Estimating the Impact of Opioids Control Policies

Team 2: Jennie Sun, Dapo Adegbile, Xiaohan Yang

Project Motivation

Due to the tremendous increase in the misuse of prescription drugs in the past two decades, there have been serious medical consequences, such as increased emergency room visits, rise in opioids addiction, and overdose deaths associated with prescription drugs. In order to tackle this problem from a regulations and policy evaluations standpoint, the main goal of the project is to estimate the the effectiveness of opioid drug prescription regulations on:

- the volume opioids prescribed
- drug overdose deaths
- potential correlations between the two statistics above

Research Design

This project aims at understanding the impact of opioid drug regulations. We are interested in exploring the causal effect of regulations on opioids prescriptions, instead of just the general correlations. Hence, we decided to use two causal inference strategies -- pre-post comparison and difference-in-difference analysis.

Pre-post comparison is the most basic strategy for causal inference. It compares how things look like before a certain event to things right after the event. In the context of our project, we compare the number of drug prescriptions in Florida before the policy went into effect to the number of drug prescriptions after the policy went into effect. If the trajectory of the number of drug prescriptions goes down right after the policy, we can infer that the drug regulation policy had an impact on Florida drug prescription.

Pre-post comparison is simple and effective, yet it tends to overlook the impact of other events. More specifically, pre-post comparison does not account for large scale, confounding effects. 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 such decrease solely to United States policy change. Therefore, we also need to introduce a difference-in-difference approach to our project. A difference-in-difference approach compares Florida's pre-post policy opioids prescriptions to other states' opioids prescriptions during the same period. If Florida's policy was effective, we expect Florida's post-policy trend to be different than other states without a policy change. The difference-in-difference approach minimizes the potential nationwide impact.

Data

In this project, we want to explore the drug policy impact for three states: Florida, Texas, and Washington. As mentioned earlier, we want to do a pre-post and difference-in-difference comparison on opioids overdose death for the three states, and on opioids prescriptions for Florida.

We were given two sets of data for this analysis:

- Mortality Data from Drug/Alcohol-Induced Cause
  It is a subset of the US Vital Statistics Mortality Data. It includes data on nationwide drug/alcohol-induced death, and each observation includes the number of deaths for each county each year.
- Opioids shipments/prescription
  It is a dataset of all prescription opioid drug shipments in the United States from 2006 to 2012.

The geographic unit we use for this analysis is county, and the temporal unit is year. However, counties in the US vary greatly in geographical size and population. The absolute number of drug overdose deaths in the first dataset is not an appropriate measurement without considering the counties' population. Instead, we want to use normalized overdose death by population. Hence we introduced one more dataset: the County Population Data from the US Census Bureau. This data contained the population of each county in a particular state on a year to year basis. It includes the population for each US county every year.

In addition, we found the opioids drug prescription dataset consists of two types of opioids drugs of different strengths. We also normalized the two types of opioids by converting them to their equivalent strengths of morphine. We decided that our final dataset for analysis would include the following information: year, state name, county name, population, number of deaths, and milligrams of equivalent morphine.

Data Cleaning & Wrangling

<u>Mortality Data</u>

Before we actually start the cleaning and wrangling process, we made sure that our final data table should have the following columns: year, state, county, deaths from drug overdose, county population of the year, and the mortality rate, which is calculated from dividing the number of deaths by county population. With the unit-of-observation in mind, our game plan was to clean the data for the state of Florida first, and apply a function with the same steps to the rest of the counties.

Looking at the raw data, we first notice that the mortality data has 13 CSV files in total, and each document only contains the data for one year. We first concatenate all of them to one dataframe so that everything is in one place. We then realize that there are many columns that we don't need for the analysis, so we drop those columns and only keep the ones we need. After this step, our dataframe has the following columns: Year, Drug/Alcohol Induced Cause, Deaths. County, and State. Next, we subset to the specific county that we want to look at, Florida in this case. Since the County column was in the format of "County Name, State Name", we format this column to make sure that it only contains the county name. As this data contains the mortality information for both drug and alcohol induced causes, we look at the description and code of each cause and only keep the ones that are drug related, which are D1 - Drug poisonings (overdose) Unintentional (X40-X44), D2 - Drug poisonings (overdose) Suicide (X60-X64), D4 - Drug poisonings (overdose) Undetermined (Y10-Y14), and D9 - All other drug-induced causes. Next, we arrange the dataframe by the unique identifiers: Year-State-County, and convert the datatype of the year column from float to int. Now we have only Year, State, County, and Deaths in the cleaned dataframe.

Once we have the mortality data ready, we can merge the dataframe with the population data to calculate mortality rate. Since the U.S. census counts the population every 10 years, we load Florida's population data from 2000 to 2009 and from 2010 to 2019 and perform the cleaning separately before merging them into one dataframe. Similar to the steps when dealing with the mortality data above, we first drop the unnecessary columns. Since the first row in the dataset is the total state population and the last few rows are the texts describing information related to sources and citations, we remove those rows from the dataframe. The County column in the 2010-2019 population data has similar formatting issues as the mortality data, so we perform the same cleaning process to make sure that we only have the name of the county. We then concatenate the two datasets and subset the concatenated dataframe to the year of 2003 to 2015 because we only have mortality in this time frame as well. Since the year information is on the first row, we use the melt function to make `Year` a column and each year as the values in this column. Finally, we group by the observations by Year and County to obtain the final population dataframe, which has three columns: Year, County, and Population.

Now we have both the mortality data and the population data cleaned, we merge these two tables into one dataframe. However, we notice that some of the counties have NaN values in the overdose death column due to the nature of the data since any county with fewer than 10 death tolls are not reported. Therefore, we interpolate the death tolls for those unreported counties by filling in random numbers generated between 0 and 9. Now our dataframe looks good with no missing values, we create an extra column

`Mortality Rate`, which is calculated from dividing the number of deaths by the number of population, on the year-state-county level. The rest of the control and comparison states are cleaned using a series of functions we created, which are illustrated in details in the following section.

Shipments 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. After filtering out the unnecessary variables, what we were left with were the County and State of where the drugs were shipped to, the base weight of the shipment in grams, the [**MME CONVERSION FACTOR**], the Drug name, and the transaction date.

To make our data viable for merging, we had to rename some of our Shipment data columns so that they matched the column names in our Population data. 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, in order to create a column of the morphine equivalent drug weight, we multiplied the morphine conversion factor by the total active weight of the drug.

Upon cleaning and properly formatting, we did a left merge on our shipment data with the corresponding states population data, on the Year and County and got our final data set.

Functions

After we have streamlined the data cleaning and wrangling process, we create several functions that help us achieve the final dataframe we need in the shortest amount of time.

- *clean_mortality*: this function takes two arguments: a dataframe, which is the concatenated mortality data from 2003 to 2015, and a state abbreviation. This function returns the cleaned mortality data with 4 columns: `Year`, `State`, `County`, and `Deaths`(number of drug induced deaths) of the county that we pass into the function.
- *clean_pop*: this function takes three arguments, which are the two dataframes that contain the 2000-2009 population and 2010-2019 population for the specific state we want to analyze, and the state abbreviation of the state we intend to

analyze. This function returns the cleaned population data with 4 columns: `Year`, `County`, `Population`, and `State`.

- *merg_mortalitypop*: this function takes two arguments, which are the 2 cleaned tables from the 2 functions above. This function returns the merged population data with mortality data with 6 columns: `Year`, `State`, `County`, `Death`, `Population`, and `Mortality Rate`.

We use this series of functions described above to create 6 intermediate files in total: 3 for the control states (FL, TX, WA) and the average mortality rate from the comparison states for each control state.

Data Summary

Summary Statistics

- **Florida & Comparison States**

  Population

Florida Population

Year	2003	2004	2005	2006	2007	2008
Population	15,756,158	15,995,838	16,444,771	16,575,080	17,323,086	17,092,495
2009	2010	2011	2012	2013	2014	2015
17,183,150	17,579,949	18,058,927	18,049,707	18,302,246	18,784,915	19,295,988

Mortality

Florida Mortality Over Population Ratio (by County and Year)

Statistics	Mean	Std	Min	Max	Median
Values	0.000145	0.000061	0.000039	0.000359	0.000141

AR, PA, NM Mortality Over Population Ratio (by County and Year)

Statistics	Mean	Std	Min	Max	Median
Values	0.000168	0.000097	0.000035	0.000981	0.000147

Opioids Shipment

Florida Milligrams of Morphine per Cap (by County and Year)

Statistics	# Counties	Mean	Std	Min	Max	Median
Values	64	1025.34	7121.00	0.45	153664.86	85.83

AR, PA, NM Milligrams of Morphine per Cap (by County and Year)

Statistics	# Counties	Mean	Std	Min	Max	Median
Values	155	363.84	190.02	0.37	1846.84	333.01

- **Texas & Comparison States**

  Population

Texas Population

Year	2003	2004	2005	2006	2007	2008
Population	14,887,036	16,000,205	17,066,993	17,522,842	18,026,618	18,908,839
2009	2010	2011	2012	2013	2014	2015
19,424,828	20,573,052	20,014,323	20,683,439	20,770,590	21,245,787	22,578,863

Mortality

Texas Mortality Over Population Ratio (by County and Year)

Statistics	Mean	Std	Min	Max	Median
Values	0.000103	0.000055	0.000014	0.000427	0.000094

CO, ID, MI Mortality Over Population Ratio (by County and Year)

Statistics	Mean	Std	Min	Max	Median
Values	0.000141	0.000070	0.000035	0.000783	0.000130

- **Washington & Comparison States**

  Population

Washington Population

Year	2003	2004	2005	2006	2007	2008
Population	5,061,063	5,429,327	5,499,086	5,567,972	5,680,423	5,885,917
2009	2010	2011	2012	2013	2014	2015
5,938,479	5,914,031	5,991,280	6,119,502	6,106,453	6,271,608	6,465,578

Mortality

Washington Mortality Over Population Ratio (by County and Year)

Statistics	Mean	Std	Min	Max	Median
Values	0.000136	0.000051	0.000043	0.000134	0.000134

CA, OR, NV Mortality Over Population Ratio (by County and Year)

Statistics	Mean	Std	Min	Max	Median
Values	0.000140	0.000075	0.000034	0.000537	0.000114

Unit of observation

Mortality:

The final variables for the mortality data are as below.

Year	State	County	Deaths	Population	Mortality Rate
2007	TX	Bell County	10	258,752	0.00003865

Shipments:

The final Shipment variables are as followed.

Year	BUYER_STATE	County	MORPHINE_EQUIV_IN_MG	Population
2006	AR	SEBASTIAN	64548.000	121,492

Data Visualization and Interpretation

The non-policy-change states we choose to compare with the policy states are as follow:

- For Florida: PA, AR, NM
- For Texas: CO, ID, MI
- For Washington: OR, CA, NV

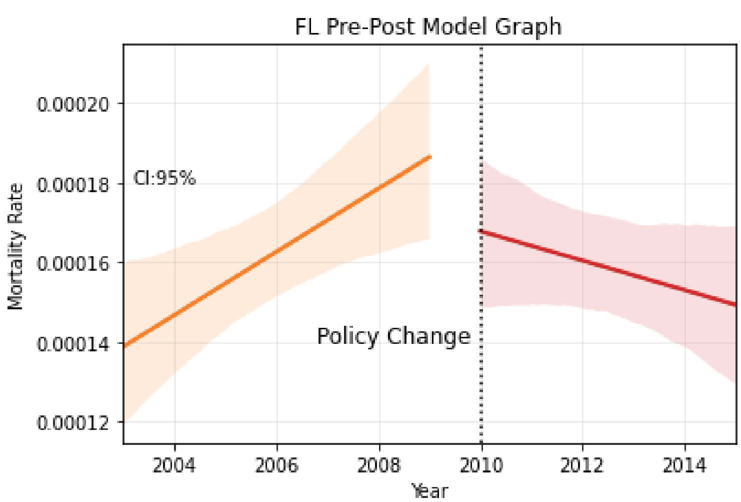
We did some background research and found out a pool of states that have not passed any regulations regarding pain clinics or pain treatments which are regulated by the policies in Florida, Texas, and Washington. We then did some comparisons using the density map on the Washington Post page. (https://www.washingtonpost.com/graphics/2019/investigations/dea-pain-pill-database/) We found that Pennsylvania, Arkansas, and New Mexico are similar to Florida in density of opioids prescription before 2010, which was when the policy took place in Florida.

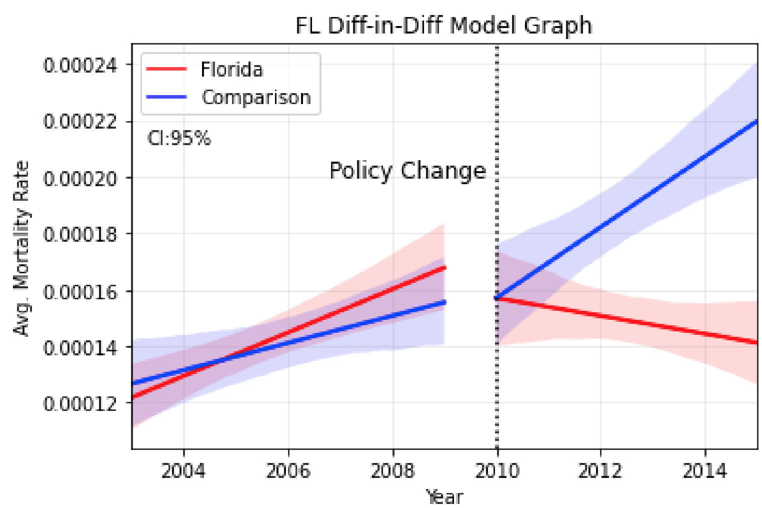
Likewise, we chose three states for Texas and Washington each based on the similar pre-policy trend they had with Texas and Washington.

We also validated our selections by scientific analysis. These states seem to have similar trajectories with the policy-change states in the pre-policy period. This is important because the assumption of a difference-in-difference design is that while our policy-change states don't have to be the same as the non-policy-change states in levels, the two groups do need to exhibit similar trends before the policy change being studied. Otherwise, the difference-in-difference may be larger even if there is no policy change, and we would not be able to draw conclusions from the graphs. We include 95% Confidence Intervals in the following plots, so we are 95% confident that the slope of the average mortality rate and shipments fall within the range.

<u>Mortality Data</u>

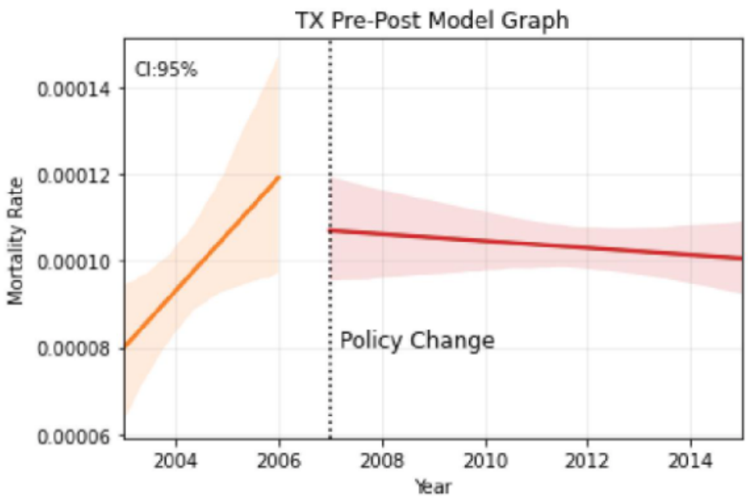
Pre-Post and Difference-In-Difference Analysis, Florida

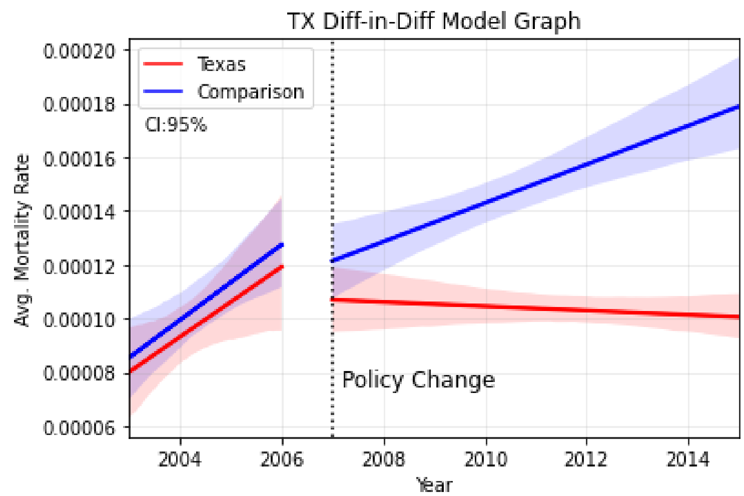




From the FL Pre-Post Model Graph (above left), it looks like the overall mortality rate by county dropped about 0.0001 right after the policy went into effect, and continued to decrease since then, which might not have been the case if the policy did not take place.
From the FL Diff-in-Diff Model Graph (above right), it looks like the average overdose deaths rate of the non-policy/comparison states exhibit a faster increasing trend after 2010, while Florida’s overdose death rate dropped after the policy change and continued to decrease after the policy went into effect. This suggests that the drug policy intervention in Florida was a successful policy.

Pre-Post and Difference-In-Difference Analysis, Texas

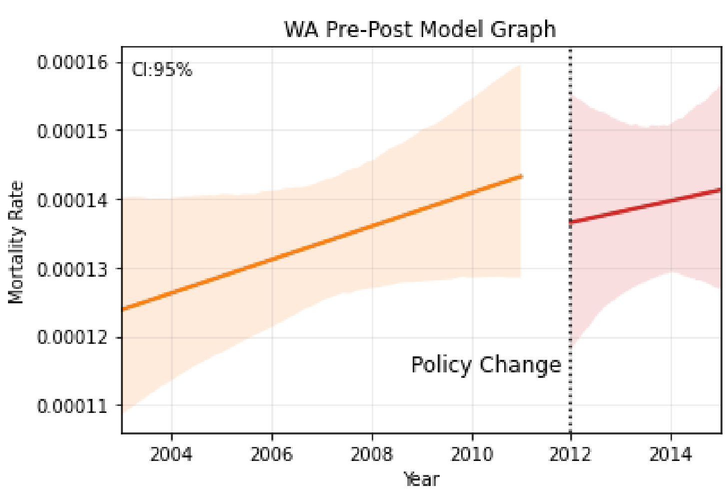


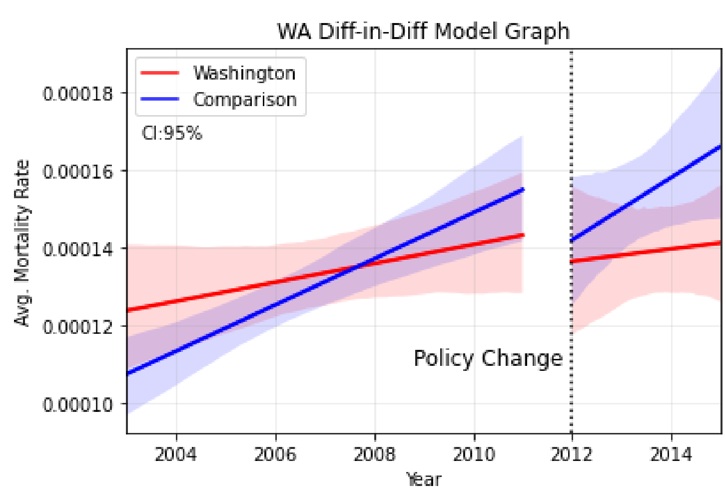


From the TX Pre-Post Model Graph (above left), it looks like the overall mortality rate by county dropped from 0.00012 to 0.00011 right after the policy went into effect, and continued to decrease at a constant rate since 2007, which might not have been the case if the policy did not take place.

From the TX Diff-in-Diff Model Graph (above right), before the policy went into effect in Texas, there are parallel trends between TX and the non-policy/comparison states. However, after the policy took place in 2007, the opioid overdose rate in TX, first dropped a little, and continued to decrease, while the non-policy/comparison states kept exhibiting an increasing trend after 2007. Therefore, we would say that the opioid prescription regulations in TX seemed to effectively control and decrease the overdose deaths rate in TX, suggesting that it was potentially a very successful policy.

Pre-Post and Difference-In-Difference Analysis, Washington



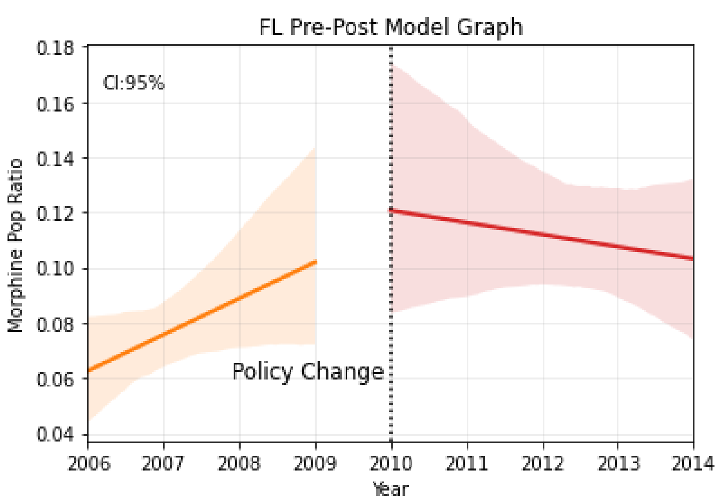


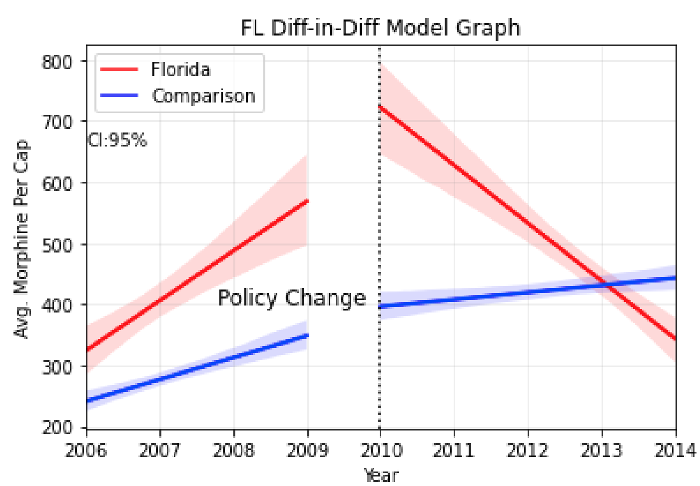
From the WA Pre-Post Model Graph (above left), it looks like the overall mortality rate by county dropped from a little over 0.00014 to a little below 0.00014 right after the policy went into effect, which might not have been the case if the policy did not take place. However, we would be hesitant to say this was potentially a successful policy because in less than 3 years of time, the mortality rate went back up to the original level right before the policy took place.

From the WA Diff-in-Diff Model Graph (above right), it looks like the overdose deaths rate in Washington state has been increasing at a lower rate after 2012 than in other states that didn't change their opioid policy. Although WA's average opioid overdose rate did drop a little after the policy took place, it continued to increase at the same rate as before the policy took place. The non-policy/comparison states showed a similar increasing trend after before and after 2012 as well. Therefore, we would say, although the opioid prescription regulations did bring down the overdose deaths rate in Washington state right after the policy change, it did not alter the pattern to a decreasing trend, suggesting that it was not a very successful policy.

<u>Shipment Data</u>

Pre-Post and Difference-In-Difference Analysis, Florida





When analyzing the Morphine Ratio Pre and Post Policy graph for Florida, we can see that from 2006 up until the year of the policy change, the ratio of Morphine to Florida county's population steadily increases. More specifically, we can see that in 2006, our morphine (in mg) to population ratio was roughly **0.06 : 1** (mg to person), until it culminated in 2009 with a **0.10 : 1** ratio, indicative of 67% increase. After policy was implemented in 2009, we can see a steady decrease from 2010 from 2014. More specifically, the ratio of morphine to population starts at **.12 : 1** in 2010 and decreases to **0.10 : 1** in 2014. Based on this we would assume that the policy was effective because we noticed a negative trend in the morphine to population ratio on a year to year basis.

Now when analyzing the Florida Difference in Difference plot, we can see that before policy change went into effect, the Average Morphine Per Capita steadily increased from 2006 up until right before the policy change for Florida and its comparison states. Conversely, after the policy change, we can see that the Average Morphine Per Capita for comparison states continued to increase at roughly the same rate, while the Average Morphine Per Capita for Florida started to decrease. Based on this graph, we can say that the policy intervention was effective because of the different post-policy trends for Average Morphine Per Capita for Florida and comparison states. The stark difference in slopes leads us to believe the policy intervention was, in fact, effective.

Assumptions

Throughout this project, we made assumptions for the sake of analysis and we want to list them here. If some of the assumptions failed, our analysis would be biased.

We made assumptions when we chose the research methodology. With the pre-post comparison method, we assumed that if the opioid policy had not been effective, the observations in the post-policy period for FL, TX, and WA would have looked the same as those in the pre-policy period. With the difference-in-difference method, we intentionally selected the comparison states that exhibit nearly identical pre-policy trends with the policy-change states (FL, TX, WA), which can be verified with our graphs.

Additionally, assumptions were made during our analysis and conclusion phase. We assumed that except for the policies we study, there was no other policy or regulation that affected drug prescription and overdose death. As mentioned during the analysis section, we observed drops in opioids prescriptions and in overdose deaths after policy change for all three states, and we hence inferred the overdose deaths drop because people could not get their hands on prescribed opioids drugs. We assumed one thing to make this inference: people could not get opioids drugs via means other than recorded opioids shipments. People had no way to obtain opioids drugs from other states or via unofficial means, so when the amount of opioids drugs shipped to FL, TX, and WA decreased, people took fewer drugs, which led to a decreased number of overdose deaths.

Conclusion

To conclude, based on the visual representation, Florida's drug policy was effective in decreasing the shipments of opioids as well as effective in shifting the overall growing trend of its mortality rate to a downward trend. Texas's drug policy was potentially very successful once as the overall trend of the average mortality rate was controlled and started to decline after the policy went into effect. Washington's drug policy was potentially not a very successful one since its average mortality rate continued to increase at the same rate after the policy took place.

We think the research design is overall beneficial in exploring the impact of drug regulation policies. Both the pre-post comparison and difference-in-difference analysis provided straightforward ways for us to see how policies changed the trend on opioids prescriptions and overdose deaths. The plots generated through the two methods are also simple enough for non-data-scientist readers to understand.

It is important to note that there are certain potential limitations of this study. Out of the consideration of privacy, the US Vital Statistics agency censors some data. If the number of deaths in a county is less than 10, the county would not appear in the data. Although we imputed the counties with missing overdose deaths with a random number from 0 to 9, 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.

Estimating the Impact of Opioids Control Policies

For Policy Makers

Team 2: Jennie Sun, Dapo Adegbile, Xiaohan Yang

Project Motivation

Due to the tremendous increase in the misuse of prescription drugs in the past two decades, there have been serious medical consequences, such as increased emergency room visits, rise in opioids addiction, and overdose deaths associated with prescription drugs. In order to tackle this problem from a regulations and policy evaluations standpoint, the main goal of the project is to estimate the the effectiveness of opioid drug prescription regulations on:

- the volume opioids prescribed
- drug overdose deaths
- potential correlations between the two statistics above

This project aims at understanding the impact of opioid drug regulations. We are interested in exploring the causal effect of regulations on opioids prescriptions, instead of just the general correlations. Hence, we decided to use two causal inference strategies -- pre-post comparison and difference-in-difference analysis.

Pre-post comparison is the most basic strategy for causal inference. It compares how things look like before a certain event to things right after the event. In the context of our project, we compare the number of drug prescriptions in Florida before the policy went into effect to the number of drug prescriptions after the policy went into effect. If the trajectory of the number of drug prescriptions goes down right after the policy, we can infer that the drug regulation policy had an impact on Florida drug prescription.

Pre-post comparison is simple and effective, yet it tends to overlook the impact of other events. More specifically, pre-post comparison does not account for large scale, confounding effects. 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 such decrease solely to United States policy change. Therefore, we also need to introduce a difference-in-difference approach to our project. A difference-in-difference approach compares Florida's pre-post policy opioids prescriptions to other states' opioids prescriptions during the same period. If Florida's policy was effective, we expect Florida's post-policy trend to be different than other states without a policy change. The difference-in-difference approach minimizes the potential nationwide impact.

Overview of the Data

In this project, we want to explore the drug policy impact for three states: Florida, Texas, and Washington. As mentioned earlier, we want to do a pre-post and difference-in-difference comparison on opioids overdose death for the three states, and on opioids prescriptions for Florida.

We were given two sets of data for this analysis:

- Mortality Data from Drug/Alcohol-Induced Cause
  It is a subset of the US Vital Statistics Mortality Data. It includes data on nationwide drug/alcohol-induced death, and each observation includes the number of deaths for each county each year.
- Opioids shipments/prescription
  It is a dataset of all prescription opioid drug shipments in the United States from 2006 to 2012.

The geographic unit we use for this analysis is county, and the temporal unit is year. However, counties in the US vary greatly in geographical size and population. The absolute number of drug overdose deaths in the first dataset is not an appropriate measurement without considering the counties' population. Instead, we want to use normalized overdose death by population like how GDP is normalized into GDP per capita. Hence we introduced one more dataset: the County Population Data from the US Census Bureau. It includes the population for each US county every year.

In addition, we found the opioids drug prescription dataset consists of two types of opioids drugs of different strengths. We also normalized the two types of opioids by converting them to their equivalent strengths of morphine.

<u>Unit of Observation</u>

Below is how each row in our final datasets look like:

The final variables for the mortality data are as below.

Year	State	County	Deaths	Population	Mortality Rate
2007	TX	Bell County	10	258,752	0.00003865

The final variables for shipment data are as followed.

Year	BUYER_STATE	County	MORPHINE_EQUIV_IN_MG	Population
2006	AR	SEBASTIAN	64548.000	121,492

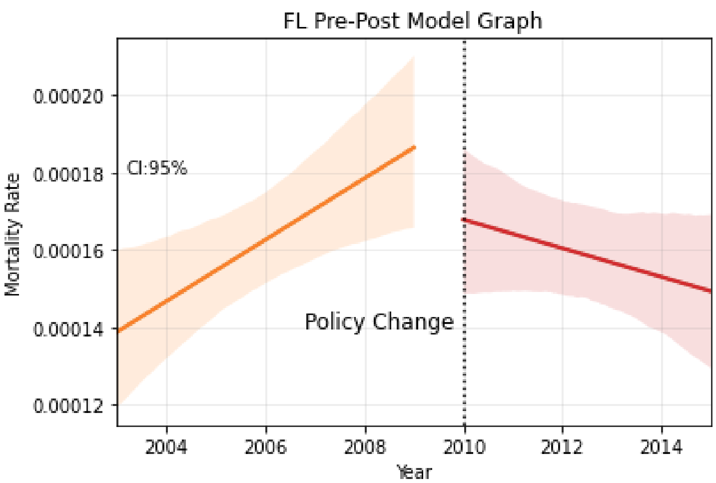
Data Visualization and Interpretation

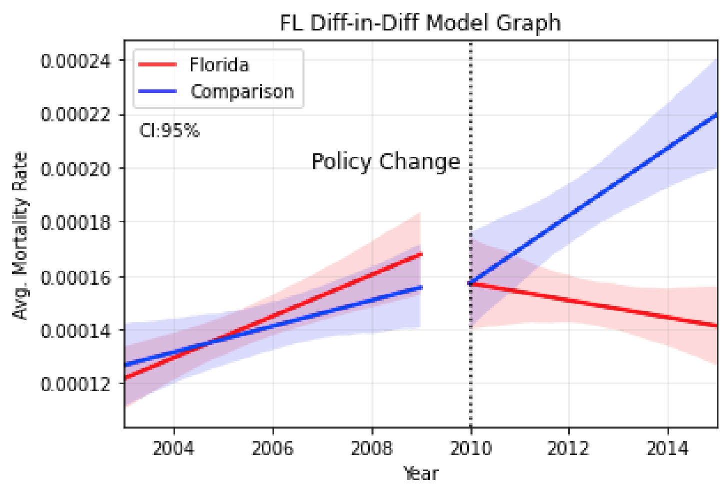
The non-policy-change states we choose to compare with the policy-change states are as follow:

- For Florida: PA, AR, NM
- For Texas: CO, ID, MI
- For Washington: OR, CA, NV

<u>Mortality Data</u>

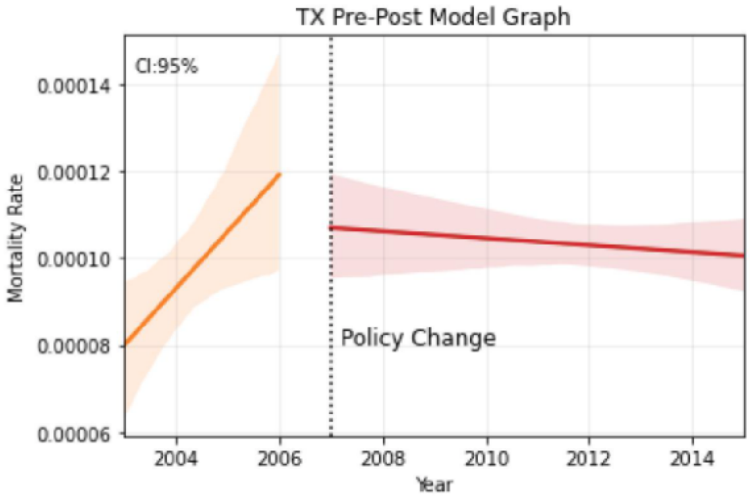
Pre-Post and Difference-In-Difference Analysis, Florida

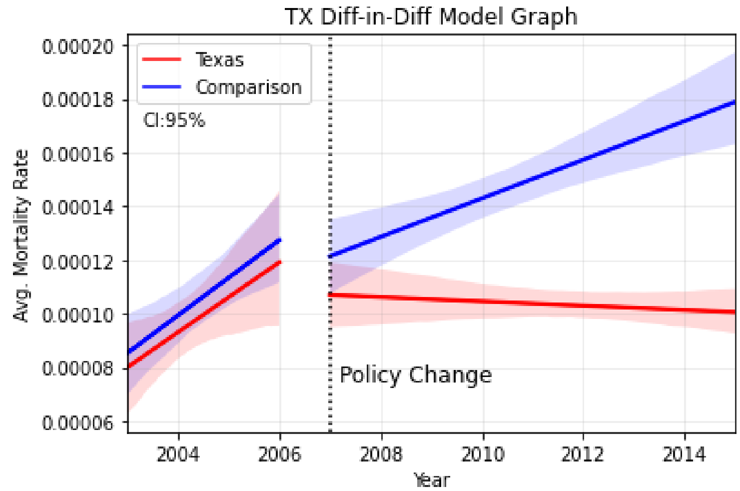




From the FL Pre-Post Model Graph (above left), it looks like the overall mortality rate by county dropped about 0.0001 right after the policy went into effect, and continued to decrease since then, which might not have been the case if the policy did not take place.
From the FL Diff-in-Diff Model Graph (above right), it looks like the average overdose deaths rate of the non-policy/comparison states exhibit a faster increasing trend after 2010, while Florida's overdose death rate dropped after the policy change and continued to decrease after the policy went into effect. This suggests that the drug policy intervention in Florida was a successful policy.

Pre-Post and Difference-In-Difference Analysis, Texas

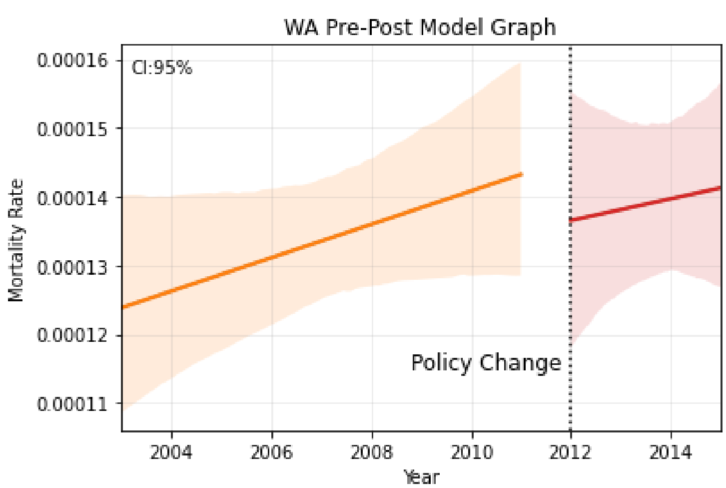


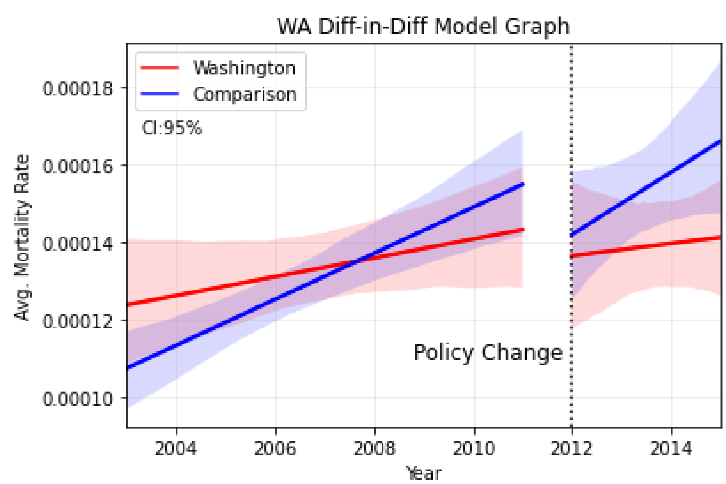


From the TX Pre-Post Model Graph (above left), it looks like the overall mortality rate by county dropped from 0.00012 to 0.00011 right after the policy went into effect, and continued to decrease at a constant rate since 2007, which might not have been the case if the policy did not take place.

From the TX Diff-in-Diff Model Graph (above right), before the policy went into effect in Texas, there are parallel trends between TX and the non-policy/comparison states. However, after the policy took place in 2007, the opioid overdose rate in TX, first dropped a little, and continued to decrease, while the non-policy/comparison states kept exhibiting an increasing trend after 2007. Therefore, we would say that the opioid prescription regulations in TX seemed to effectively control and decrease the overdose deaths rate in TX, suggesting that it was potentially a very successful policy.

Pre-Post and Difference-In-Difference Analysis, Washington



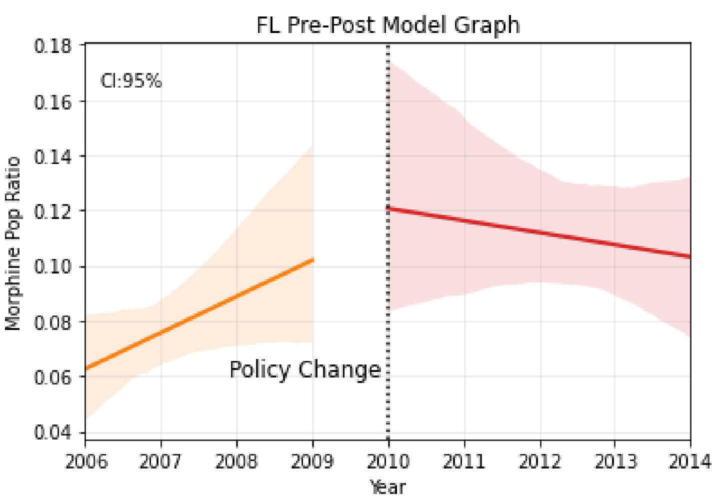


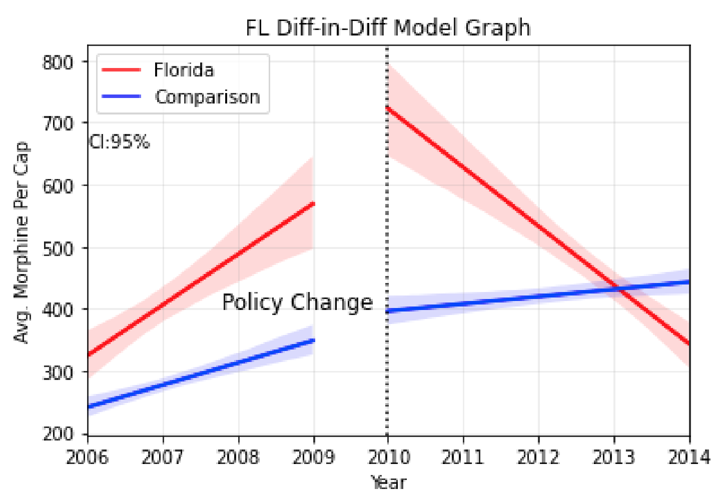
From the WA Pre-Post Model Graph (above left), it looks like the overall mortality rate by county dropped from a little 0.00014 to a little below 0.00014 right after the policy went into effect, which might not have been the case if the policy did not take place. However, we would be hesitant to say this was potentially a successful policy because in less than 3 years of time, the mortality rate went back up to the original level right before the policy took place.

From the WA Diff-in-Diff Model Graph (above right), it looks like the overdose deaths rate in Washington state has been increasing at a lower rate after 2012 than in other states that didn't change their opioid policy. Although WA's average opioid overdose rate did drop a little after the policy took place, it continued to increase at the same rate as before the policy took place. The non-policy/comparison states showed a similar increasing trend after before and after 2012 as well. Therefore, we would say, although the opioid prescription regulations did bring down the overdose deaths rate in Washington state right after the policy change, it did not alter the pattern to a decreasing trend, suggesting that it was not a very successful policy. The reason why we see this trend, as we suppose, could be similar to what happened in Florida. Buyers of the drugs may have just gotten their opioids drugs in a non-policy-change state.

<u>Shipment Data</u>

Pre-Post and Difference-In-Difference Analysis, Florida





When analyzing the Morphine Ratio Pre and Post Policy graph for Florida, we can see that from 2006 up until the year of the policy change, the ratio of Morphine to Florida county's population steadily increases. More specifically, we can see that in 2006, our morphine (in mg) to population ratio was roughly **0.06 : 1** (mg to person), until it culminated in 2009 with a **0.10 : 1** ratio, indicative of 67% increase. After policy was implemented in 2009, we can see a steady decrease from 2010 from 2014. More specifically, the ratio of morphine to population starts at .**12 : 1** in 2010 and decreases to **0.10 : 1** in 2014. Based on this we would assume that the policy was effective because we noticed a negative trend in the morphine to population ratio on a year to year basis.

Now when analyzing the Florida Difference in Difference plot, we can see that before policy change went into effect, the Average Morphine Per Capita steadily increased from 2006 up until right before the policy change for Florida and its comparison states. Conversely, after the policy change, we can see that the Average Morphine Per Capita for comparison states continued to increase at roughly the same rate, while the Average Morphine Per Capita for Florida started to decrease. Based on this graph, we can say that the policy intervention was effective because of the different post-policy trends for Average Morphine Per Capita for Florida and comparison states. The stark difference in slopes leads us to believe the policy intervention was, in fact, effective. .

One of the potential reasons why the mortality rate experiences an increase while the shipment data decreases is because people from Florida might go to neighboring states or acquire drugs illegally. The decrease of access to prescription drugs would lead to the increase in the use of illegal drugs resulting in lower opioid shipments, but higher opioid drug deaths.

Conclusion

To conclude, based on the visual representation, Florida's drug policy was effective in decreasing the shipments of opioids as well as effective in shifting the overall growing trend of its mortality rate to a downward trend. Texas's drug policy was potentially very successful once as the overall trend of the average mortality rate was controlled and started to decline after the policy went into effect. Washington's drug policy was potentially not a very successful one since its average mortality rate continued to increase at the same rate after the policy took place.

We think the research design is overall beneficial in exploring the impact of drug regulation policies. Both the pre-post comparison and difference-in-difference analysis provided straightforward ways for us to see how policies changed the trend on opioids prescriptions and overdose deaths. The plots generated through the two methods are also simple enough for non-data-scientist readers to understand.

It is important to note that there are certain potential limitations of this study. Out of the consideration of privacy, the US Vital Statistics agency censors some data. If the number of deaths in a county is less than 10, the county would not appear in the data.

Although we imputed the counties with missing overdose deaths with a random number from 0 to 9, 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.