Final Report Team Red

PART I - For Policy Makers

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I. Executive Summary

The opioid epidemic, tracing back to its root, started in the late 1990s when pharmaceutical companies failed to reveal the truly addictive nature of opioid pain relievers to the medical community. Increased opioid prescriptions led to widespread substance abuse in communities across the country[1]. According to the CDC, more than half a million people in the United States died of opioid drug overdose from 1999 to 2020[2], leaving families in devastation from losing their loved ones. Many state legislatures passed laws in an attempt to contain drug overdose deaths by restricting the over-prescription of opioids. The goal of this project is to estimate the effectiveness of policy interventions in Texas, Florida, and Washington. The analysis is crucial because it teases out effective policy interventions and provides a reference to future legislative changes that aim to save thousands of lives.

Given the research interest, we performed two types of analyses: the pre-post analysis and the difference-in-difference analysis. The pre-post analysis evaluates the legislative impact on opioid shipments and overdose death before and after policy interventions. If opioid prescriptions and drug-related deaths climb upward prior to policy implementations, we expect effective policies will manifest through downward trends in the years post-implementation. On the other hand, we expect similar growth in the graphs if the policy fails to produce an effect. Furthermore, we employed difference-in-difference analysis to answer the question of whether changes in the number of opioid prescriptions and overdose deaths were truly the results of policy interventions. We compared the opioid shipment per capita and drug mortality rate from 2003 to 2015 between target states (Texas, Florida, and Washington) and surrounding states that did not place regulations on opioids.

From our analysis, we concluded that the series of legislations in Florida was the most effective in limiting opioid shipments and moderately effective in reducing drug overdose deaths. Texas's approach to combating the opioid epidemic also had a positive impact on lowering the mortality rate. We observed a slow decline in drug-induced mortality after the state legislation went into effect. On the contrary, the policy intervention in Washington seemed to be the least effective. Overdose deaths continued to increase even at a faster rate than before policy changes. While opioid shipments dropped initially and then plateaued after policy adoption in

[1] https://www.hhs.gov/opioids/about-the-epidemic/index.html
[2] https://www.cdc.gov/opioids/basics/epidemic.html

Washington, the surrounding states experienced similar trends. Therefore, we cannot attribute the reduction in opioid shipments to the state's legislative actions.

II. Data

Mortality from Drug Overdose

We used The U.S. Vital Statistics records from the years 2003 to 2015. For this specific dataset, we wanted to understand the number of overdose deaths in a given county per year.

Opioid Drug Prescriptions

The second dataset we used was Opioid Prescriptions by the Washington Post between 2003 and 2015. In this dataset, we acquired the number of opioid prescriptions in a given county per year. Due to HIPPA regulations, we had to assume that supply equals demand. In other words, the number of opioid shipments is the same as the number of opioids prescribed.

Population

The last dataset that we chose to use was County Population Data from the years 2000 to 2020. The data gives us information on the population size in a given country per year.

III. Analysis

<u>Washington Opioid Shipments Analysis</u>

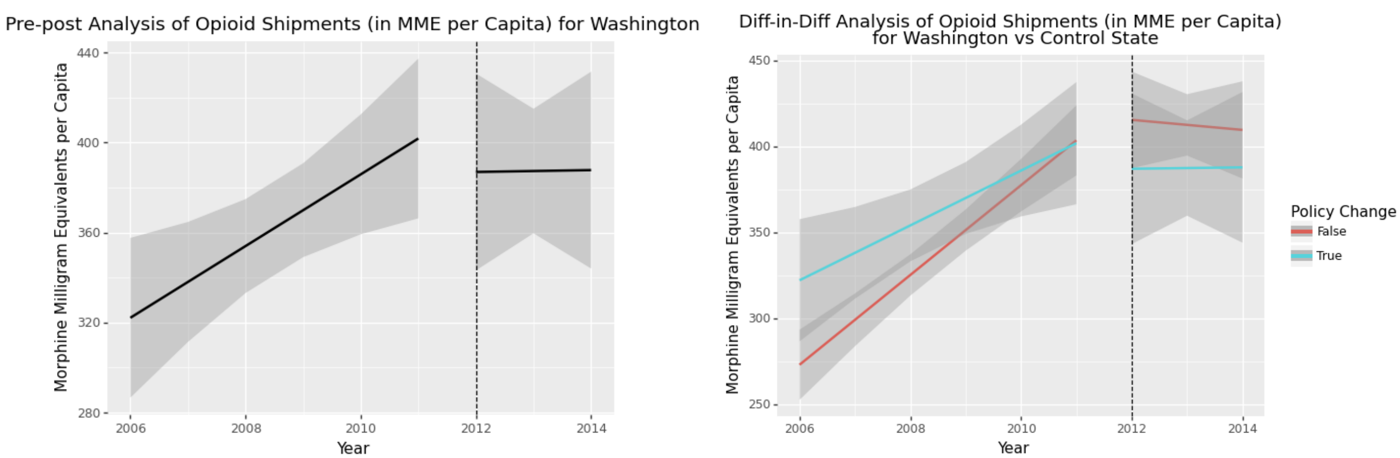

Figure 1. *Washington opioid shipments before and after 2012*
(from left to right: pre-post plot and diff-in-diff plot)

Pre-Post Analysis

We identified an increasing trend of opioid shipments measured in morphine milligram equivalent (MME) per capita in Washington prior to the implementation of the policy from the year 2006 to 2008. After the policy implementation, the opioid shipments dropped and stayed around 390 morphine milligram equivalent per capita between 2012 and 2014. Therefore, it seems that the policy took effect, although there was no significant decrease in opioid shipments observed.

Difference-in-Difference Analysis

From the diff-in-diff analysis plot above, we explored whether the trend of slight decline and stability of the opioid shipments in Washington was merely the result of government regulation towards drug abuse. However, the sharp contrast of the steep increase in the prescription amount per capita followed by a downward trend after policy implementation among the control groups (Oregon, California, Nevada, Idaho, and Montana) indicate a regional decline in opioid shipments post-2012. Therefore, the regulation in Washington did not prove to be effective in lowering the opioid shipments.

Washington Drug Mortality Rate Analysis

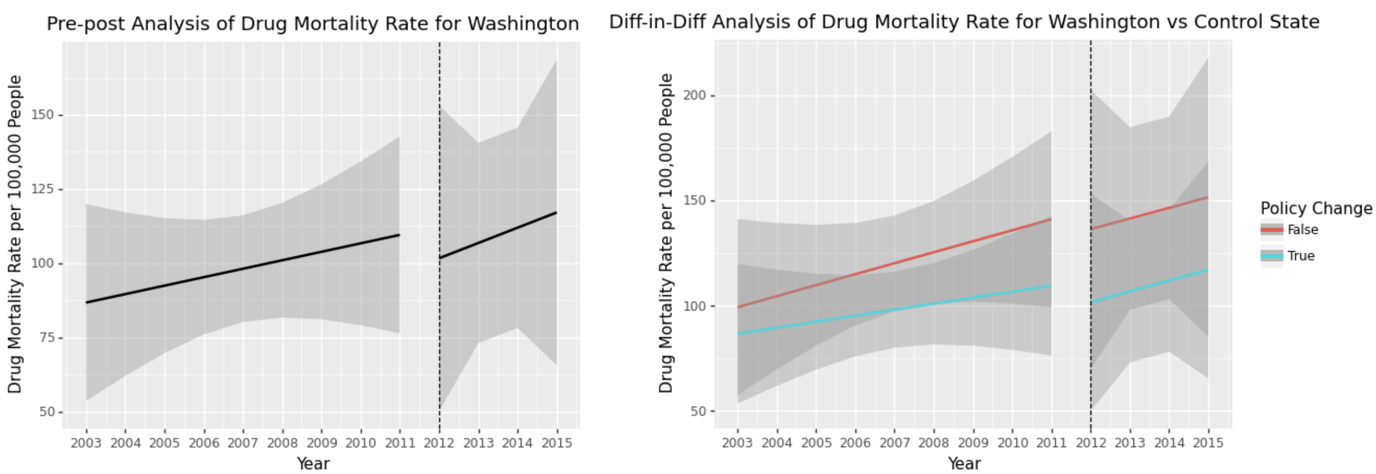

Figure 2. *Washington drug mortality rate before and after 2012*
(from left to right: pre-post plot and diff-in-diff plot)

Pre-Post Analysis

The graph above shows an upward climbing trend for the drug mortality rate before the policy implementation. We noticed that the opioid-related deaths grew faster than before, after an initial reduction. We believe the policy might have a temporary effect on reducing drug overdose deaths.

Difference-in-Difference Analysis

From the graph above, the slope of the line post-policy implementation is the same as that of the control group, while both indicate a rising trend prior to policy implementation. As such, we believe the policy adoption didn't produce a positive effect on the drug overdose problem.

Florida Opioid Shipments Analysis

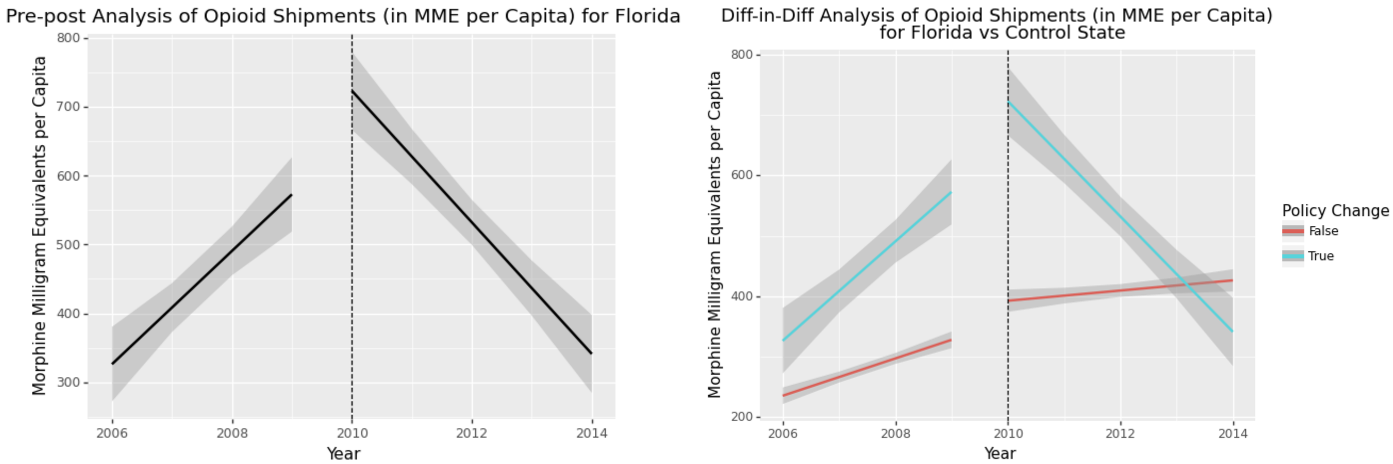

Figure 3. *Florida opioid shipments before and after 2010*
(from left to right: pre-post plot and diff-in-diff plot)

Pre-Post Analysis

From the pre-post analysis plot for Florida above, there was an increasing trend of opioid shipments measured in MME per capita between the years 2006 and 2008. As the local government issued the policy to combat the drug abuse problem in 2010, we observed a sharp decline in the opioid shipments from the year 2010 to the year 2014. This illustrates the policy may be effective to alleviate the proliferation of drugs in Florida.

Difference-in-Difference Analysis

From the diff-in-diff analysis plot above, we explored the trend of opioid shipment between Florida and its control states (Georgia, South Carolina, Alabama, Mississippi, and Louisiana) before and after the policy implementation. We observed continuous growth of opioid shipments in the control states while the shipments in Florida drastically declined after policy implementation in 2010. Therefore, we can infer that the policy posed a huge impact on the improved drug prescription problem in Florida.

<u>**Florida Drug Mortality Rate Analysis**</u>

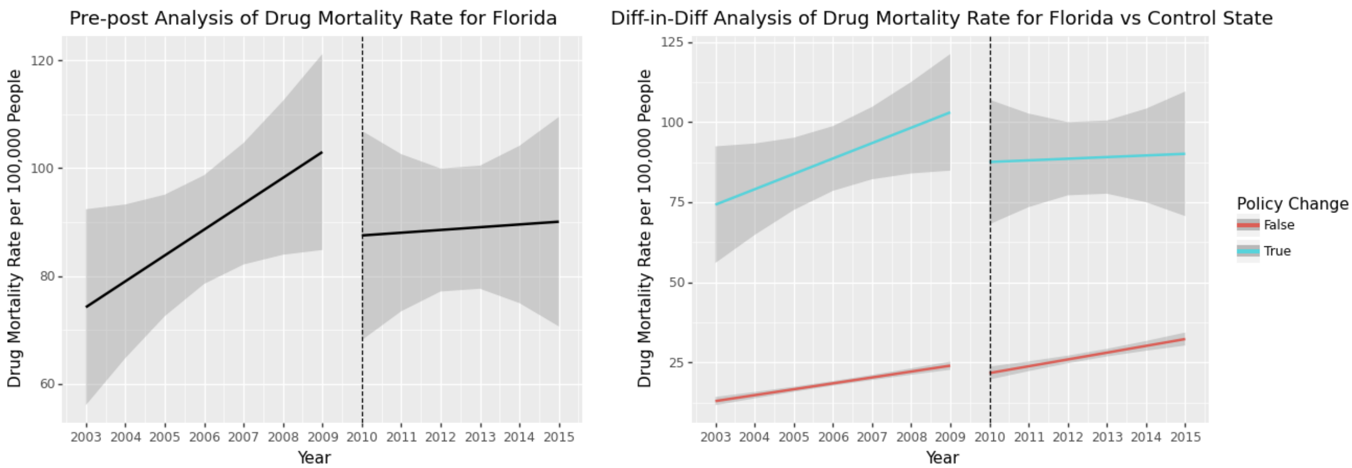

Figure 4. *Florida drug mortality rate before and after 2010*
(from left to right: pre-post plot and diff-in-diff plot)

Pre-Post Analysis

From the graph above, we noticed that the drug mortality rate in Florida climbed upward prior to the policy implementation. After policy adoption, the graph shows a relatively slow growth: We can infer that the policy in Florida effectively reduced drug overdose deaths.

Difference-in-Difference Analysis

We can conclude that the policy changes in Florida produced a positive effect on remedying the drug overdose problem in Florida. Drug-induced mortality grew at a much slower rate after the legislative changes, while the drug mortality rate steadily increased in the control states.

<u>**Texas Drug Mortality Rate Analysis**</u>

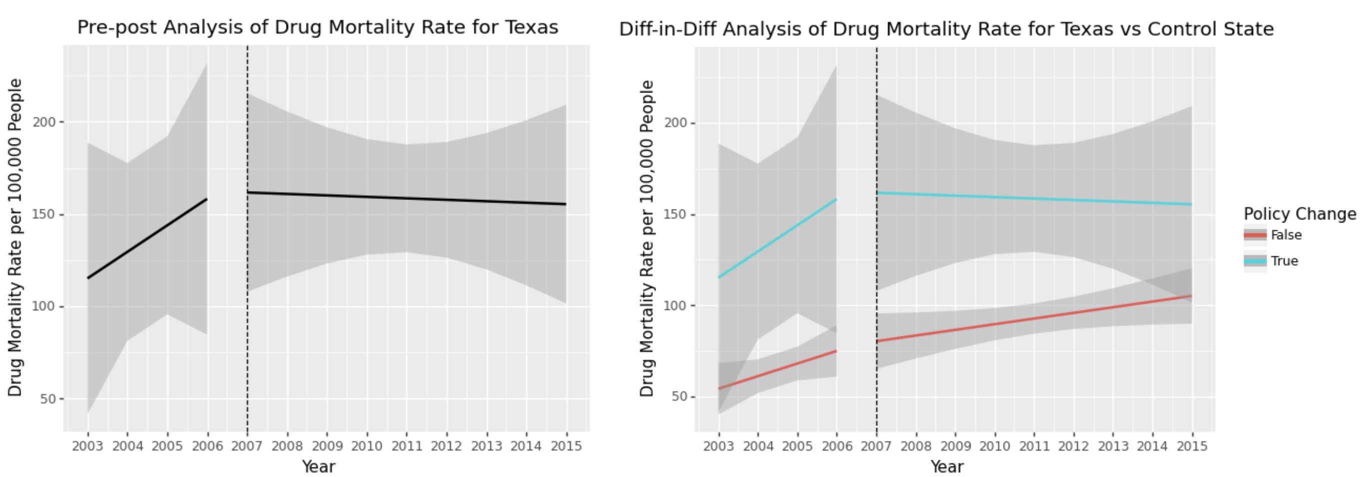

Figure 1. *Texas drug mortality rate before and after 2007*
(from left to right: pre-post plot and diff-in-diff plot)

Pre-Post Analysis

The drug mortality rate in Texas exhibits a downward trend after the legislation took effect. The drug mortality rate rose sharply before policy changes but started to decrease post-policy implementation, indicating the regulations likely worked well on containing drug overdose deaths.

Difference-in-Difference Analysis

The policy implementation in Texas had a positive influence on the drug mortality rate. The slope after policy changes is smaller than that of pre-policy implementation, which provides a clear contrast to the mortality rate in the control states.

IV. **Limitations**

The first limitation of our analysis is that we have to assume the number of opioid shipments equates to the number of opioids prescribed. Due to HIPPA regulations, we are not able to obtain data at the doctor-to-patient prescription level. While opioid shipment data is an appropriate substitute, it does not provide the same level of information.

The second limitation of our analysis is that it only assesses the impact of state legislative regulations on opioid circulation in the legal markets. However, in retrospect, we know that heroin and illicit synthetic opioids also fueled the epidemic, causing thousands of drug-related overdose deaths.

The third limitation of our analysis is that we only looked into regulatory changes reinforced by law. Though the control states we selected did not pass legislation towards restricting opioid shipments until 2015, some of these states had quasi-regulatory guidelines in place during the early 2010s that may impact the accuracy of our analysis.

V. **Conclusion**

Based on the results of the pre-post and the difference-in-difference analyses on drug mortality rate and opioid shipments, we concluded that the opioid regulations in Florida exhibit a positive effect in reducing drug overdose and opioid shipments, and drug policies in Texas contribute to the improvement in the drug overdose situation. In Florida, opioid shipments decreased drastically and the drug mortality rate flattened after the implementation of the drug policies, whereas both were increasing steadily prior to legislative changes. The drug policy in Texas also played a positive role in dwindling drug overdose deaths. The slope of the drug mortality rate in Texas is now negative, compared to the continuous positive growth in the control states.

On the contrary, Washington's opioid policy was not successful. We observed a small decline in overdose deaths and opioid shipments at the start of policy implementation. However, the same is observed in the control states, indicating that the decline is not a result of the policy changes. The drug mortality rate in Washington also grew much faster after the initial reduction. Additionally, though we observed a smaller decline and relatively flat growth of opioid shipments in Washington, similar or slightly better trends are identified in the control states. Therefore, we believe the opioid policies in Washington had little effect on reducing opioid prescriptions.

Beyond estimating the impact of opioid regulations, our analysis also hopes to provide a reference to future legislation. We believe the success of Florida's opioid policies in reducing opioid prescriptions can be attributed to reinforcement strategies such as statewide raids that resulted in numerous arrests, seizures of assets, and pain clinic closures. In addition, the state also had regulations for physicians and drug wholesale distributors, which effectively reduced the influx of opioids. This finding indicates that combating the opioid epidemic requires continuous effort. Regulations help, but reinforcements of law boost the effect.

PART II - For Data Scientists (like Nick)

I. Motivation

The opioid epidemic, tracing back to its root, started in the late 1990s when pharmaceutical companies failed to reveal the truly addictive nature of opioid pain relievers to the medical community. Increased opioid prescriptions led to widespread substance abuse in communities across the country[3]. According to the CDC, more than half a million people in the United States died of opioid drug overdose from 1999 to 2020[4], leaving families in devastation from losing their loved ones. Many state legislatures passed laws in an attempt to contain drug overdose deaths by restricting the over-prescription of opioids. The goal of this project is to estimate the effectiveness of policy interventions in Texas, Florida, and Washington. The analysis is important because it teases out effective policy interventions and provides a reference to future legislative changes that aim to save thousands of lives.

The goal of this project is to estimate the effectiveness of policy interventions in Texas, Florida, and Washington. The analysis is important because it teases out effective policy interventions and provides a reference to future legislative changes that aim to save thousands of lives. Texas was the first state to act in January 2007[5]. Their guidelines require thorough patient evaluation, informed consent to opioid treatment, periodic review of drug use, and complete medical records. Florida followed suit and began a series of policy interventions in February 2010[6]. They first placed regulations on pain clinics across the state, then conducted raids to reinforce the rules. The state also banned physicians from prescribing schedule II or III drugs and further regulated the wholesale distributors by setting up a designated task force. Finally, in January 2012, Washington adopted policies restricting access to excessive opioid prescriptions[7]. Their regulatory changes include but are not limited to periodic reviews, maximum daily dosage, and mandatory pain management consultation.

II. Research Design

Given the research interests, we performed two types of analyses: the pre-post analysis and the difference-in-difference analysis. Our focus is to assess the effectiveness of policy interventions in Florida, Texas, and Washington. The pre-post analysis aims to understand how policy changes impact opioid shipments and overdose death over time. If opioid prescriptions and drug-related deaths climb upward prior to policy implementations, we expect effective

[3] What is the U.S. Opioid Epidemic?
[4] Understanding the Opioid Overdose Epidemic
[5] Minimum Requirements for the Treatment of Chronic Pain
[6] Decline in drug overdose deaths after state policy changes - Florida, 2010-2012
[7] WSR 11-12-025

policies will promote downward trends in our plots for the years post-implementation. However, we expect similar growth in the graphs if the policy fails to produce an effect.

Furthermore, the difference-in-difference analysis ensures that trends observed in the pre-post analysis are the results of policy interventions. In other words, we want to confirm that no unknown factors, such as tightened national importation of opioids, reduce opioid shipments and drug overdose deaths during the same period. To conduct the analysis, we compared the opioid shipment per capita and drug-related mortality rate between target states with policy changes and control states with no state-wide policy interventions. We selected five control states for each treatment state. The control states are chosen based on geographic proximity. We believe states within the same region share socioeconomic and cultural similarities, and therefore, they are likely to experience similar trends in the opioid epidemic. We also confirmed that these control states did not implement policies to restrict opioid shipments within the observation years for the treatment states from 2003 to 2015.

III. Datasets

We selected five control states for each treatment states based on the geographical location due to socioeconomic and cultural similarities:

State		Florida (FL)	Texas (TX)	Washington (WA)
Year of Policy Change		2010	2007	2012
Control States	1	Georgia (GA)	New Mexico (NM)	Oregon (OR)
	2	South Carolina (SC)	Oklahoma (OK)	California (CA)
	3	Alabama (AL)	Arizona (AZ)	Nevada (NV)
	4	Mississippi (MS)	Colorado (CO)	Idaho (ID)
	5	Louisiana (LA)	Louisiana (LA)	Montana (MT)

Source Data Preprocessing

Opioid Prescriptions Data (2006-2014)

The opioid prescription data was gathered from the Washington Post. We assumed that the opioid shipment is equivalent to opioid prescription in this study since the data of opioid prescription was hard to acquire due to privacy reasons. After checking the national dataset[8], we realized the data only goes up to 2012. Therefore, we downloaded individual datasets by state

[8] How to download and use the DEA pain pills database - The Washington Post

from the Washington Post DEA database[9] that include the opioid shipment per county for the years 2006-2014. We then selected columns of interest with “Buyer State”, “Buyer County”, “Transaction Year”, and “Morphine Milligram Equivalents (MME)”. The transaction year was extracted from the transaction date in the original dataset. We also removed buyer counties with missing names and concatenated the opioid shipment dataset for each treatment state and their respective control states.

Mortality Data caused by Drug Overdose (2003-2015)

The mortality data was obtained from the US Vital Statistics. The dataset includes a summary of mortality for drug and non-drug-related causes for each U.S. county from 2003-2015. Since the mortality data is kept in the individual .txt file for each year, we first concatenated all the mortality data and kept only columns of interest: “County”, “County Code”, “Year”, “Drug/Alcohol Induced Cause”, “Drug/Alcohol Induced Cause Code”, and “Deaths”. We then subsetted the dataset based on the drug-induced cause code to limit our focus on the drug overdose deaths:

- D1 - Drug poisonings (overdose) Unintentional (X40-X44)
- D2 - Drug poisonings (overdose) Suicide (X60-X64)
- D4 - Drug poisonings (overdose) Undetermined (Y10-Y14)
- D9 - All other drug-induced causes

Although D3 – Drug poisonings (overdose) Homicide (X85) – is also relevant to our research interest, all data are missing under the category, and hence D3 is excluded from our analysis. After subsetting the dataset to all drug-related causes, we collapsed the dataset to obtain the total number of deaths per county per year and finished our initial preparation of the mortality dataset.

County Population Data (2003-2015)

We also incorporated county-level population data from the United States Census Bureau[10] into our analysis. The reason is that we wanted to normalize the aforementioned datasets for meaningful comparison across all counties by calculating the opioid mortality rate per 100,000 people and the prescribed opioid rate per capita. To process the raw data, we first consolidated the county population data for 2000-2009 and 2010-2020. We then filtered the columns based on research interest and transformed the dataset to include only State Name, County Name, and yearly population data between 2000-2009 and 2010-2020. At last, we concatenated the datasets from the two time periods and renamed the county name “LaSalle Parish” to align with the county name “La Salle Parish” in the 2000-2009 dataset. We also subsetted the years 2003-2015 for further analysis convenience.

[9] DEA database: Where the pain pills went - Washington Post
[10] Index of /programs-surveys/popest/datasets

Further Data Cleaning and Merging

Opioid Shipments per Capita Data (2006-2014)

For data normalization, we merged the opioid shipment data with the county population data. The state names are abbreviated in both datasets. The county names in the opioid shipment dataset are all in capital letters, and the county names of the population data are in letter case including suffixes such as “County” or “Parish”. To align the discrepancies, we removed words like “County” or “Parish” from the county names in the population dataset and set the county name in the prescription dataset to title-case.

We also found mismatches between the county names in the two datasets. For example, “DeKalb” in the population dataset is written as “De Kalb” in the opioid prescription dataset, and “McDuffie” in the population dataset is noted as “Mcduffie” in the prescription dataset. After aligning the county names in the opioid shipments data with the ones in the population data, we confirmed that the misalignment of county names no longer exists. We then merged the two datasets using columns, “Year”, “State”, and “County”. The opioid shipments per capita is calculated by dividing the sum of opioid shipments in MME for a given county in a given year over the county’s population of that year.

Drug Overdose Mortality Rate per 100,000 People Data (2003-2015)

To obtain the drug mortality rate per 100,000 people, we merged the drug overdose mortality dataset with the county population dataset. The mortality dataset contains a column called “County Code”, which represents a unique combination of a county in a state. The county code is also commonly known as the FIPS code in similar analyses. Therefore, we decided to incorporate FIPS code[11], sourced from GitHub, into our population dataset. In the process, we renamed the county "Dọa Ana County" to "Doña Ana County" in the FIPS code dataset to align the naming convention with the population data. We also resolved a misalignment between the population and FIPS code datasets by assigning the FIPS code for Shannon County, SD (FIPS 46113) to Oglala Lakota County, SD. Oglala Lakota County is not available in the FIPS code dataset because the county was known as Shannon County (FIPS 46113) until May 2015. Our FIPS code dataset has not reflected the name change.

After the data wrangling steps above, we were finally able to merge the population and mortality datasets by FIPS code and year. We then subsetted the data based on the treatment and control states of interest. The drug mortality rate per 100,000 people is calculated by first dividing the sum of total deaths in a given county and year by the county’s total population in that year, then times 100,000 for better readability.

It is worth noting that the mortality data does not include death counts for counties with less than ten deaths due to privacy concerns. Since the data is missing systematically related to

[11] [GitHub - kjhealy/fips-codes]

unobserved variables, it is missing not at random (MNAR). Therefore, we need to select an appropriate imputation strategy. Though there are specific imputation methods developed to manage data MNAR, such as the selection models and pattern-mixture models, these methods are not yet mature enough to be applied. In this case, we imputed the missing values using the average deaths of a state in a given year. The rationale is that counties in a state are likely to experience similar death trends. However, we are also aware that this assumption introduces a degree of bias into our analysis because the imputation strategy produces optimal results when working with data missing at random.

IV. Summary Statistics

The tables below provide the summary statistics of mortality and shipment per capita for each target state and their control states.

Summary Statistics of Opioid Overdose Mortality per 100,000 People

	Florida (FL)	Control States	Texas (TX)	Control States	Washington (WA)	Control States
Mean	88.7	22.43	151.79	84.03	101.57	127.5
Std	111.42	25.03	712.41	183.65	178.45	530.15
Min	3.83	0.31	0.83	2.23	4.26	0
25%	13.63	7.69	15.02	15.98	14.81	7.14
Median	23.97	14.74	38.3	30.25	31.09	14.18
75th Q	134.22	27.61	104.79	69.39	101.14	44.49
Max	538.68	339.57	16132.98	1811.17	1114.22	7482.44

Among the three treatment states, Florida is observed to have the lowest mortality rate per capita on average, while Texas has the highest mortality rate per capita. However, we must note that the summary statistics can be masked by a large population. In other words, a lower average mortality rate does not directly translate to fewer deaths in Florida. The relatively small number can be attributed to the large population size of the state.

Summary Statistics of Opioid Shipments per Capita

	Florida (FL)	Control States	Washington (WA)	Control States
Mean	495.82	352.67	370.45	363.19
Std	311.17	224.53	155.37	212.24
Min	71.36	0.11	100.55	0.01
25%	277.11	195.55	254.71	212.44
Median	437.19	308.37	336.55	323.50
75th Q	623.62	459.95	450.75	479.63
Max	2279.13	2624.69	878.74	1353.77

From the above table, it can be found that the opioid shipments per capita in treatment states is generally higher than that of their control states. Meanwhile, Florida has higher opioid shipment per capita than Washington state.

V. Analysis

Analysis Methods and Crucial Assumptions

The Pre-Post analysis focuses on comparing the opioid shipment data and drug mortality data before and after the implementation of the drug policy to see whether the intervention of policies was effective. However, some unknown factors, such as national policy changes, shortage of opioid supply, and local-wide campaigns against opioids, may influence the results of the analysis. This may lead to policymakers wrongly attributing the decline of the opioid shipments and the drug mortality rate to the implementation of drug policies in control states.

To address the problem, we applied the Difference-in-Difference method to determine whether the states without the policy change were experiencing the same scale of declining opioid shipments or drug mortality rate as the states with drug policy change. This type of analysis helps us control the effects of nationwide changes. However, difference-in-difference methods are not bullet-proof because it is based on the assumption that the treatment state and control state exhibit similar trends pre-policy changes.

Opioid Shipments Analysis

Pre-post analysis for each treatment state

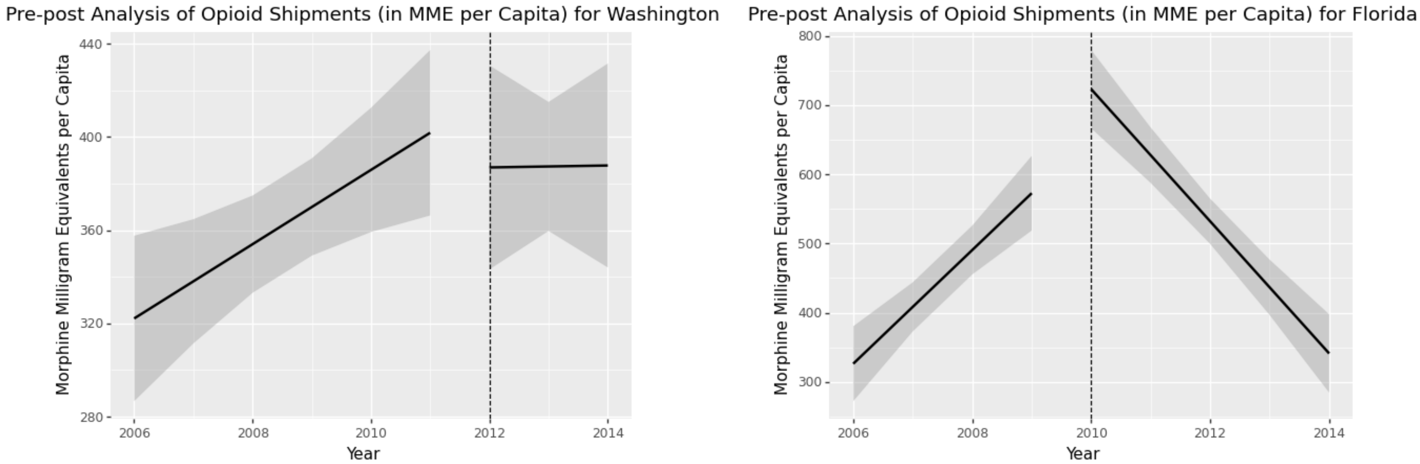

Figure 6. *Pre-Post analysis graphs for opioid shipments*
(from left to right: Washington and Florida)

Interpretation: From the graph above, we could see that the implementation of drug policy may have a positive effect on lowering the opioid shipments to some degree. The opioid shipments dropped rapidly after the policy implementation in Florida, while in Washington, the opioid shipments dropped slightly at the beginning of implementation and plateaued afterward. This suggests the implementation of policies might affect the trend of opioid shipments. It is necessary to check the difference-in-difference analysis to ensure the decline in opioid shipments was independent due to the policy implementation.

Diff-in-diff analysis for each treatment state and selected control states

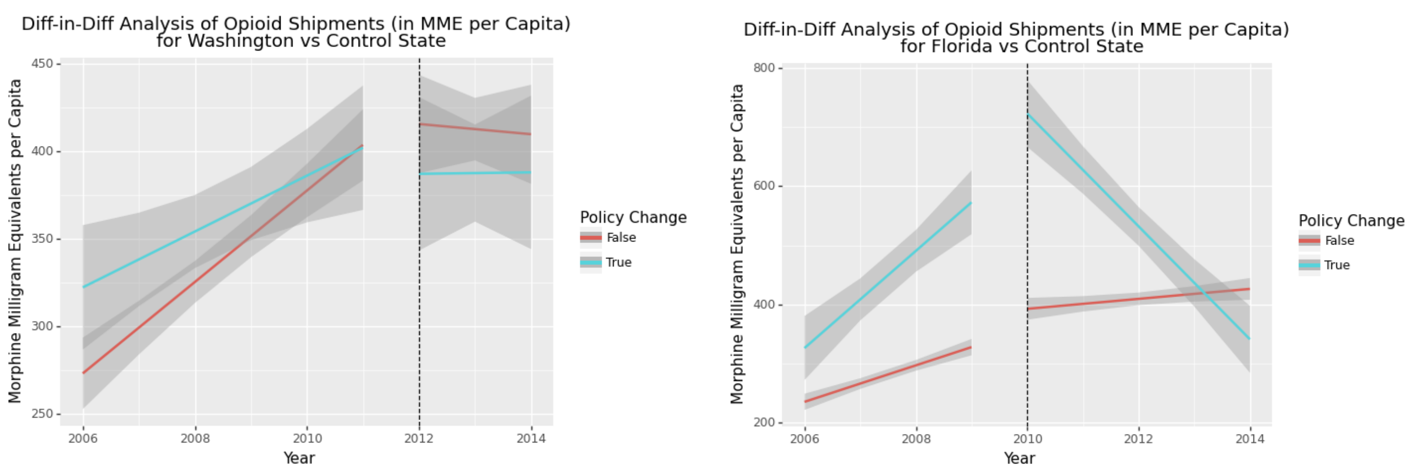

Figure 7*. Difference-in-Difference analysis graphs for opioid shipments*
(from left to right:Washington and Florida)

Assumption Check: From the graph above, we observed that the two treatment states, Washington and Florida, showed similar upward trends with their respective control states before the policy change. Therefore the difference-in-difference assumption is satisfied in this case and makes the analysis valid.

Interpretation: A slight decline in opioid shipments post-policy change in Washington, when compared to its control states, indicates that the government regulation had a limited effect on the drug abuse problem. Meanwhile, the control states of Florida showed that opioid shipments continued to grow after policy implementation while Florida experienced a sharp decline. This illustrates the drug policy worked effectively in Florida when controlling other confounding factors, such as national policy change.

Drug Mortality Rate Analysis

Pre-post analysis for each treatment state:

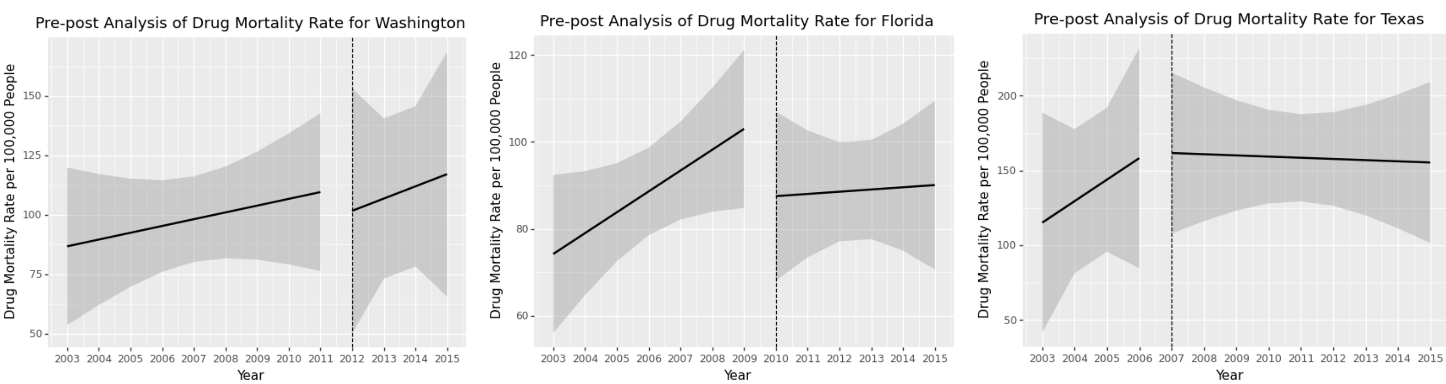

Figure 8. *Pre-Post analysis graphs for drug mortality rate*
(from left to right: Washington, Florida, Texas)

Interpretation: From the graph above, we observed that the implementation of the opioid policies had a positive effect on lowering the drug mortality rate to some levels. The drug mortality rate flattened after the policy implementation in Florida, while the mortality rate dropped slightly at the beginning of policy adoption in Washington, followed by sharp increase. Compared to Florida, the regulation in Washington seemed to have little effect on reducing the drug mortality rate. The drug mortality rate in Texas rose rapidly prior to the policy change. After policy implementation, we observed a slow decline, suggesting the regulation likely had a positive effect on the drug mortality rate in Texas.

Diff-in-diff analysis for each treatment state and selected control states

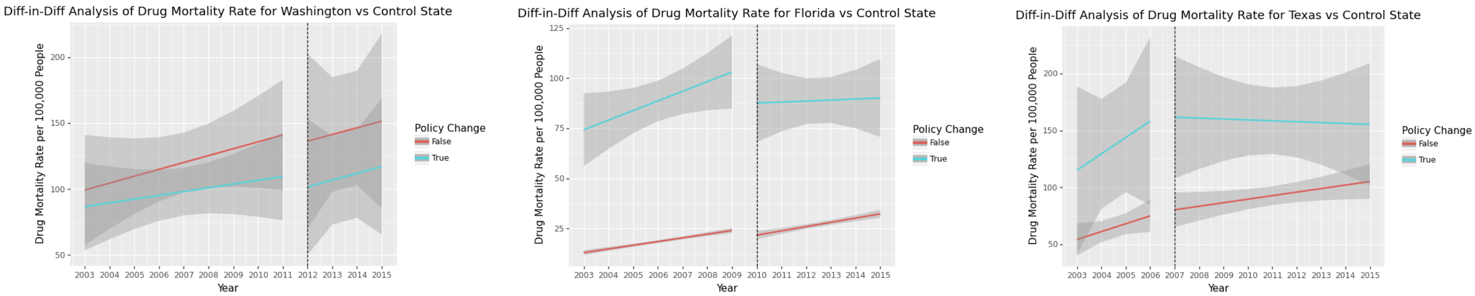

***Figure 9**. Difference-in-Difference analysis graphs for drug mortality rate*
(from left to right: Washington, Florida, Texas)

Assumption Check: From the graph above, we observed that both target states and control states exhibit the same similar trends, which confirms the assumption of our diff-in-diff analysis.

Interpretation: The opioid policies showed a positive effect in Florida. The control states reflected a continuous growth of the drug mortality rate in the year after policy implementation, while the drug mortality rate in Florida dropped after 2010 followed by slow growth. For Washington, we observed a temporary decline followed by continuous growth in deaths post-policy adoption, indicating the regulation had little effect on addressing the opioid epidemic. For Texas, we could see that the drug-related mortality started to decrease after policy implementation. This indicates that opioid policy in Texas indeed helped lower the drug mortality rate.

VI. **Limitations**

The first limitation of our analysis is that we have to assume the number of opioid shipments equates to the number of opioids prescribed. Due to HIPPA regulations, we are not able to obtain data at the doctor-to-patient prescription level. While opioid shipment data is an appropriate substitute, it does not provide the same level of information.

The second limitation of our analysis is that we do not have data for counties with fewer than ten deaths. Because of our strategy that imputes missing mortality data of a county using the average deaths of a state in a given year. Our analysis inevitably carries a degree of bias. The current constraint, however, can be better managed in future studies when imputation techniques of data not missing at random mature.

The third limitation of our analysis is that it only assesses the impact of state legislative regulations on opioid circulation in the legal markets. However, in retrospect, we now know that illicit synthetic opioids also fueled the opioid epidemic, causing thousands of drug-related overdose deaths.

The fourth limitation of our analysis is that we only looked into regulatory changes reinforced by law. Though the control states we selected did not pass legislation towards restricting opioid shipments until 2015, some of these states had quasi-regulatory guidelines in place during the early 2010s that may impact the accuracy of our analysis.

VII. **Conclusion**

Based on the results of the pre-post and the difference-in-difference analyses on drug mortality rate and opioid shipments, we concluded that the opioid regulations in Florida exhibit a positive effect in reducing drug overdose and opioid shipments, and drug policies in Texas contribute to the improvement in the drug overdose situation. In Florida, opioid shipments decreased drastically and the drug mortality rate flattened after the implementation of the drug policies, whereas both were increasing steadily prior to legislative changes. The drug policy in Texas also played a positive role in dwindling drug overdose deaths. The slope of the drug mortality rate in Texas is now negative, compared to the continuous positive growth in the control states.

On the contrary, Washington's opioid policy was not successful. We observed a small decline in overdose deaths and opioid shipments at the start of policy implementation. However, the same is observed in the control states, indicating that the decline is not a result of the policy changes. The drug mortality rate in Washington also grew much faster after the initial reduction. Additionally, though we observed a smaller decline and relatively flat growth of opioid shipments in Washington, similar or slightly better trends are identified in the control states. Therefore, we believe the opioid policies in Washington had little effect on reducing opioid prescriptions.

Beyond estimating the impact of opioid regulations, our analysis also hopes to provide a reference to future legislation. We believe the success of Florida's opioid policies in reducing opioid prescriptions can be attributed to reinforcement strategies such as statewide raids that resulted in numerous arrests, seizures of assets, and pain clinic closures. In addition, the state also had regulations for physicians and drug wholesale distributors, which effectively reduced the influx of opioids. This finding indicates that combating the opioid epidemic requires continuous effort. Regulations help, but reinforcements of law boost the effect.