# Estimating the Impact of Opioid Control Policies

(Report for Policy Makers)

Mohammad Anas, Sydney Donati-Leach, Deekshita Saikia and Aarushi Verma

November 23, 2021

## Motivation

This report describes the effect opioids have had on the U.S. population in terms of deaths caused by overdose and analyzes the impact of different states' policies to control opioid shipments in the hopes to decrease mortality rates. Opioids are medically prescribed pain medication that can come in the form of pills, patches, or nasal sprays. Opioid addiction has been a growing cause for concern, and the U.S. Department of Health and Human Services (DHSS) has declared a public health alert on opioid addiction and dependence. Patients who take opioids for an extended period can slowly stop experiencing the pain relief they had prior to taking them. In addition, the body can start to depend on the drug which causes withdrawal symptoms if the patient stops taking them. These factors are what lead to addiction because patients can become heavily dependent on the drug or take more than the prescribed amount. This often results in numerous incidents of overdose and subsequently, death.

Opioids have been a controversial topic that policy makers have been discussing in the last decade. Florida, Washington, and Texas are three states that have implemented policies to combat the opioid overdose epidemic. Texas was the first to regulate opioids in January 2007 which put a few hurdles in place before a practitioner could prescribe any opioid medication. These included patient evaluation, review of medical history, patient consent, periodic patient review, and complete medical records. This was followed by Florida, where, in 2010, a report was published which showed that of the top 100 opioid prescribing practitioners in the country, 98 were conducting practice in Florida. The policy aimed to regulate the many "pain clinics" that had popped up during the 2000's which housed many patients addicted to opioids. Florida saw more regulations in February 2011 when it started to conduct raids of the pain clinics and closed many. The last policy change occurred in 2012 when Florida created a task force specifically devoted to regulating wholesale drug distributors. Finally, Washington's regulation went into effect in January 2012 that added several requirements in place before a practitioner could prescribe opioids. Similar to Texas, these requirements included periodic patient reviews, milligram thresholds, strict documentation guidelines, and consultations with pain management experts.

# Methodology

Throughout the scope of this paper, we performed two types of analysis to evaluate the effect of the opioid regulation in their respective states: pre-post analysis and the difference in difference analysis.

Our pre-post analysis will look at the change over time for all the states to see if policy implementations influenced overdose deaths or opioid shipments. If policy did not have an effect, our plot will show overdose deaths and opioid shipments continuing to increase over time. If policy did have an effect, our plot will show overdose deaths and opioid shipments starting to decrease over time.

However, to effectively analyze the effect of the policy, we need to isolate the causal effect of the policy from other unknown factors that might be affecting our variables of interest simultaneously. These factors in this case could be the U.S. Customs making a policy change that affects imports of opioids in the U.S. This would likely reduce the shipment amount, and therefore, overdose deaths throughout the entire country. If we were just to use our pre-post analysis to compare Florida in 2009 to Florida in 2011, we would see a decline in the shipment amount and overdose deaths and wrongly attribute that to Florida's policy change.

A difference-in-difference approach seeks to answer the question of whether there were bigger changes in overdose deaths or opioid shipments in Florida between 2009 and 2011 than in other states that did not implement any regulations on opioids. To do this, we must look at states that did not implement a policy change in relation to opioids. We will choose three states to serve as our control group (i.e., the ones that did not implement a policy change) corresponding to each treatment state. Then, we will evaluate the effect of policy in that state using a pre-post analysis and compare the control and the treatment groups.

# Data

We used the Opioid Prescriptions by The Washington Post to obtain the quantity of opioids prescribed, which was available in the data at monthly level for the years 2006 to 2012. The US Vital Statistics records provided us with the information on deaths caused by opioid overdose for each county within the United States. To account for the population of each county, we combined these datasets with the County Population Data by The National Historical Geographic Information System (NHGIS), which contained the population estimates from 2009 to 2019. From this, we were able to calculate shipments per capita and the deaths per capita for each county for the respective years.

We used the Income data by IPUMS National Historical Geographic Information System (NHGIS) which consisted of the median household income for each county and state in 2010. We chose 2010 because it was relatively centered in relation to the years we had in the other data sets.

# Analysis

## Pre-post and Difference-in-difference analysis

## Florida

<u>Effect of regulations on opioid shipments</u>

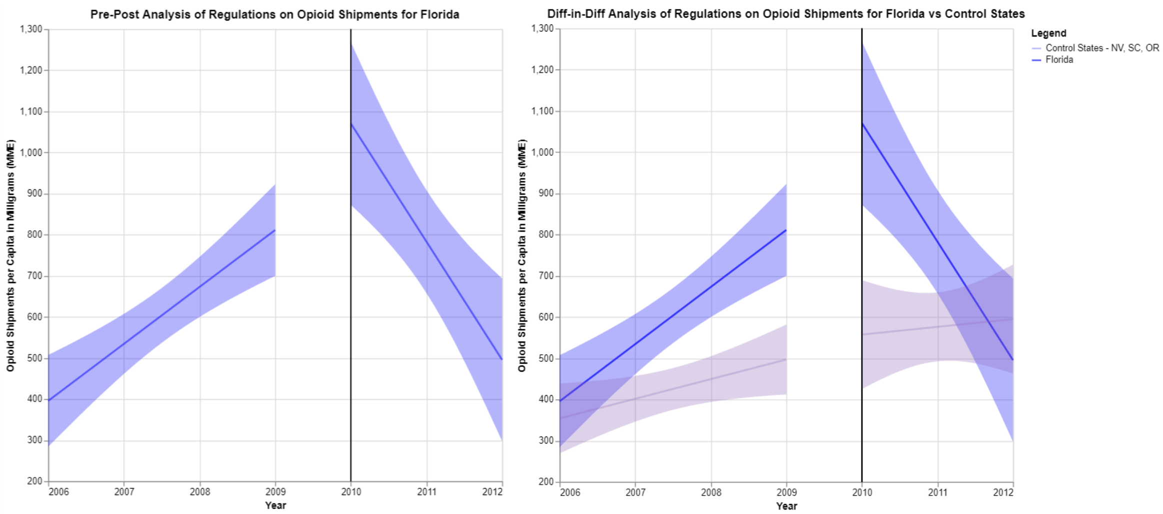


Fig.1.1: Snapshot of opioid shipments, before and after implementation of policy, which came into effect in Florida in February 2010. There is a noticeable decline in the number of shipments, as is evident from the graph on the left. The graph on the right shows the comparison between FL and control states (SC, NV, OR), which did not implement policies. The volumes of opioid shipments for these states post 2010 do not decline.

When looking at the opioid prescriptions per capita before and after the policy was implemented, we note that opioid shipments exhibited an increasing trend before the policy was implemented. However, after the regulation was put into effect, there was a sharp decline in the shipments per capita. This can be clearly seen in the pre – post analysis graph above (left). To understand whether this sharp decline was solely due to the restrictions implemented, we also look at how the shipments per capita changed during the same years for the control states - Nevada, South Carolina, and Oregon. We note that for these states the shipments per capita continued to increase throughout the years after the policy was implemented in Florida in 2010. This indicates that the policy was successful in curbing the shipments per capita influx for Florida.

<u>Effect of regulations on mortality rate from drug overdose</u>

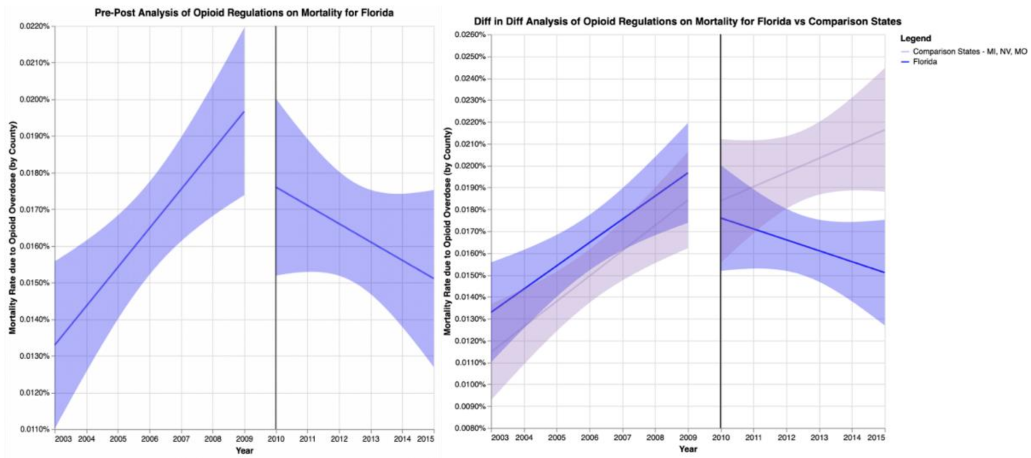


Fig.1.2: Snapshot of mortality rate from drug overdose, before and after implementation of policy, which came into effect in Florida in February 2010. There is a decline in mortality rate, as is evident from the graph on the left. The graph on the right shows the comparison between FL and control states (MI, NV, MO), which did not implement policies. The mortality for these states post 2010 do not decline.

From the graph on the left above, we observe that the average mortality rate due to drug overdose rises until the implementation of the policy year in 2010, peaking at about 0.02% in 2009. The mortality rate drops post the implementation of the policy, and continues a downward trend, which might not have been the case if the policy was not implemented. From the difference-in-difference analysis, we observe that the average mortality rates for the comparison states continue their upward trend, before and after 2010. This suggests that the opioid regulations had a positive impact in reducing the mortality rate in the state of Florida.

## Washington

<u>Effect of regulations on mortality rate from drug overdose</u>

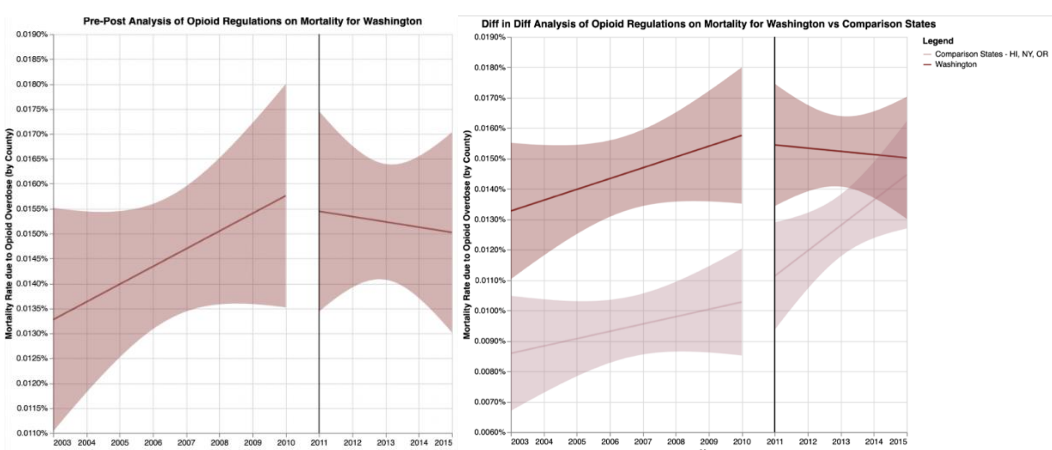


Fig. 2: Snapshot of mortality rate due to drug overdose, before and after implementation of policy, which came into effect in Washington (WA) in 2011. There is a slight decline in mortality rate, as is evident from the graph on the left. The graph on the right shows the comparison between WA and control states (HI, NY, OR), which did not implement policies. The mortality for these states post 2010 show an increasing trend.

From the graph on the left above, we observe that the average mortality rate due to drug overdose rises until the implementation of the policy in Washington in January 2012, peaking at about 0.02% in 2010. The mortality rate drops post the implementation of the policy, although not by a significant amount. From the difference-in-difference analysis, we observe that the average mortality rates for the comparison states, whose rates were lower than Washington, continue their upward trend, before and after the implementation of the policy. This suggests that the opioid regulations had a positive impact in the state of Washington, although the success of the policy would be questionable, given the magnitude of the impact.

## Texas

Effect of regulations on mortality rate from drug overdose


Fig.3: Snapshot of mortality rate due to drug overdose, before and after implementation of policy, which came into effect in Texas (TX) in 2007. No significant effect of the policy can be observed from the graph on the left. The graph on the right shows the comparison between TX and control states (IL, NY, OR), which did not implement policies. The mortality for these states post 2007 show a sharper increase in comparison to TX.

When looking at the pre-post analysis for Texas, we observe that the trend for mortality rates for drug overdose increases up until the implementation of the regulations in Texas in 2007. The mortality rate rises to close to 0.008% in 2006. However, post the policy implementation, we observe that the trend for mortality continues to rise. If we compare this analysis with the difference-in-difference analysis, we observe that Texas has lower rates than its comparison states, before and after the implementation of the policy. However, even though Texas has lower rates, we cannot conclude that the policy had any effect in this state.

## Insights from Income

We also explore if the household incomes of different counties had an effect of the opioid regulations policies. Specifically, we are interested in how the effect varies for high income and low-income counties. The counties within each of our treatment states were classified into high and low-income counties based on certain threshold levels specific to our states of interest. We calculated this threshold by considering the average median household income for all the counties within that state. Counties with median household income above the average were classified as high-income counties and the rest were classified as low income.

## Florida

Effect of regulations on opioid shipments by Income

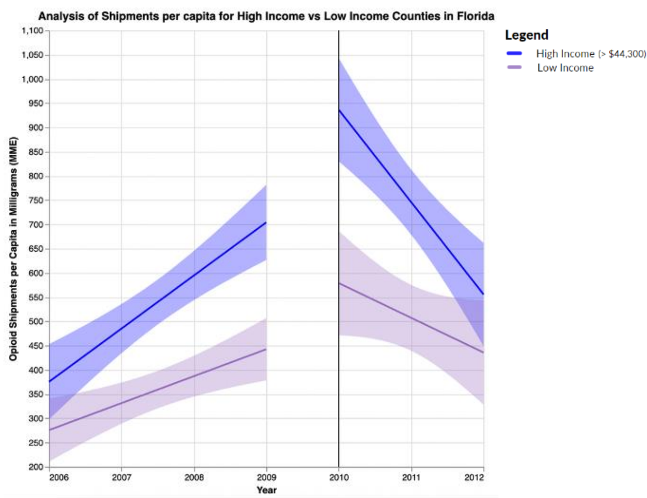


Fig.4.1: We observe that post the policy changes, the higher income counties of Florida witnessed a sharper decline in opioid shipments than the lower income counties.

We see that the high-income counties had higher shipments per capita, and this trend continues to move upward before the policy was implemented. The shipments per capita for lower income counties also increased in the years leading up to the implementation of the policy. However, the slope for this trend does not increase as sharply for the low-income counties, as it does for the high-income counties. After the policy was implemented, there was a greater decline in the shipments per capita for the high-income counties in comparison to low-income counties. This decreasing trend continued successively over the years after the policy was implemented.

Effect of regulations on mortality rate by Income


Fig.4.2: Shows the pre-post policy comparison on mortality rates at an income level for Florida (FL). We observe a steep rise in the death rates for lower income counties leading up to the policy year. Post policy implementation reflects a steeper decline in mortality rate for lower income households than high income households

When we look at the effect of policy on mortality rates, we notice that before 2010, the mortality rates for both high and low-income counties was increasing steadily. In 2009, the mortality rate for the high and low-income counties was approximately the same. The policy proved to be effective in decreasing the mortality rate for both high and low-income counties. The decline in mortality rate for low-income was sharper as compared to the high-income counties.

## Washington

Effect of regulations on mortality rate by Income

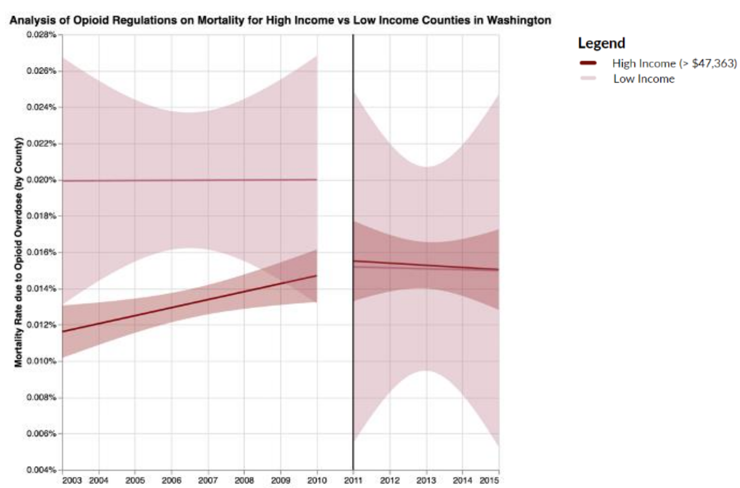


Fig.5: Shows the pre-post policy comparison on mortality rates at an income level for Washington (WA). The low-income households have a constant mortality rate before policy implementation. We observe a decline in the death rates for both low-income and high-income counties post the implementation of the policy. The decline is slow, however its more for high income counties than low-income counties.

When we look at the effect of policy on high and low-income counties in Washington, we see that the mortality rate for low-income counties was unchanging but significantly higher than the high-income counties before the policy was implemented. Although, the high-income counties had a lower mortality rate in comparison to the low-income counties, we observe an increasing trend until the policy was implemented. Post policy implementation, the mortality rate fell significantly for low-income counties. For the high-income counties, the policy was able to control the increasing trend in mortality rate that was observed before 2011. After 2011, we see that the mortality rate for both high and low income counties starts to decrease, however at a very low rate.

### Texas

<u>Effect of regulations on mortality rate by Income</u>

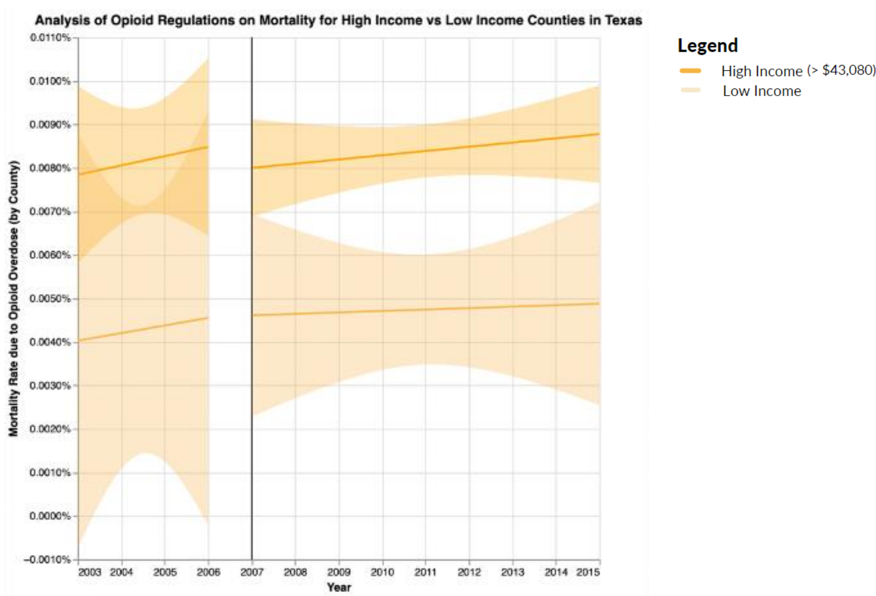


Fig.6: Shows the pre-post policy comparison on mortality rates at an income level for Texas (TX). There policy does not seem to be very effective, since the mortality rate for both high- and low-income households continues to increase post policy implementation. We do observe that rate of increase has reduced.

For Texas, in high income counties, the mortality rate caused by opioid overdose were considerably higher than the low-income counties before and after the policy. The opioid regulation in Texas seems to be quite ineffective as the trend for mortality rates remain unchanged in the periods before and after the policy changes. However, the rate of increase in mortality rates for both high- and low-income counties decreases by a small fraction after the policy was put into effect.

# Limitations

The first limitation of our analysis is that we only included counties with population above 400,000 due to counties with missing mortality rates. Therefore, we can assume the calculations would be higher than they are appearing if we were to include all counties and get the exact number of deaths per capita. Secondly, while identifying the control states in the analysis, we selected the states where the opioid regulation policies were not implemented by the force of law. However, some of these states had quasi-regulatory guidelines which are enforced through fines and penalties.

# Conclusion

Based on the graphs of our pre-post and difference-in-difference analysis, Florida's drug policy was effective in decreasing the shipments of opioids as well as effective in declining the overall growing trend of its mortality rate. Texas's drug policy was not very successful as the overall trend of the average mortality rate did not decline after the policy went into effect. The increasing slope is not as steep as it was before the policy change, but the rate is still increasing, nonetheless. Washington's drug policy was potentially successful since its average mortality rate declined after the policy was implemented.

Why was Florida so successful and Texas unsuccessful? If we look into these policies, we can see a distinct difference. In Florida, the policies were directed towards the physicians and the pain clinics dispensing the medication. The strategy was to go to the source by conducting raids and closing pain clinics to stop the influx of opioids there. In Texas, the freedom was given to the people. It did not set any thresholds on the number of opioids a patient could receive, but instead only required patient consent to receive opioids. Since addiction is already a key issue with opioids, patients most likely did not change their intake, so it makes sense why Texas did not see a decrease in deaths per capita.

Both the pre-post comparison and difference-in-difference analysis provided straightforward ways for us to see how policies affected the trend on opioid shipments and mortality rate due to drug overdose. However, we must keep in mind that the work is far from over. Even after a successful policy change, there are still opioid overdose deaths occurring. Additionally, a decreasing trend can potentially start to increase again if policies are not adjusted to keep up with societal changes. Policy makers must be vigilant, and the key to that is understanding which policies work and which do not.

# Citations


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Mid-Semester Project, Practical Data Science

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Opioids have been a controversial topic that policy makers have been discussing in the last decade. Florida, Washington, and Texas are three states among a few that have implemented policies to combat the opioid overdose epidemic. Texas was the first to regulate opioids in January 2007 which put a few hurdles in place before someone could get an opioid medication. These included patient evaluation, review of medical history, patient consent, periodic patient review, and complete medical records. This was followed by Florida, where, in 2010, a report was published which showed that of the top 100 opioid prescribing practitioners in the country, 98 were conducting practice in Florida. The policy aimed to regulate the many "pain clinics" that had popped up during the 2000's which housed many patients addicted to opioids. Florida saw more regulations in February 2011 when it started to conduct raids of the pain clinics and closed many. The last policy change occurred in 2012 when Florida created a task force specifically devoted to regulating wholesale drug distributors. Finally, Washington's regulations went into effect in January 2012 that added several requirements in place before a practitioner could prescribe opioids. Like Texas, these requirements included periodic patient reviews, milligram thresholds, strict documentation guidelines, and consultations with pain management experts.

The goal of our project is to estimate the effectiveness of opioid drug prescription regulations on:

- The quantity of opioids prescribed
- Deaths due to drug overdose
- Both parameters at an income level

# Research Design Motivation

To effectively analyze the impact of the policy changes in Florida, Washington, and Texas we must look at states that did not implement a policy change in relation to opioids. We are looking at the causal effect of these regulations on opioid prescriptions rather than the correlation between them. However, the issue we face is to isolate the effect of the policy change from other confounding variables. We tackle this problem by choosing 3 states that serve as our control group for each state that implemented a policy change. Then we evaluate the effect of policy in that state using two causal inference methods to compare the control and the treatment groups:

a. Pre-post analysis: It is a basic causal inference strategy that compares how our variable of interest looks before an event takes place (in this case the policy implementation) to how it looks after the event. For our study, we will be comparing the number of opioid prescriptions and death rate due to drug overdose, right before and after the policy went into effect for each of our states (Florida, Texas, and Washington). If the trend of number of opioid prescriptions (per capita) and death rate due to drug overdose tends to fall after policy implementation, we can infer that the policy had a positive impact. On the contrary if this trend doesn't change and tends to increase further, we can infer that the policy was ineffective. While pre-post comparison is simple, it overlooks the fact that there may be other factors at play at a given point in time. For example, if US Customs service managed to significantly reduce fentanyl imports into the United States, this would likely reduce the number of overdose deaths. But it would be unfair to attribute this decrease solely to the policy implemented. Therefore, we also need to introduce a difference-in-difference approach to our project.

b. Difference in difference analysis: Through this approach, we look at our treatment states' pre-post policy impact to the other states' pre-post policy impact during the same period. If the policy was effective, we expect treatment states' post-policy trend to be different than other states without a policy change. The difference-in-difference approach minimizes the potential nationwide impact of any other external factors that may have been at play.

# Datasets

We were provided with two datasets for this project that needed cleaning and reorganization to make them more usable. The datasets were as follows:

1. Opioid Prescriptions by *The Washington Post*: This data included prescription opioid drug shipments in the United States from 2006 to 2012. This was a large dataset, which included columns that were not required for analysis. To facilitate working with large data, we only imported the required columns while reading the file which included the State and County of the drug buyer, transaction date, MME conversion factor, and total weight of the drug shipments. The data included observations for multiple kinds of opioids and to standardize our analysis and ease of drawing conclusions we calculated the total morphine equivalent in milligrams for each drug using the morphine conversion and weights provided in the data. Next, the total morphine equivalent (MME) attribute was grouped by Year, State

and County to proceed with our analysis. We utilize these aggregated values to calculate shipments per capita.

2. Mortality due to drug overdose by *The US Vital Statistics records*: This data included information on the annual number of deaths for each county in each state. We separated the 2 letter State ID from the county column into a new column to be able to view our analysis at a state level. We took a subset of the data for only drug overdose related deaths and aggregated the number of deaths, grouped the data by Year, State and county to proceed with our analysis.

Our objective in the analysis is to compare the impact of opioids on the number of deaths and shipments, before and after policy implementation. For this purpose, considering the absolute values for death and shipments would not be indicative of the actual scenario. Since states and counties differ in terms of geographical areas and population, using values normalized by population for our analyses would be appropriate. Therefore, we also fetch population data to use with our existing datasets.

3. County Population Data by *The National Historical Geographic Information System (NHGIS)*: This data included population estimates at the county level for each state for the years 2000 to 2019, along with the census values for years 2000 and 2010. The FIPS codes in this dataset serve as a key to merge with the shipment dataset.

With these three datasets we have State and County level information for each year on opioid shipments from 2006 to 2012, drug overdose deaths from 2003 to 2015 and population data from 2000 to 2019. We then calculate the overdose deaths and opioid shipments per capita by dividing the overdose deaths and morphine equivalents of shipments by the corresponding county population of each state.

4. Income data by *IPUMS National Historical Geographic Information System (NHGIS)*: This data consists of the median household income for each county and state in 2010. We chose 2010 because it was relatively centered in relation to the years, we had in the other data sets. Income can be compared against the shipment or the death data to see if there is any correlation or trend between high or low-income counties, and the rate of deaths in or amount of opioid shipments to that area.

## Merging

Mortality Data

Before starting the analysis, we made sure that our final dataset included the following columns: year, state, county, deaths from drug overdose, county population for the year, and the mortality rate. We concatenated mortality data across all years into a single dataframe and dropped the irrelevant columns. We filtered our mortality data only to drug related deaths, as listed below:

- Drug poisonings (overdose) Unintentional (X40-X44)
- Drug poisonings (overdose) Suicide (X60-X64)
- Drug poisonings (overdose) Undetermined (Y10-Y14)
- Drug poisonings (overdose) Homicide (X85)

- All other drug-induced causes

Some counties in the mortality dataset had values as "Missing" in the overdose death column due to the nature of the data since any county with fewer than 10 death tolls are not reported. We replaced these with NAs and then grouped the deaths for each county per year to match the level of observation with our population dataset. The mortality rate is calculated by dividing the number of deaths by the population of each county. With the unit-of-observation in mind, we cleaned the data for all states to make the comparison for our difference-in-difference method easier. This also helps us reduce the size of the data making it easier to work with.

The census data obtained from the IPUMS NHGIS was available in two datasets

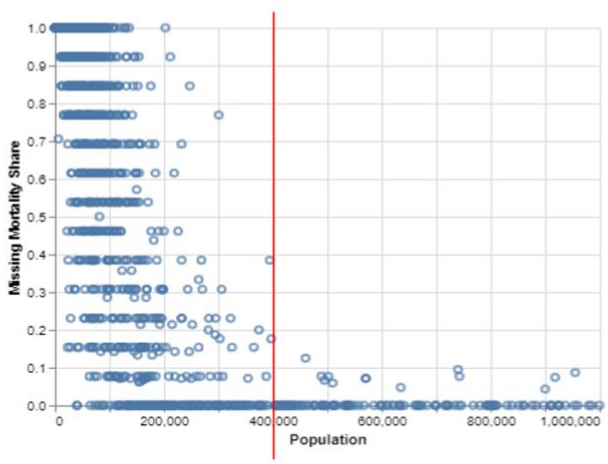
i) Census 2000 numbers, and the population estimates for 2001 to 2009

ii) Census 2010 numbers along with the estimates for 2011 to 2020

The population estimates are available at a county level. Moreover, state codes from an external source were also merged to this dataset for ease of merging with the mortality dataset.

After merging our mortality data with the population dataset, we check for nulls, and found that over 80% of the counties in our data did not have a value for the number of deaths across years. Since it is not advisable to impute this proportion of nulls in our dataset, we instead look at the proportion of counties across all years for which mortality data is available.

Missing mortality share per county vs. Population




From the plot above, we focus on the counties for which we have data populated across all the years (value 0.0 on the y-axis). We choose a population threshold of 400,000, as we can observe from the graph above, that beyond this threshold, counties have less missing mortality rates across years. We are left with 17 counties with missing mortality data, the values for which we impute using a k-nearest neighbour approach.

Shipment Data

Our initial dataset allowed us to take a deep look into the surge of legal pain pills that fueled the prescription opioid epidemic, which resulted in nearly 130,000 deaths during the nine-year time frame ending in 2014. When parsing through the dataset we can see that the original dataset contained 41 different variables.

We wound up narrowing the variables down to the pertinent ones, that would help us more closely analyze the distribution of legal opioids throughout the country, on a county level. Additionally, the morphine conversion factor was in units of milligrams, so for the sake of uniformity in our dataset, we converted the total active weight of the drug from grams to milligrams. Lastly, to create a column of the morphine equivalent drug weight, we multiplied the morphine conversion factor by the active weight. To merge the shipment data with the population data, we had to map the County FIPS code in both our datasets since there were a high number of mismatches in terms of county names between the 2 datasets. The FIPS code is a 5 digit unique identifier for each county wherein the first 2 digits represent the state and the following 3, the county. Using the state and county FIPS codes available in the dataset, we concatenate these values to generate a unique 5-digit FIPS code for each county, which serves as a key to merge with the shipment dataset.

After cleaning, properly formatting, and merging our shipment data with the corresponding counties' population data, this serves as the analysis-ready dataset. It is worth noting that, not all the population values for all counties were available in the census data. Upon closer inspection, we observe that most of the missing values correspond to U.S. territories, which we do not consider in our analysis. The population for the Montgomery County of Arkansas was also missing, which was manually inserted into the dataset.

## Comparison States

The goal of our analysis is to determine if these policy changes had an impact on the opioid epidemic in the states where policies were implemented (treatment) as compared to the states where policies were not implemented (control/comparison). To do this, we need to ensure in our selection process that the treatment states and the control states are similar in nature. Depending on the outcome variable of interest (i.e., deaths per capita or shipments per capita) we observe the trend of this outcome before the years the policy was implemented in the states of interest.

We created several plots with the years on the x-axis and the outcome variable (deaths-per-capita or shipment-per-capita) on the y-axis for all the control states and a random selection of other states *(Appendix Figures 1-4)*. Note that the timeline will be different for the two different outcome variables as well as the different states. For deaths-per-capita, the timeline begins in 2003 for all the states, and for shipment-per-capita, the timeline begins in 2006. This is purely due to the data that was available at the time of this analysis.

Our strategy was to use these plots to select which states to use for comparison for each state that implemented a policy by looking for states that had similar trends before the policy was implemented. Our second criteria when choosing control states was to ensure the comparison state did not implement a policy change in the timeframe that we were concerned about. This helps us single out the effect of the policy implemented in our treatment states and assess its effectiveness. We used a list from the Arizona Department of Health Services which included requirements with the force of law, quasi-regulatory guidelines, and advisory guidelines. If a state had requirements with the force of law that were enacted during our review period, we did not include these states in any control group. For clarity, we have included the table below which outlines the year each treatment state implemented its policy change, the outcome variable of either deaths per capita or shipment per capita, and the three control states for each treatment state.

| State | | Florida (FL) | Texas (TX) | Washington (WA) |
|---|---|---|---|---|
| Year of Policy Change | | 2010 | 2007 | 2011 |
| Comparison States for Mortality | 1 | Michigan (MI) | Illinois (IL) | New York (NY) |
| | 2 | Nevada (NV) | New York (NY) | Hawaii (HI) |
| | 3 | Missouri (MO) | Oregon (OR) | Oregon (OR) |
| Comparison States for Shipment | 1 | Oregon (OR) | | |
| | 2 | Nevada (NV) | | |
| | 3 | South Carolina (SC) | | |

Table 1: List of Comparison States selected for each Treatment State

Florida is the only state in which we can understand how opioid shipments were impacted by policy change because of the timeframe of the shipment data. If we were to analyze Texas against the shipment data, there is only one year before its policy change in 2007 which is not enough evidence to say if policy had an impact or not. Similarly, if we were to analyze Washington against the shipment data, there is only one year of data after its policy change in 2011 for us to determine if there was an impact or not.

# Summary Statistics

The tables below are a brief overview of what occurred in each state both before and after the policy implementation. We observe the measures of central tendency as exploratory analysis for our data.

| Summary Statistics for Mortality Rate | | | | | | |
|---|---|---|---|---|---|---|
| State | Year of Policy Implementation | Statistics | Mean | Median | Min | Max |
| Florida | 2010 | Before | 0.017% | 0.016% | 0.005% | 0.035% |
| | | After | 0.016% | 0.015% | 0.005% | 0.037% |
| Control | | Before | 0.015% | 0.015% | 0.005% | 0.027% |
| (MI, NV, MO) | | After | 0.020% | 0.020% | 0.008% | 0.036% |
| Washington | 2011 | Before | 0.015% | 0.014% | 0.007% | 0.027% |
| | | After | 0.015% | 0.015% | 0.010% | 0.023% |
| Control | | Before | 0.009% | 0.009% | 0.001% | 0.026% |
| (IL, NY,OR) | | After | 0.013% | 0.012% | 0.006% | 0.031% |

| Summary Statistics for Mortality Rate | | | | | | |
|---|---|---|---|---|---|---|
| State | Year of Policy Implementation | Statistics | Mean | Median | Min | Max |
| Texas | 2007 | Before | 0.008% | 0.008% | 0.002% | 0.019% |
| | | After | 0.008% | 0.008% | 0.002% | 0.015% |
| Control | | Before | 0.008% | 0.007% | 0.001% | 0.024% |
| (NY, HI, OR) | | After | 0.011% | 0.010% | 0.004% | 0.031% |

Table 2: Summary Statistics for Treatment and Comparison States for Mortality Rate. The Table shows comparison of summary statistics before and after policy implementation for each treatment states respectively.

From the table above, we can infer that the mean mortality rate per capita in Florida was 0.0165% in the years before the policy was implemented and decreased by 0.0001% to 0.0164% in the years after the policy change. The opposite was true in Washington and Texas which both have an increase in the mean mortality rate per capita after the policy was implemented. In contrast, the control states for Washington and Texas have a much larger jump in the mean mortality rate per capita after 2011 and 2007 respectively.

| Summary Statistics for Opioid Shipments per Capita (in Milligrams (MME) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| State | Year of Policy Implementation | Statistics | Total opioids per capita | Mean | Median | Min | Max |
| Florida | 2010 | Before | 2413.93 | 603.48 | 581.85 | 418.87 | 831.35 |
| | | After | 2349.01 | 783 | 796.94 | 488.5 | 1063.55 |
| Control | | Before | 5106.13 | 425.51 | 433.54 | 289.79 | 593.62 |
| (NV, SC, OR) | | After | 5186.3 | 576.26 | 535.61 | 486.67 | 725.61 |

Table 3: Summary Statistics for Florida and Comparison States for Opioid Shipments per capita. The Table shows comparison of summary statistics before and after policy implementation for Florida

When we look at the numbers of opioid shipments per capita in milligrams, we can see a clear decrease in total amount of opioids after the policy was implemented in Florida. The total opioid shipments per capita went down by 2.6% to 2,349 milligrams after the policy regulations were introduced. However, it appears as though the mean opioid shipments per capita are increasing after the policy change. It is possible this can be attributed to the opioid shipments peaking at the beginning of 2010, which is included in our "after" statistics.

# Analysis

## Assumptions

Before we look at our results, we must first talk about a few assumptions. First, if the deaths per capita or the shipments per capita are decreasing after the policy change, we will assume that the policy was successful. If the deaths per capita or the shipments per capita continue to increase after the policy change, we will assume the policy was unsuccessful. Secondly, for our control states, since they did not implement a policy, we will assume an increase in deaths per capita or shipments per capita will be a result of the state not taking action to control these metrics. A decrease in deaths per capita or shipments per capita for the control states would be unexpected and we would not be able to determine to what we should attribute that decline. Third, we will assume that these calculations of deaths per capita are not entirely accurate because we did not include counties with a population below 400,000. Therefore, we can assume the calculations would be higher than they appear if we were to include all counties and get the exact number of deaths per capita.

# Pre-post and Difference-in-difference Analysis

## Florida

Effect of regulations on opioid shipments

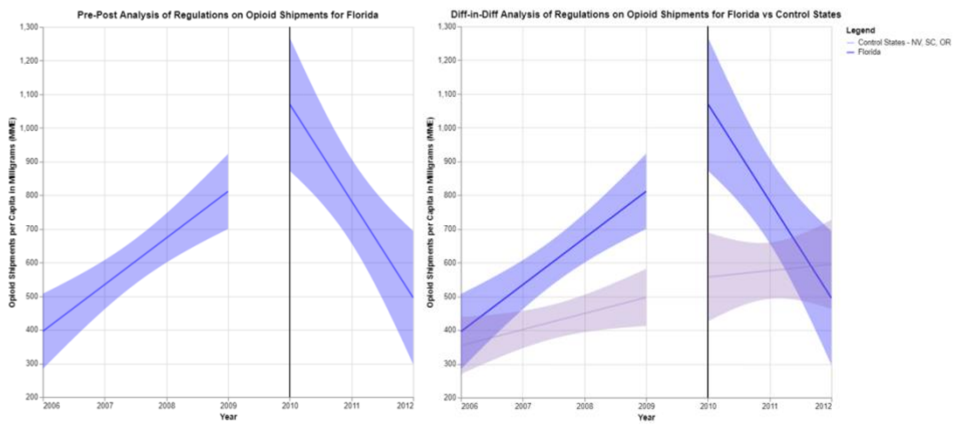



Fig.1.1: Snapshot of opioid shipments, before and after implementation of policy, which came into effect in Florida in February 2010. There is a noticeable decline in the number of shipments, as is evident from the graph on the left. The graph on the right shows the comparison between FL and control states (SC, NV, OR), which did not implement policies. The volumes of opioid shipments for these states post 2010 do not decline.

When observing the morphine ratio pre and post implementation of policies in Florida, we observe that from 2006 up until the year of the policy change, the ratio of morphine to Florida county's population has an upward trend. The annual morphine (in milligram equivalent) to population ratio was roughly 400: 1 (mg to person), which rose to nearly 800:1 in 2009, signifying an almost 200% increase. Post implementation of regulations in 2009, we observe a downward trend in shipments, with the morphine to population ratio falling to about 500:1 in 2012. If we look at the difference-in-difference analysis, we can see that before the policy change went into effect, the average MME per capita shipments continue their upward trend from 2006 till 2012, for the comparison states. Based on this difference in slopes, we can infer that the policy was effective as we observe a downward trend in the MME to population ratio on a year-to-year basis.

Effect of regulations on mortality rate from drug overdose

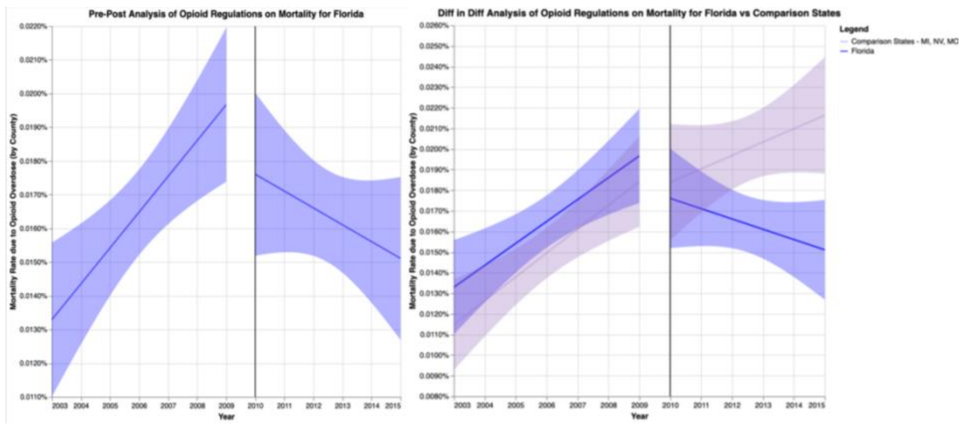



Fig.1.2: Snapshot of mortality rate from drug overdose, before and after implementation of policy, which came into effect in Florida in February 2010. There is a decline in mortality rate, as is evident from the graph on the left. The graph on the right shows the comparison between FL and control states (MI, NV, MO), which did not implement policies. The mortality for these states posts 2010 do not decline.

From the graph on the left above, we observe that the average mortality rate due to drug overdose rises until the implementation of the policy year in 2010, peaking at about 0.02% in 2009. The mortality rate drops post the implementation of the policy, and continues a downward trend, which might not have been the case if the policy was not implemented. From the difference-in-difference analysis, we observe that the average mortality rates for the comparison states continue their upward trend, before and after 2010. This suggests that the opioid regulations had a positive impact on reducing mortality rates in the state of Florida.

## Washington

Effect of regulations on mortality rate from drug overdose

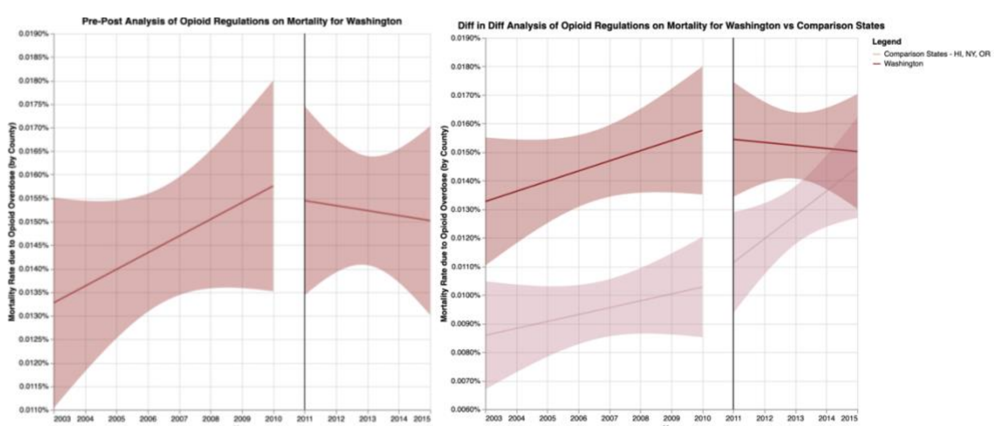



Fig. 2: Snapshot of mortality rate due to drug overdose, before and after implementation of policy, which came into effect in Washington (WA) in 2011. There is a slight decline in mortality rate, as is evident from the graph on the left. The graph on the right shows the comparison between WA and control states (HI, NY, OR), which did not implement policies. The mortality for these states post 2010 show an increasing trend

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From the graph on the left above, we observe that the average mortality rate due to drug overdose rises until the implementation of the policy in Washington in January 2012, peaking at about 0.02% in 2010. The mortality rate drops post the implementation of the policy, although not by a significant amount. From the difference-in-difference analysis, we observe that the average mortality rates for the comparison states, whose rates were lower than Washington, continue their upward trend, before and after the implementation of the policy. This suggests that the opioid regulations had a positive impact in the state of Washington, although the success of the policy would be questionable, given the magnitude of the impact.

## Texas

<u>Effect of regulations on mortality rate from drug overdose</u>

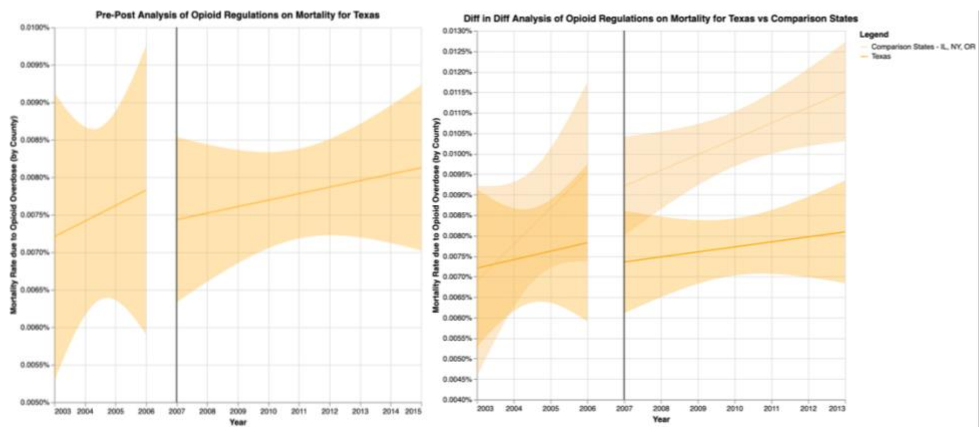


Fig.3: Snapshot of mortality rate due to drug overdose, before and after implementation of policy, which came into effect in Texas (TX) in 2007. No significant effect of the policy can be observed from the graph on the left. The graph on the right shows the comparison between TX and control states (IL, NY, OR), which did not implement policies. The mortality for these states post 2007 show a sharper increase in comparison to TX.

When looking at the pre-post analysis for Texas, we observe that the trend for mortality rates for drug overdose increases up until the implementation of the regulations in 2007. The mortality rate rises to close to 0.008% in 2006. However, post the policy implementation, we observe that the trend for mortality rate continues to rise. If we compare this with the difference-in-difference analysis, we observe that Texas has lower rates than its comparison states, before and after the implementation of the policy. However, even though Texas has lower rates, we cannot conclude that the policy had any effect in this state.

## Insights from Income

We also explore if the household incomes of different counties had an effect on the opioid regulations policies. Specifically, we are interested in how the effect varies for high income and low-income counties. The counties within each of our treatment states were classified into high and low-income counties based on certain threshold levels specific to our states of interest. We calculated this threshold by considering the average median household income for all the counties within that state. Counties with median household income above the average were classified as high-income counties and the rest were classified as low income.

Our analysis included the median income per household for the year 2010 only. The variation in income between years was very minimal compared to difference in income among counties and therefore, we assumed that the relative incomes of all the counties varied each year similarly.

## Florida

Effect of regulations on opioid shipments by Income

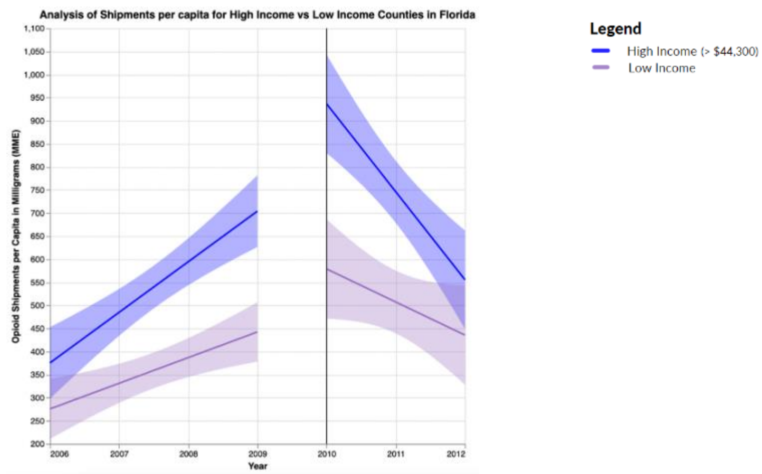


Fig.4.1: Shows the pre-post policy comparison on mortality rates at an income level for Florida (FL). We observe that post the policy changes, the higher income counties of Florida witnessed a sharper decline in opioid shipments than the lower income counties.

We see that the high-income counties had higher shipments per capita, and this trend continues to move upward before the policy was implemented. The shipments per capita for lower income counties also increased in the years leading up to the implementation of the policy. However, the slope for this trend does not increase as sharply for the low-income counties, as it does for the high-income counties. After the policy was implemented, there was a greater decline in the shipments per capita for the high-income counties in comparison to low-income counties. This decreasing trend continued successively over the years after the policy was implemented.

Effect of regulations on mortality rate by Income

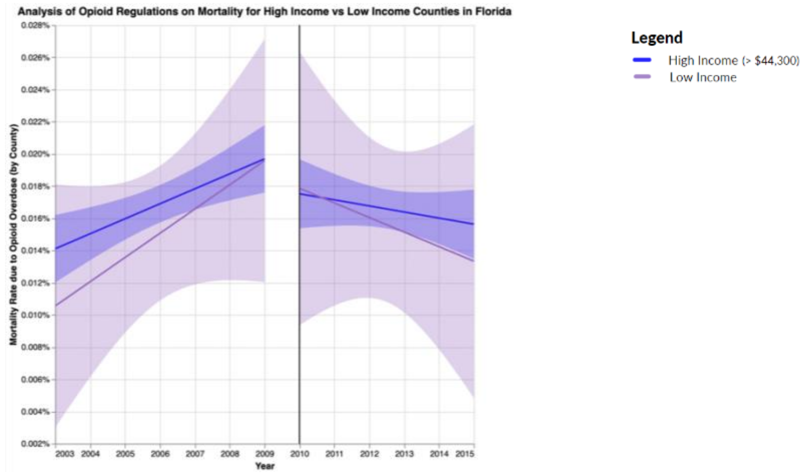


Fig.4.2: Shows the pre-post policy comparison on mortality rates at an income level for Florida (FL). We observe a steep rise in the death rates for lower income counties leading up to the policy year. Post policy implementation reflects a steeper decline in mortality rate for lower income households than high income households

When we look at the effect of policy on mortality rates, we notice that before 2010, the mortality rates for both high and low-income counties were increasing steadily. In 2009, the mortality rate for the high and low-income counties was approximately the same. The policy proved to be effective in decreasing the mortality rate for both high and low-income counties. The decline in mortality rate for low-income counties was sharper as compared to the high-income counties.

## Washington

Effect of regulations on mortality rate by Income

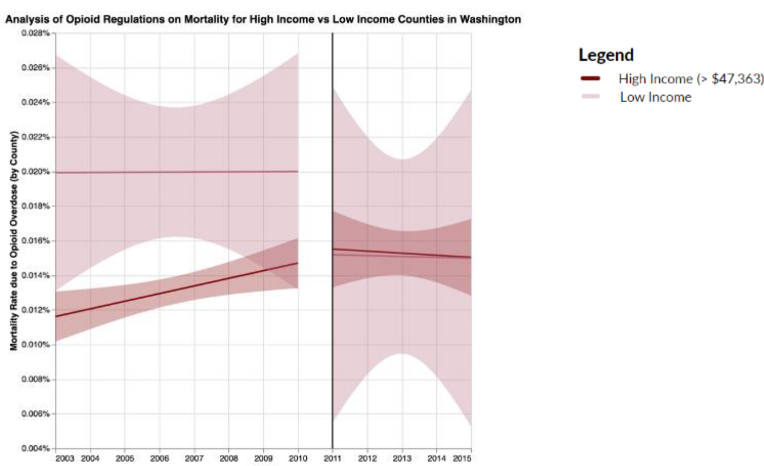


Fig.5: Shows the pre-post policy comparison on mortality rates at an income level for Washington (WA). The low-income households have a constant mortality rate before policy implementation. We observe a decline in the death rates for both low-income and high-income counties post the implementation of the policy. The decline is slow, however its more for high income counties than low-income counties.

When we look at the effect of policy on high and low-income counties in Washington, we see that the mortality rate for low-income counties was unchanging but significantly higher than the high-income counties before the policy was implemented. Although, the high-income counties had a lower mortality rate in comparison to the low-income counties, we observe an increasing trend until the policy was implemented. Post policy implementation, the mortality rate fell significantly for low-income counties. For the high-income counties, the policy was able to control the increasing trend in mortality rate that was observed before 2011. After 2011, we see that the mortality rate for both high- and low-income counties starts to decrease, however at a very low rate.

Effect of regulations on mortality rate by Income

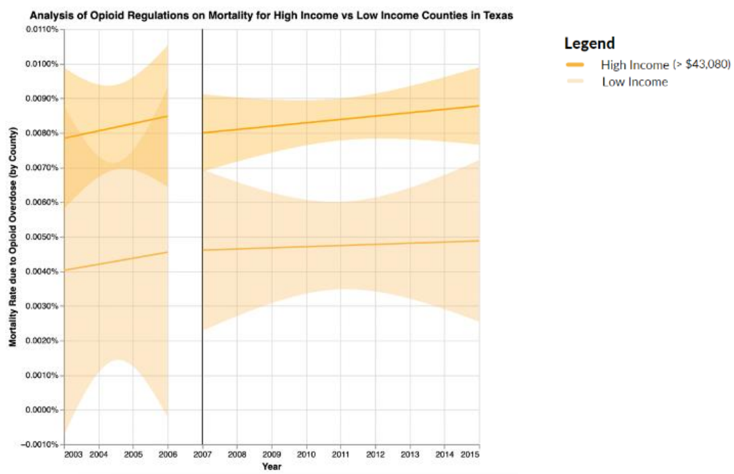


Fig.6: Shows the pre-post policy comparison on mortality rates at an income level for Texas (TX). There policy does not seem to be very effective, since the mortality rate for both high income and low-income households continues to increase post policy implementation. We do observe that rate of increase has reduced.

For Texas, in high income counties, the mortality rate caused by opioid overdose was considerably higher than the low-income counties before and after the policy. The opioid regulation in Texas seems to be quite ineffective as the trend for mortality rates remain unchanged in the periods before and after the policy changes. However, the rate of increase in mortality rates for both high- and low-income counties decreased by a small fraction after the policy was put into effect.

# Conclusion

Based on the graphs of our pre-post and difference-in-difference analysis, Florida's drug policy was effective in decreasing the shipments of opioids as well as effective in declining the overall growing trend of its mortality rate. Texas's drug policy was not very successful as the overall trend of the average mortality rate did not decline after the policy went into effect. The increasing slope is not as steep as it was before the policy change, but the rate is increasing, nonetheless. Washington's drug policy was potentially successful since its average mortality rate declined after the policy was implemented.

Why was Florida so successful and Texas unsuccessful? If we investigate these policies, we can see a distinct difference. In Florida, the policies were directed towards the physicians and the pain clinics dispensing the medication. The strategy was to go to the source by conducting raids and closing pain clinics to stop the influx of opioids there. In Texas, the freedom was given to the people. It did not set any thresholds on the number of opioids a patient could receive, but instead only required patient consent to receive opioids. Since addiction is already a key issue with opioids, patients most likely did not change their intake, so it makes sense why Texas did not see a decrease in deaths per capita.

It is important to note the potential limitations of this study. Out of the consideration of privacy, the US Vital Statistics agency censors some data. Although we imputed the counties with missing overdose deaths using K – nearest neighbor imputation method, it is likely that our imputation result deviates from the real death counts. Therefore, this imputation may introduce slight bias and further analysis with a more thorough data collection approach is needed to resolve this issue. The scope of our analysis is limited to counties with high population (>400,000). A deeper dive into all counties in the states considered may give us a clearer picture of the outcome of the policies implemented.

Both the pre-post comparison and difference-in-difference analysis provided straightforward ways for us to see how policies affected the trend on opioid shipments and mortality rate due to drug overdose. However, we must keep in mind that the work is far from over. Even after a successful policy change, there are still opioid overdose deaths occurring. Additionally, a decreasing trend can potentially start to increase again if policies are not adjusted to keep up with societal changes. Policy makers must be vigilant, and the key to that is understanding which policies work and which do not.

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# Appendix

Figure 1

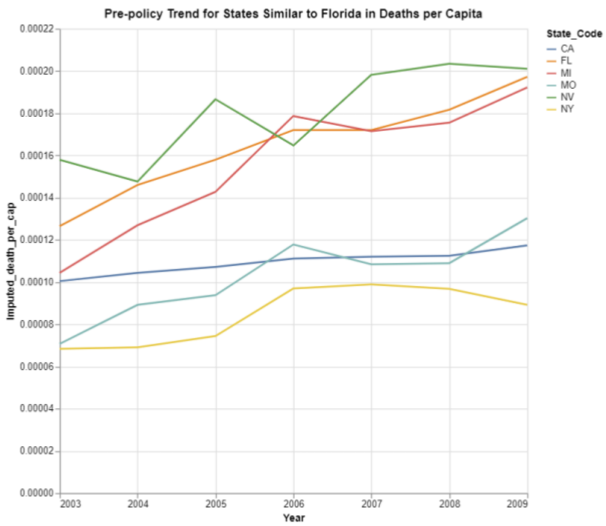


Figure 2

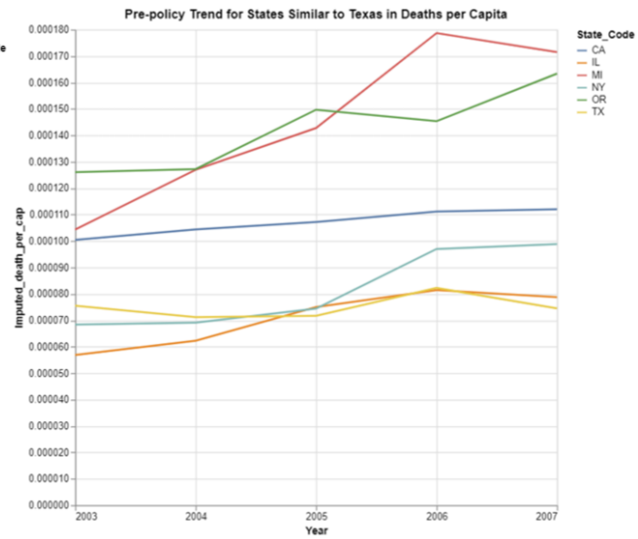


Figure 3

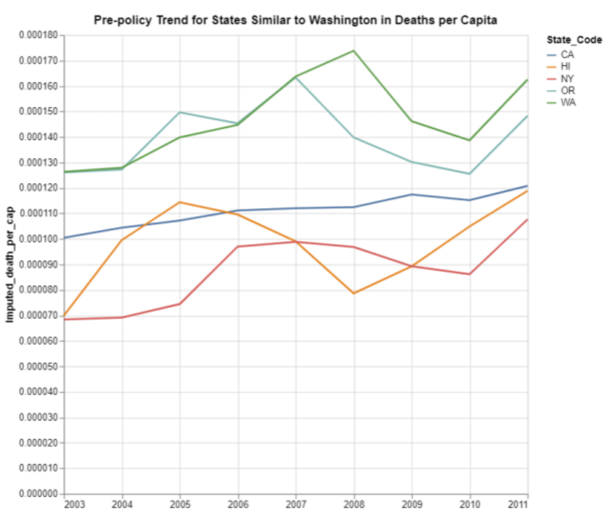


Figure 4