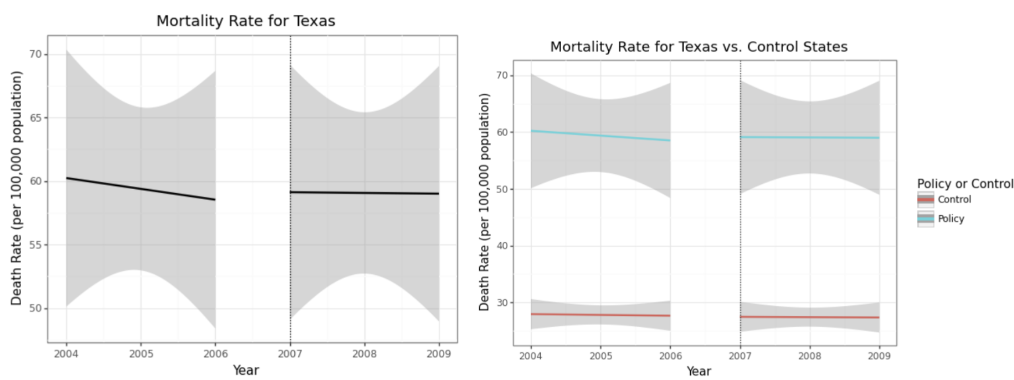

Figure 3. *Diff-in-Diff Model and Pre-Post Model for Mortality Rate in Taxes*

This figure shows the pre-post graph for the death rate related to drug use per 100,000 people in Texas and the difference-in-difference graph for control states (Arkansas, California, Georgia, Missouri, New York, and Wyoming). Texas showed a downward trend in the death rate before 2007, when the opioid policy was implemented. The pre-post graph showed that after implementing the policy, the death rate continued to decrease. The slope, however, is not as steep as before. Meanwhile, the difference-in-difference analysis showed that the death rate in the control states stagnated after policy implementation in 2007. This increasing graph for Texas hints that the opioid policy had little impact in decreasing drug-related death in Texas.

Florida: Mortality Rate

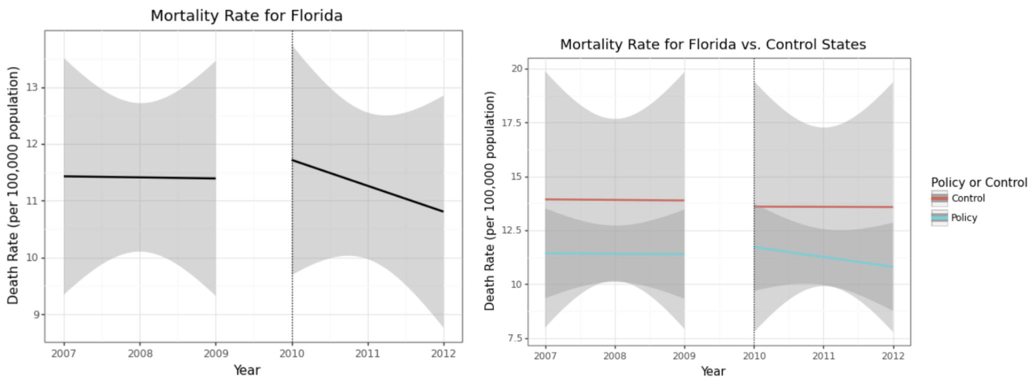

Figure 4. *Diff-in-Diff Model and Pre-Post Model for Mortality Rate in Florida*

This figure shows the pre-post graph for the death rate related to drug use per 100,000 people in Florida and the difference-in-difference graph for control states (California, Nevada, New York, and Texas). Florida showed a downward trend in the death rate before 2010, when the opioid policy was implemented. The pre-post graph showed that the death rate dropped even more significantly after implementing the policy. Meanwhile, the difference-in-difference analysis showed that the death rate in the control states remained stable. This decreasing graph for Florida hints that the opioid policy had a positive impact on decreasing drug-related death in Florida.

Florida: Prescription & Shipment Rate

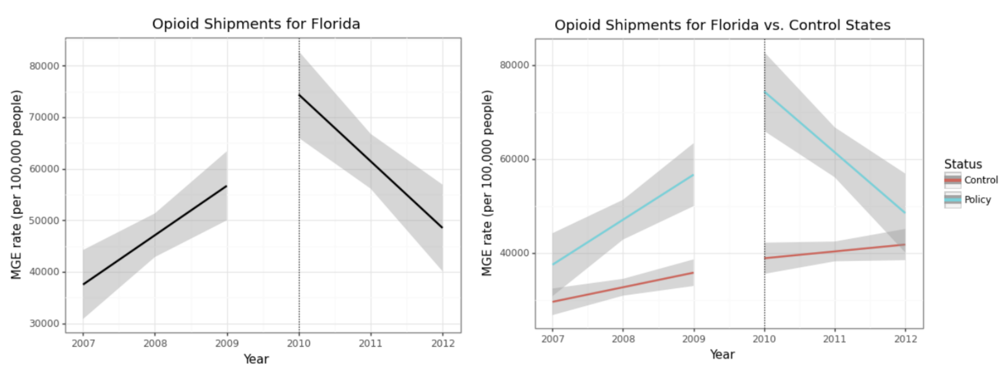

Figure 5. *Diff-in-Diff Model and Pre-Post Model for Prescription Rate for Florida*

Figure 5 shows the pre-post graph for opioid shipment in Morphine Gram Equivalent in Florida and the difference-in-difference graph for control states

(Nevada, New York, California). Florida showed an upward trend of opioid shipment per 100,000 people before 2010. But, after opioid policy implementation in 2010, the shipment rate dropped constantly from around 70,000 in 2010 to below 50,000 in 2012. Meanwhile, the difference-in-difference analysis showed that the opioid shipment in the control states kept increasing after policy implementation in 2010. This decreasing graph for Florida hints that the opioid policy had a significant positive impact on decreasing opioid shipments in Florida.

Discussion and Future Work

Our results show that states that implement policies to curb the opioid crisis have a decrease in mortality rates and shipment rates. Our analysis is concentrated from 2007 to 2014, with the policy states having their pre and post years somewhere within that bound. Important policies that were implemented in the policy states are those related to treatment. Treatment for an opioid addiction can come in many forms: naloxone for any overdose, methadone for opioid cessation, counseling for mental health, etc. However, it's widely known that white people receive better and more motivated treatment from doctors when compared to other racial groups (Implicit Bias among Physicians and its Prediction of Thrombolysis Decisions for Black and White Patients, Green et. al.).

Between 2019 and 2020, the rate of opioid overdose for African Americans increased from 24.7 to 36.8, which is 16.3% higher than the rate of opioid overdose for white people (US drug overdose mortality rates by race and ethnicity before and during the COVID-19 pandemic, Friedman, et. al). The figure below is taken from their paper and visualizes the differences, year to year, in opioid deaths per one-hundred thousand.

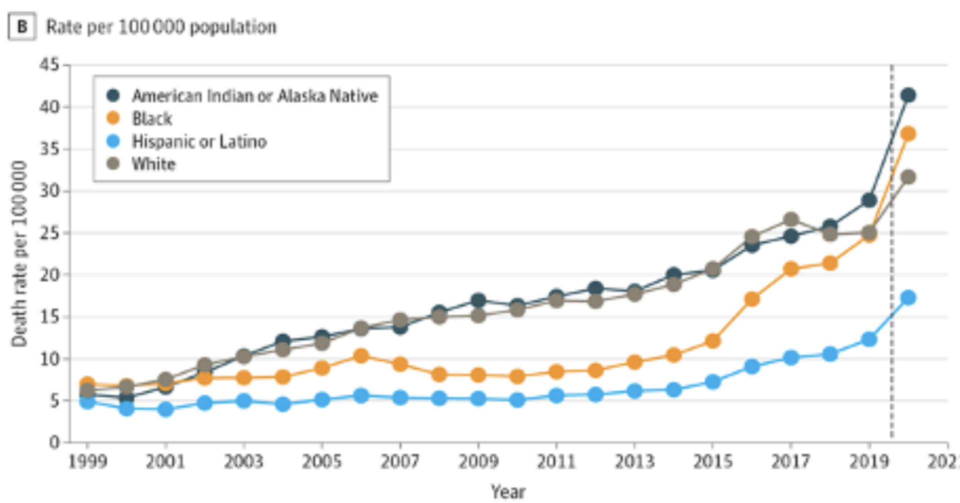

Figure 6. *"US drug overdose mortality rates by race and ethnicity before and during the COVID-19 pandemic," Friedman, et. al, 2022*

It is native to believe that treatment policies aimed at decreasing opioid deaths and opioid shipments will have an equal effect across races. Our analysis did not include race as a separate factor, instead we have an aggregate of all the deaths, where race is summarized into one number and not considered at all. Given that the doctors and providers that follow the opioid guidelines have an implicit bias against non-whites, we have no evidence to suggest that the policies had any effect on any group other than white people. This claim is supported by Friedman, et. al.

In the future, we hope to combine the research methodology of our analysis and compare how successful policies are between racial groups, as well as update our control and policy states for a more modern list. We also want to look into who is using the treatment options from the policies. We seek to ask: if only white people are able to utilize the treatment, then is it really a good treatment? And, what are the options for improving an equal access to opioid treatments?

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Estimate the Impact of Opioid Control Policies (for policymakers)

Beibei Du, Wafiakmal Miftah, Suzanna Thompson, Alisa Tian

December 12, 2022

Motivation

For this project, we are trying to address the problem of rising opioids usage and its connection with death by drugs in the United States. We have two specific questions: What effect did the opioids policies in Texas, Washington, and Florida have on the number of opioid deaths and overall drug deaths in those states? In other words, how do opioids deaths and overall drug deaths differ in Texas, Washington, and Florida from our chosen control states? We will mention how we decide the control states in the Overview of the Data part.

Evaluating the effectiveness of policy interventions designed to address the opioid crisis is critical for policymakers. The widespread use of opioids for chronic pain management has contributed to a surge in drug overdose deaths. The neurological effects of opioids can cause feelings of happiness and control over the central and peripheral nervous systems (Janice C. Froehlich). However,opioid overdose can lead to severe problems, including death. In order to reduce the likelihood of overdose, it is essential to study the effectiveness of interventions aimed at reducing opioid use and availability. By answering the two research questions outlined above, we can gain a deeper understanding of the opioid crisis and develop more effective policy changes for addressing it.

Overview of the Data

Upon choosing the control states, we aim to select the states with similar social-demographic characteristics. The following factors are considered: state population, education ranking, average income, and drug-related death rate, as well as the state's policy response to the opioid crisis. We choose the individual treatment state as the baseline. For example, when calculating the state's average income based on that of Florida, we divide the individual state's population by Florida's population. A percentage close to 100% means the state's population is similar to Florida's.

After calculating the similarity for these five indicators (state population, education ranking, average income, rate of drug-related death, and state's policy response to opioid crisis), the States are chosen by a combined weighted metric. Percentages are summed and divided by 4. The population is over-impacting the combined metric for Texas, so it is excluded. Our control states are decided based on if they are in the interval (80%, 120%). Also, due to the county designations confusion in Alaska in 2010, we have excluded Alaska from our control states.

The list of our treatment states and accompanying control states:

Treatment State	Control States
Texas	Arkansas, California, Georgia, Missouri, New York, Wyoming
Washington	Hawaii, Iowa, Kansas, Maine, Massachusetts, Minnesota, Montana, Nebraska, North Dakota, Oregon, South Dakota, Virginia, and Wyoming
Florida	California, Nevada, New York

The source of our data are:

1. Opioids Prescription/Shipment data (Washington Post):

   In this dataset, it holds all the information of the opioids prescription across the years in all states in the United States. This dataset is about 100Gb and we select the three states and their controlled states to preprocess. The unit of observation for this dataset is at the county level. We sum all the data of all counties in a state and take that into our analyses.

2. Mortality Rate data (CDC Wonder):

   In this dataset, we have state, county, year, opioid-related cause of death and the number of deaths per county and state. The unit of observation for this data is at the county level.

3. Population data (CDC Wonder):

   CDC is a reliable system for holding public health data and information across the United States.

   For the shipment & prescription question, we are excluding Texas as we do not have an adequate sample of data.

Analysis

Our methodology for this project is pre-post and difference-in-difference analysis.

Hypothesis:

We hypothesize that there is a causal effect between policy change in opioid use and the case of overdose deaths in Florida, Washington, and Texas State. We also hypothesize that while opioid prescriptions decrease, drug-related deaths as a whole increase or remain stable. We suggest this result as there is evidence to suggest that removing a drug from an addict does not necessarily imply that the addict will recover. In some cases, the addict will switch to a new drug of choice. In other cases, the opioid addict will be in recovery and later overdose once they're able to find an opioid. This is a well known phenomena as addicts may forget that their tolerance for the opioid decreases during times of recovery and then try to use the same opioid dose as they were using active addiction. In turn, the addict will accidentally overdose. We also suppose that opioid prescriptions decrease in Texas, Washington, and Florida.

Interpretation of the Analysis (Strengths and Limitations)

Florida

Effects of Regulations on Opioid Shipments

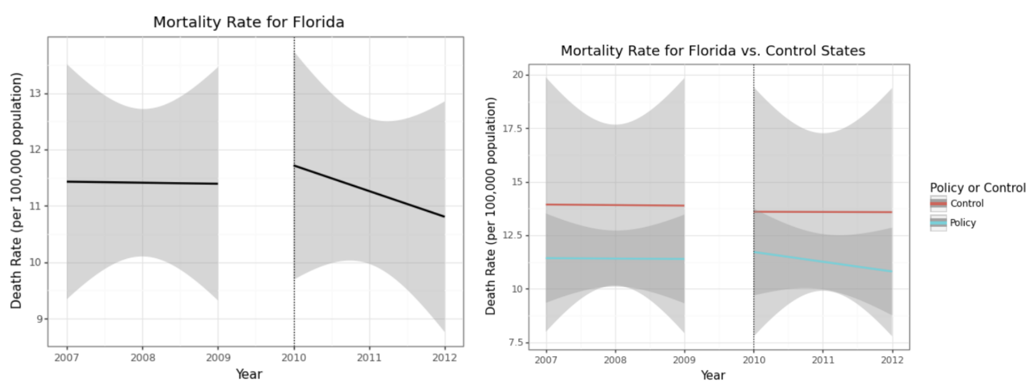

Figure 1. *Pre-Post and Diff-in-Diff Model for Mortality Rate in Florida and All Control States*

This figure shows the pre-post graph for the death rate related to drug use per 100,000 people in Florida and the difference-in-difference graph for control states (California, Nevada, New York, and Texas). Florida showed a downward trend in the death rate before 2010, when the opioid policy was implemented. The pre-post graph showed that the death rate dropped even more significantly after implementing the policy. Meanwhile, the difference-in-difference analysis showed that the death rate in the control states remained stable. This decreasing graph for Florida hints that the opioid policy had a positive impact on decreasing drug-related death in Florida.

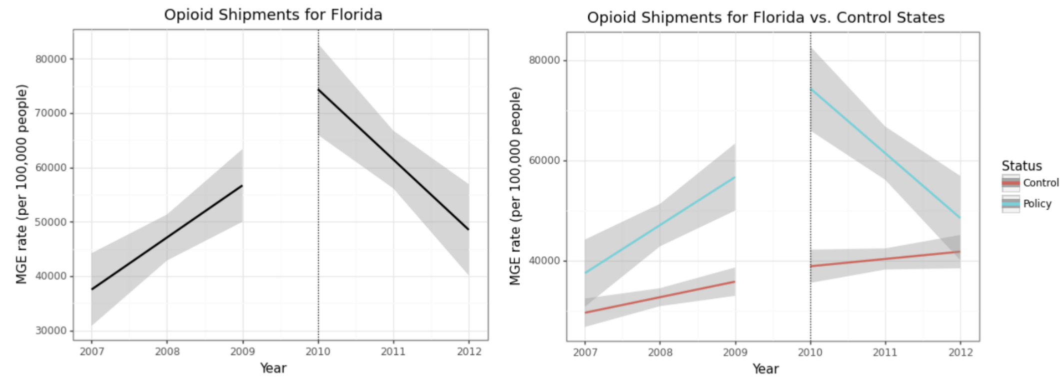

Figure 2. *Diff-in-Diff Model and Pre-Post Model for Mortality Rate in Florida*

Figure 2 shows the pre-post graph for opioid shipment in Morphine Gram Equivalent in Florida and the difference-in-difference graph for control states (Nevada, New York, California). Florida showed an upward trend of opioid shipment per 100,000 people before 2010. But, after opioid policy implementation in 2010, the shipment rate dropped constantly from around 70,000 in 2010 to below 50,000 in 2012. Meanwhile, the difference-in-difference analysis showed that the opioid shipment in the control states kept increasing after policy implementation in 2010. This decreasing graph for Florida hints that the opioid policy had a significant positive impact on decreasing opioid shipments in Florida.

Texas

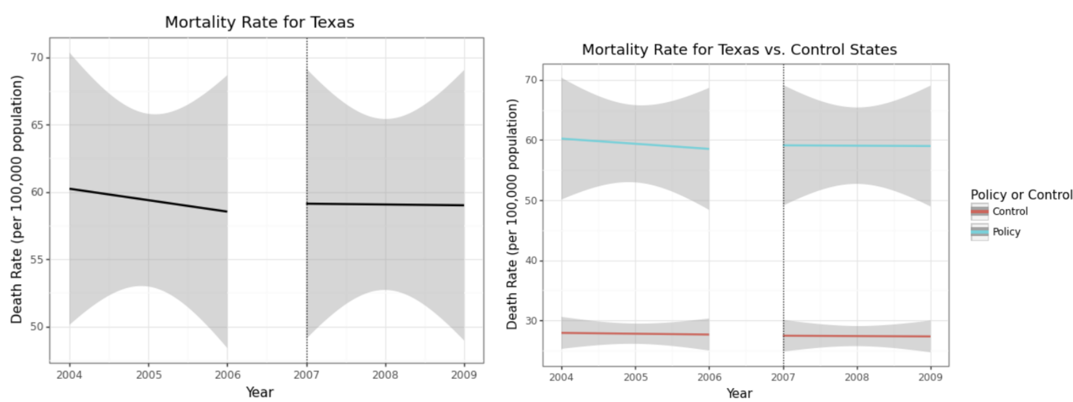

Figure 3. *Pre-Post and Diff-in-Diff Model for Mortality Rate in Texas and All Control States*

Figure 3 shows the pre-post graph for the death rate related to drug use per 100,000 people in Texas and the difference-in-difference graph for control states (Arkansas, California, Georgia, Missouri, New York, and Wyoming). Texas showed a downward trend in the death rate before 2007, when the opioid policy was implemented. The pre-post graph showed that after implementing the policy, the death rate remained upward and even steeper from before. Meanwhile, the difference-in-difference analysis showed that the death rate in the control states stagnated after policy implementation in 2007. This increasing graph for Texas hints that the opioid policy had a negative impact in decreasing drug-related death in Texas. The pre-post graph showed that after implementing the policy, the death rate continued to decrease. The slope, however, is not as steep as before. Meanwhile, the difference-in-difference analysis showed that the death rate in the control states stagnated after policy implementation in 2007. This increasing graph for Texas hints that the opioid policy had little impact in decreasing drug-related death in Texas.

Washington

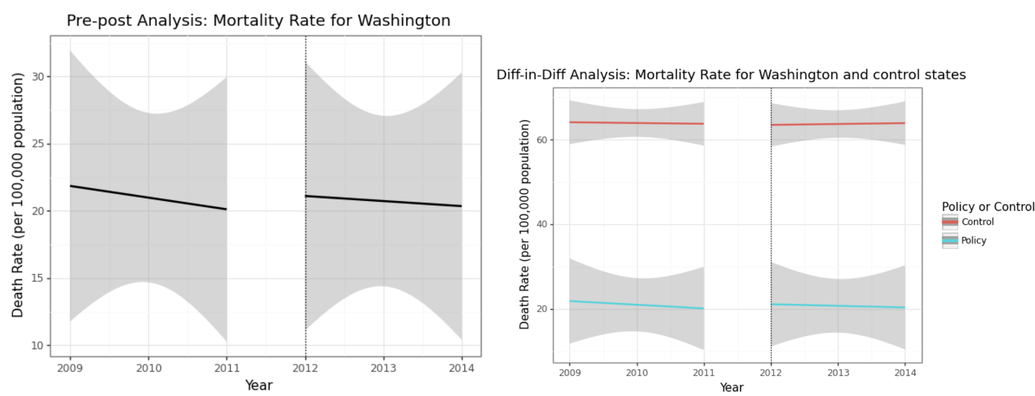

Figure 4. *Pre-Post and Diff-in-Diff Model for Mortality Rate in Washington and All Control States*

Figure 4 shows the pre-post graph for the death rate related to drug use per 100,000 people in Washington and the difference-in-difference graph for control states (Hawaii, Iowa, Kansas, Maine, Massachusetts, Minnesota, Montana, Nebraska, North Dakota, Oregon, South Dakota, Virginia, Wyoming). Washington showed a stagnant trend in the death rate before 2012, when the opioid policy was implemented. The pre-post graph showed that after implementing the policy, the death rate decreased and showed a downward trend, but not as steep as before. Meanwhile, the difference-in-difference analysis showed that the death rate in the control states was stagnant after policy implementation in 2012. This slightly decreasing graph for Washington hints that the opioid policy had a positive impact in decreasing drug-related death in Washington. Meanwhile, the difference-in-difference analysis showed that the death rate in the control states increased after policy implementation in 2012. This comparison between Washington and the control states hints that the opioid policy had a positive impact in decreasing drug-related death in Washington.

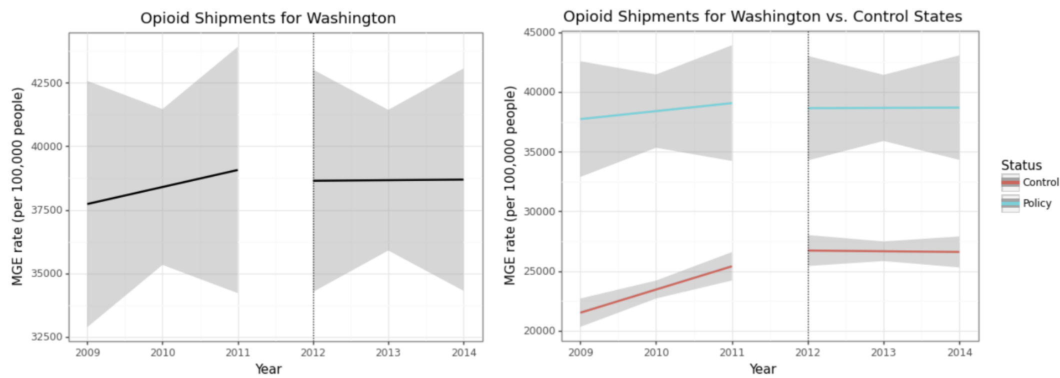

Figure 5. *Pre-Post and Diff-in-Diff Model for Opioid Shipments in Washington and All Control States*

Figure 5 shows the pre-post graph for opioid shipment in Morphine Gram Equivalent in Washington and the difference-in-difference graph for control states (Hawaii, Iowa, Kansas, Maine, Massachusetts, Minnesota, Montana, Nebraska, North Dakota, Oregon, South Dakota, Virginia, Wyoming). Washington showed an upward trend of opioid shipment per 100,000 people before 2012, when the opioid policy was implemented. The pre-post graph also showed the shipment rate in a stagnant trend after implementing the policy. Meanwhile, the difference-in-difference analysis showed that the opioid shipment in the control states also stagnated after policy implementation in 2012. This stagnated graph for Washington hints that the opioid policy had a slightly positive impact on decreasing opioid shipments in Washington.

Conclusion

It is with great importance that you, the policymaker, should take appropriate action when handling the opioid crisis. Our analysis has shown that implementing a broad spectrum suite of policies can decrease opioid-related deaths. The policies have an approximately casual relationship with the decrease of opioid-related deaths and the rate of shipment. This means that policy implementation can save many lives and end the opioid crisis. We urge you to support H.R.6279: Opioid Treatment Access Act of 2022. This bill is cosponsored by Kentucky Senator Rand Paul and Massachusetts Senator Ed Markley. The goal of H.R. 6279 is to improve the access of methadone, which is a drug used to curb withdrawals and cravings. Improving access to methadone will enable more addicts to receive the treatment they need and reduce the need for naloxone, which will lessen a taxpayer's burden.

We also recommend that you introduce new legislation that will create larger education programs on the dangers of opioids, expand the legal protection of the Good Samaritan Law, and give more funding to the DEA for new programs like PDMP Reporting, Pain Clinic Regulation, and Prescriber Guidelines. The suggestions we have just stated are taken directly from the states that had success in their policy implementations. We believe that these recommendations must be executed in order to end the opioid crisis.

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