Exploring the effect of drug control policies in the U.S. (For Prof. Nick Eubank)

Preet Khowaja, Erika Fox, Shining Yang, Minjung Lee

Ⅰ. Summary

In this report, we analyze the effect of drug (in particular, opioid) control policies in Florida, Texas and Washington on the opioid shipments and deaths caused by drug overdose in these states. Florida and Texas implemented policies that had a reductive effect on both opioid shipments and deaths caused by drug overdose. In comparison, Washington did not display a significant effect compared to its control states when measuring these trends.

Ⅱ. Introduction

Drug control policies have been up for hot debate as accessibility to drugs has changed in recent years with the rise of communication media. In 2019 alone, the United States saw 49,860 opioid overdose deaths. From 2018 to 2019, no U.S. state experienced a significant decrease in deaths by opioid overdose, prompting policy-makers to question how the problem could be curbed. An analysis of previous drug policies is a great place to gauge the efficacy of various governmental measures.

In this report, we use two theoretical frameworks to analyse the effect of drug policy interventions in Florida (2010), Texas (2007) and Washington (2012). The first is a pre-post analysis, where we compare the states before and after policy interventions. For Florida and Washington, the comparison metric includes deaths per capita caused by opioid overdose and opioid shipment per capita on a yearly basis. For Texas, since we only have opioid shipment data for one year before the policy, we conduct the analysis on a monthly basis instead. Opioid shipment per capita is measured in MME per capita, where MME is the morphine milligram equivalent, which is the standard used to compare opioids with one another. The second framework we use is a difference-in-difference analysis, which asks whether the changes in states with policy changes had bigger changes than their control states. In terms of "control states", we pick states that are geographically adjacent to our policy states to form control groups. We use this strategy because we assume the neighbor states would have similar features and cultures, making them compatible when it comes to opioid shipments and overdose deaths. In this case, we pick Georgia, South Carolina, Mississippi, Alabama as control states for Florida; Louisiana, Oklahoma, New Mexico as control states for Texas; Montana, Oregon, Idaho as control states for Washington.

Ⅲ. Data

1. Datasets

We use four datasets to complete the analysis. The details are as follows:

1) Opioid Prescription Data (hereinafter referred to as opioid shipment data)

   We use data of all prescription opioid drug shipments in the United States from 2006 to 2014, obtained from the *Washington Post*. As Texas only has one year of data before policy, we are not able to conduct analysis on opioid shipment data for Texas. Every row in the raw data represents a single drug transaction including the information about transaction date, reporter location, buyer location, drug type, drug strength, etc. Our variables of interests are:
   - *BUYER_STATE*: State of entity receiving shipments from reporter.
   - *BUYER_COUNTY*: County of entity receiving shipments from reporter.
   - *TRANSACTION_DATE*: Date shipment occurred. (*TRANSACTION_DATE* was in dd-mm-yy format, so we extract the last 4 digits of this variable to get the **year** in which shipment occurred; for Texas, we extract the **month** as well)
   - *MME*: The measurement of drug amount. (*MME* stands for Morphine Milligram Equivalents, a measurement pain management physicians use to determine how different opioids relate to each other.)

2) Vital Statistics Mortality Data (hereinafter referred to as overdose deaths data)

   We use data obtained from the US Vital Statistics records, which include every death in the US from 2003-2015.

   Every single row of the data represents a certain type of death that happened in a particular county in a particular year. Since we are only interested in the deaths caused by drug overdose, we filter out other causes and only keep the drug-induced deaths.

   Our variables of interests are:
   - *County*: County the deaths occurring.
   - *County Code*: FIPS code of that county.
   - *Year*: Year the deaths occurring.
   - *Deaths*: Total number of drug-induced deaths. (After filtering out other irrelevant causes, we sum up the drug-induced deaths on county-year level)

3) FIPS Code Data

   We merge FIPS code on opioid shipment data with the aim of using FIPS as a unique identifier in later merging work. However, there are several inconsistencies between the county names in opioid shipment data and that in FIPS code data. We unified conflicts as follows for compatibility:
   - ST JOHN THE BAPTIST → ST. JOHN THE BAPTIST
   - SAINT → ST.
   - DODA ANA → DONA ANA
   - DE SOTO → DESOTO
   - DE KALB → DEKALB
   - DE WITT → DEWITT

4) <u>Population Data</u>

As counties have different populations, it is meaningless to look at the total opioid shipments and overdose deaths in each county. We would like to standardize them by obtaining per capita value. Therefore, we need to acquire population data of each county between 2003-2015.

We obtained our population data from the US Census Bureau. It contains the total population of every county in the US from 2003 to 2015. Since the Census Bureau conducts the US census every ten years, we only have actual population data in 2010, and population estimates for other years.

2. Merging strategy

Considering the time span discrepancy between opioid shipment data and overdose deaths data, we think it is better to merge the opioid shipment data with the population data and the overdose deaths data with the population data separately. We use FIPS code as a unique identifier and conduct **outer merging**. The reason we use outer merging is that we don't want to exclude the missing counties in opioid shipment data and overdose deaths data, because losing too many observations will lead to bias in our analysis. Instead, we would like to keep all the observations and do some reasonable data imputation, which we will discuss in the next section.

Here are some corrections we made during merging:

1) While merging the overdose deaths data with the population data:
    - The independent city of Bedford (FIPS 51515) in Virginia merged into Bedford County (FIPS 51019) in 2013.
      The change was only reflected in population data in 2015, but not in the overdose deaths data. For convenience, we changed it back to 51019 in the population data.
    - The independent city of Clifton Forge (FIPS 51560) merged into Alleghany county (FIPS 51005) in 2001.
      The 2015 FIPS code of Clifton Forge in overdose deaths data was not correct, so we changed it to 51005 in compliance with the population data.
    - Drop Alaska in the dataset (As Nick requires)
2) After merging, we generate two county-year level new variables:
    - MME per cap: MME divided by population
    - Overdose deaths per cap: Drug-induced overdose deaths divided by population

3. Handling missing values

As we mentioned above, there are amounts of missing values after conducting outer merging. Here are our imputation strategies:

1) <u>Opioid shipment data</u>

Opioid shipment data does not always exist for every county-year. We treat all of these missing values as 0, because we know there are no opioid shipments in these counties.

2) <u>Overdose deaths data</u>

However, missing values in overdose death data is different from opioid shipment data. For privacy, if less than 10 people died from a specific cause in a specific county in a given year, the exact number is not recorded in the data. Instead of treating them as 0, we interpolated them because we knew it meant a number is less than 10 rather than exactly zero. The interpolation method is as follows:

1. Aggregated population on state-year level
2. Aggregated number of drug-related deaths on state-year level
3. Calculated the ratio between these two and obtain state-year level drug-related mortality rate
4. Replace the missing values with the corresponding state-year level mortality rates

4. Summary Statistics

Our variables of interest in this analysis are MME per capita and overdose deaths per capita, therefore we provide summary statistics for these two variables both before and after the policy implementation. Since we analyze Texas's opioid shipment data on a monthly basis, there are more observations for Texas and its control states in the first table. The total observation numbers of the two tables differ, because the year range differs: the opioid shipment data runs from 2006-2014, while the overdose deaths data runs from 2003-2015.

[Table 1. Summary statistics for MME per cap]

	Florida		Control for FL		Texas		Control for TX		Washington		Control for WA	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
N	272	340	1432	1790	2682	21360	2035	16247	240	120	834	417
Mean	430.90	522.74	268..57	403.56	12.97	17.29	21.78	31.95	351.94	377.75	259.53	334.09
Median	379.38	450.64	242.07	362.58	11.04	16.09	19.85	30.03	324.15	341.87	236.31	322.63
Max	1749.64	2279.13	1476.92	2624.69	91.84	99.17	88.56	181.78	878.91	809.33	950.29	1002.28
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

[Table 2. Summary Statistics for Overdose Deaths per cap]

	Florida		Control for FL		Texas		Control for TX		Washington		Control for WA	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
N	476	408	2506	2148	1020	2295	708	1593	360	160	1251	556
Mean	1.06E-4	1.11E-4	3.71E-5	5.65E-5	4.01E-4	4.57E-5	6.79E-5	9.18E-5	8.61E-5	9.25E-5	2.72E-5	4.20E-5
Median	7.54E-5	7.51E-5	2.32E-5	3.96E-5	3.30E-5	3.72E-5	4.46E-5	6.35E-5	6.30E-5	6.74E-5	1.74E-5	3.06E-5
Max	3.59E-4	4.08E-4	4.74E-4	5.26E-4	4.27E-4	3.55E-4	4.71E-4	9.81E-4	3.07E-4	2.31E-4	3.23E-4	3.07E-4
Min	3.93E-5	3.90E-5	1.10E-5	1.74E-5	1.44E-5	1.81E-5	2.71E-5	4.07E-5	4.25E-5	5.68E-5	0.00E-0	1.76E-5

Ⅳ. Result

1. Methods

The frameworks we used, as mentioned before, are the pre-post comparison and difference-indifference analysis. Both frameworks are far from perfect and have their limitations, but they provide a reasonable starting place to analyze drug policy efficacy. The main reason we use them is because they allow us to make causal inferences. If the assumptions they make hold true, we can say whether or not drug policy implementations affected how much opioid was supplied in the state and the number of deaths caused by drug overdose. Such statements cannot be made from observing correlations alone. The caveat to these frameworks is that the assumptions they require are difficult to meet in reality.

1) Pre-Post Comparison

The main assumption of this framework is that the state after imposing a policy would have trends similar to its pre-policy trends *had the policy not been implemented.* For example, we assume that Florida after 2010 would look like Florida before 2009 if drug policies had not been enacted. Since we don't actually observe a post 2010 Florida with no policy, this helps us compare a world with the drug policy in effect, to a world without it.

2) Difference-in-Difference Analysis

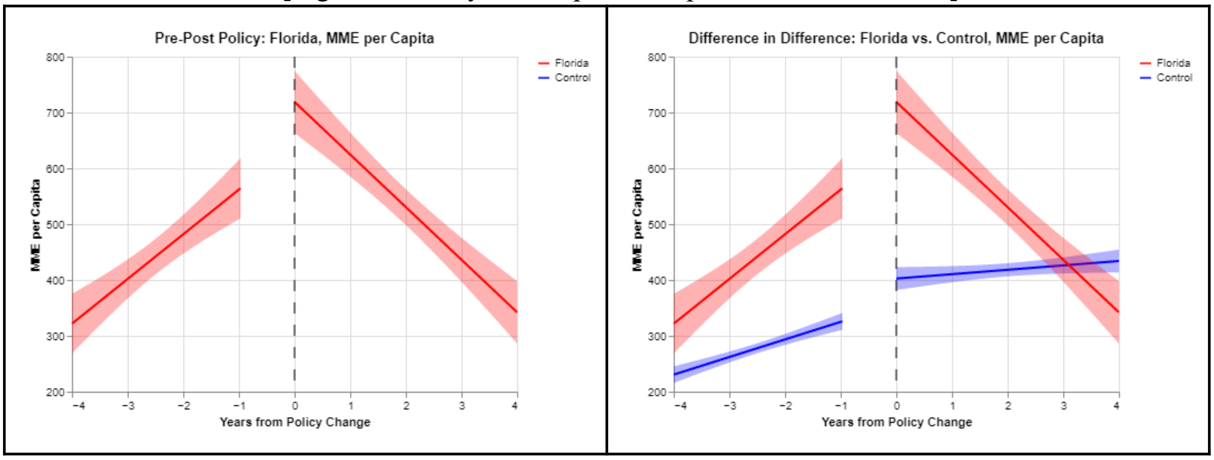
Pre-Post comparison is an effective method of analysis. However, it is possible that the declines in overdoses in states were not due to policy changes, but something that happened nationally. To verify this, we compare the pre-post difference in states with no policy changes (control states) to that in states with policy changes over the same period. This adds a layer of nuance to our model. Any causal inference we make will be stronger if we have compared the change in trends to a set of control states where no such policies were in effect.

2. Plots and Analysis

Our plots, bounded by 95% confidence intervals, provide some interesting insight as to how effective the policy changes in each state were. We found that in some states the policy change seemed to make more of an impact than in others. Here is the breakdown:

1) Florida : MME per Capita

[Figure 1. Analysis of Opioids shipment data for Florida]

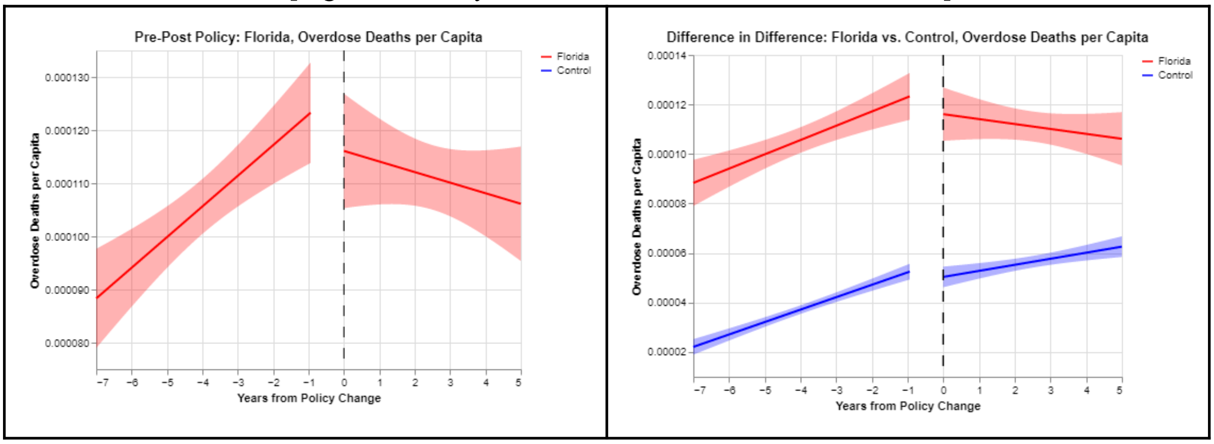


In terms of reducing the amount of opioids present in the state per capita, these plots demonstrate that the 2010 policy change in Florida was effective. Judging purely off the pre-post policy plot for Florida (left), it is clear that in the years after the policy change was implemented, *MME_per_cap*, our MME per capita variable, completely flipped trajectories. In other words, it appears that in the years leading up to 2010 in Florida, the amount of MME per capita was increasing steadily, however, in the years after 2010, the amount of MME per capita started to steadily decline instead.

The difference-in-difference plot on the right puts our findings from the pre-post policy plot into context. This plot compares Florida's pre/post trends for MME per capita against a control group including the geographically close states: Georgia, Alabama, Mississippi, and South Carolina. This comparison reveals a clear difference between trends for the control group and Florida in the post-policy years, reaffirming the idea that the change in trends was specific to Florida and not part of unconfounded national, regional or cultural factors. This is part of the reason we picked states that were adjacent geographically. For example, Florida and South Carolina are both southern states with access to the beach and have somewhat similar cultures to each other, along with some similarities in climate/weather. However, while they both show an increasing trend, the regression line for Florida and the control group don't quite align in the years leading up to the policy change, which lets us know that we should still be skeptical of these insights.

2) Florida : Overdose deaths per Capita

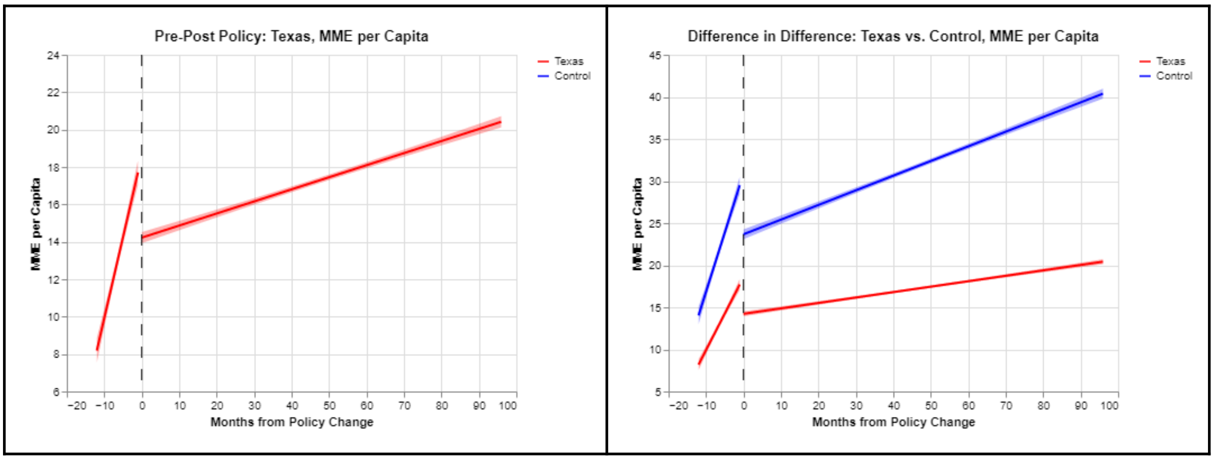
[Figure 2. Analysis of Overdose deaths data for Florida]



Similar to what we saw when analyzing the MME per capita metric in Florida, the 2010 policy change appears to be effective in changing the trend for Florida overdose deaths per capita. The pre-post plot for this metric shows that although overdose deaths per cap were steadily increasing before the change in 2010, once the change occurred, they began decreasing. The difference in difference plot on the right affirms this interpretation, showing that in states where there was no policy change, overdose deaths continue to have an increasing trend. Additionally, in the years leading up to the policy trend, the regression lines for Florida and the control group share a very similar slope, which allows us to make a stronger argument here that the 2010 Florida policy change made a positive impact when it comes to reducing overdose deaths.

3) Texas: MME per Capita (Monthly)

[Figure 3. Analysis of Opioids shipment data for Texas]

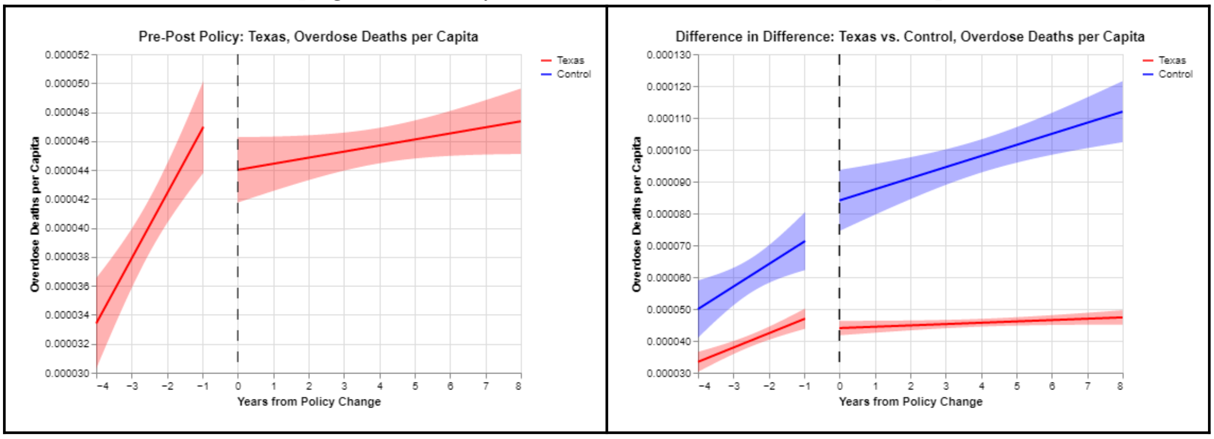


Texas changed its opioid policy in 2007. Since the opioid shipment data we have is from 2006, we only have one year's worth of data before the policy change. That means, unlike Florida or Washington, we can't make plots based on the year the policy changed. As an alternative, we made plots by month instead of year. After the policy change, Texas' opioid shipments still show an increasing trend, but the slope is much milder than before. On the other hand, in control states of Texas (Oklahoma, New

Mexico, and Louisiana), opioid shipments are increasing with a steep slope as before even after the policy change.

4) Texas : Overdose deaths per Capita

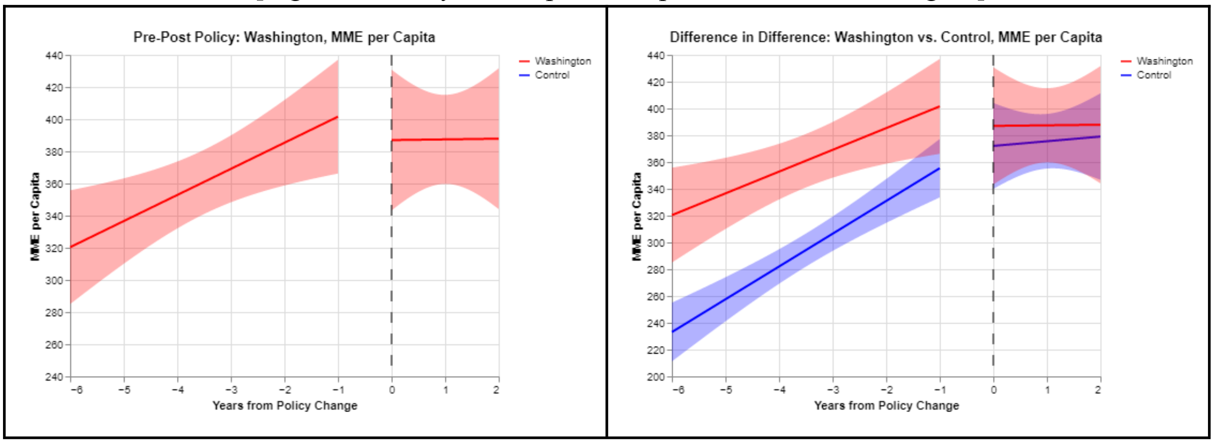
[Figure 4. Analysis of Overdose deaths data for Texas]



The 2007 Texas policy change appears to be effective when it comes to reducing overdose deaths per capita according to these plots. On the left, the pre/post plot shows that the policy trend marked a change in trajectory for the *deaths_per_cap* variable. On the right, we can see that this change in trajectory is not shared by the control group we used for Texas, including the states Oklahoma, New Mexico, and Louisiana. The control group and Texas even share a similar slope in the regression line in the years leading up to the policy change.

5) Washington : MME per Capita

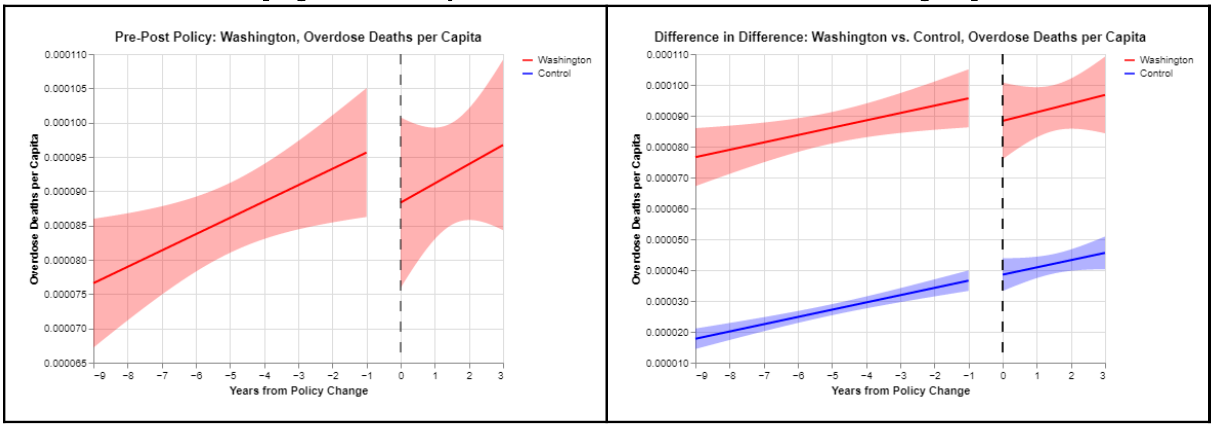
[Figure 5. Analysis of Opioids shipment data for Washington]



Unlike Florida, where opioid shipments declined dramatically, Washington's policy change is not significantly different. The regression line, which showed a gently increasing trend before the policy change, seems to have stagnated without any change after the policy change. On the other hand, the control group (Idaho, Montana, and Oregon) continued to increase even after the policy change in Washington in 2012. However, since we have data up to 2014 on opioid shipments and that means we have data for only two years after the policy change. Therefore, it will be difficult for us to determine the effectiveness of policy changes from this analysis alone.

6) Washington : Overdose deaths per Capita

[Figure 6. Analysis of Overdose deaths data for Washington]



Unlike Florida and Texas, Washington exemplifies a state in which its policy change does not seem to have made much of a difference. The pre/post plot for the Washington policy change shows almost no difference in the slopes of the regression lines for *deaths_per_cap* in the years before and after 2012, when the policy change was implemented. The difference-in-difference plot on the right reaffirms the conclusion that the policy was ineffective, in that the regression line for Washington shares a similar slope with its control states both in the years before and after the change was implemented.

Ⅴ. Conclusion

According to the plots above, we can conclude that the opioid control policy in the US was most effective in Florida, where the opioid shipment as well as overdose deaths per capita yield completely reverse (downward) trends after the policy implementation compared to its control states. The 2007 Texas policy is the second most successful one, as after the policy, although the opioid shipments and overdose deaths are still increasing, they yield a much milder and flatter trend compared to the control states. However, the policy doesn’t seem to be effective in Washington, since the trends of the two datasets after the policy are not much different from their control states, and they are still increasing at the same rate before policy implementation.

Upon examination of the opioid control policy implemented in these states, we noticed that Washington’s regulation included doctors having to refer patients to pain specialists if they were taking high doses of opioids and their underlying condition was not improving. In comparison, Florida’s 2007 policy was harsher, involving arrests and fines for pain clinics that were prescribing large quantities of opioids. This could serve as a possible explanation as to why the policy in Florida seemed to have immediate effects on the usage of opioids and deaths caused by drug overdose but Washington's was not as effective in churning out results.

There are limitations to the frameworks that we have used. These include the assumptions we have made. For example, we assume that Florida would be the same in a post-2010 world if it did not implement a drug policy, to itself pre-2010. This is a strong assumption and many unmeasured factors could have changed from 2009-11. Further, the assumption we make is that the control states look the same as our policy states in a pre-policy world. However, in reality there are differences between them that could possibly result in the bias of our analysis. In addition to this, we interpolate the missing values in overdose deaths data using the state-year level drug-related mortality rate. This might overestimate or underestimate the result, as we are doing a large-scale imputation.

Exploring the effect of drug control policies in the U.S. (For a Policymaker)

Preet Khowaja, Erika Fox, Shining Yang, Minjung Lee

Ⅰ. Summary

For this report, we examined the effectiveness of three opioid policy changes from within the past two decades from three states: Texas (2007), Florida (2010), and Washington (2012), with a goal of gaining insight as to what kind of policies are effective in managing overdose deaths and opioid per capita.

Ⅱ. Motivation

Excessive usage of opioids in the United States has been a significant concern in the last two decades. In 2019 alone, nearly 50,000 people died an opioid-related death in the United States. Several attempts to manage opioid use have been made, including different kinds of policy changes made across different states in the country. These policy changes vary in nature, in that some of them involve changes that have more to do with putting forceful restrictions on local pain clinics, while others have more to do with regulating how opioids are prescribed to patients. The motivation behind this analysis is to gather an understanding as to what elements make up a successful policy change, by examining changes implemented in Texas (2007), Florida (2010), and Washington (2012).

Policy summaries:

1. Texas (2007)
    a. required patient evaluation before prescribing opioids
    b. required informed consent from patients before prescribing opioids
    c. required periodic review of opioid treatment
    d. required the upkeep of a complete medical record of treatment
2. Florida (2010)
    a. required pain clinics using opioids to register with the state
    b. conducted statewide raids, resulting in numerous arrests, seizures of assets, and pain clinic closures
    c. prohibited physician dispensing of schedule II or III drugs
    d. Mandated dispenser reporting to the prescription drug monitoring program
3. Washington (2012)
    a. Implemented new prescribing requirements, including
        i. an annual periodic review for stable patients taking non-escalating doses of 40mg MED/day or less

ii. a consultation with a pain management specialist if adults exceed the threshold of 120 mg MED/day
iii. documentation for each mandatory consultation

Ⅲ. Overview of Data

The following is a list of the main datasets that were used in this analysis.

1. Opioid Prescription Data
   This dataset from the *Washington Post* contains information about opioid shipments in the U.S. from the years 2006-2014. Every row in this set represents a single drug transaction including the information about transaction date, reporter location, buyer location, drug type, drug strength, etc. Opioid shipment is measured in MME, where MME is the morphine milligram equivalent, which is the standard used to compare opioids with one another.
2. Vital Statistics Mortality Data
   This dataset from the US Vital Statistics records contains information on every death in the U.S. from the years 2003-2015. Every row in this set represents a certain type of death that happened in a particular county in a particular year. We filtered this data to only include drug-related deaths (overdose).

In addition to these two primary datasets, we also used county population data in order to answer our questions of interest.

Ⅳ. Analysis

In order to examine the effectiveness of our policies of interest, we used two main approaches:

1. Before/After Analysis: For each state, we compared trends from the time before the policy was implemented to trends from the time after.
2. State Comparison: For each state, we also compared what we found from the Before/After Analysis to the one from other geographically similar states. We assume the neighbor states would have similar features and cultures, making them compatible when it comes to opioid shipments and overdose deaths. In this case, we pick Georgia, South Carolina, Mississippi, Alabama to compare with Florida; Louisiana, Oklahoma, New Mexico to compare with Texas; Montana, Oregon, Idaho to compare with Washington.

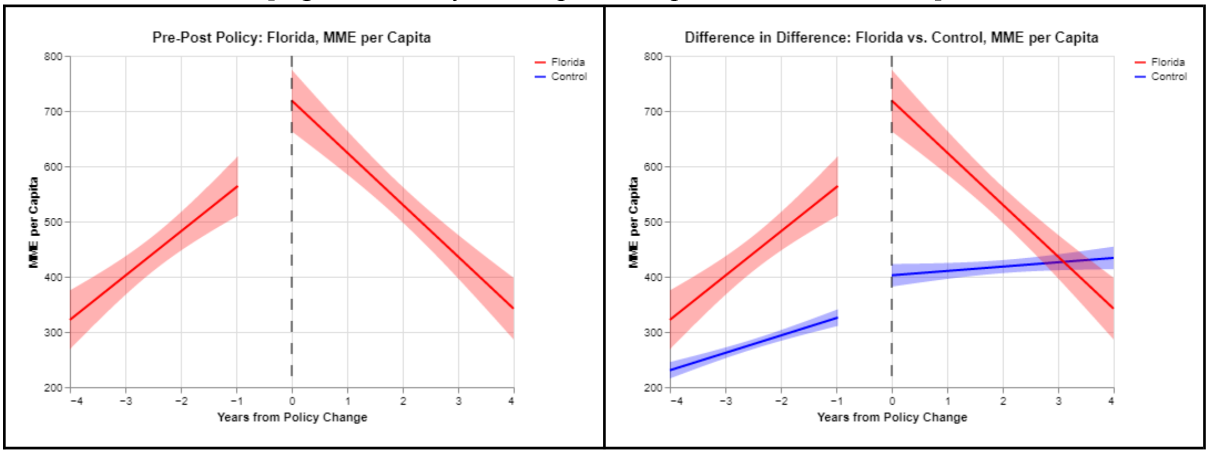
We did each of these approaches for all three states, using both the amount of overdose deaths and the amount of opioids per capita as measures as to how much of an effect the policies made.

Ⅴ. Insights

Our plots provide some interesting insight as to how effective the policy changes in each state were. We found that in some states the policy change seemed to make more of an impact than in others. Here is the breakdown:

1) Florida : MME per Capita

[Figure 1. Analysis of Opioids shipment data for Florida]



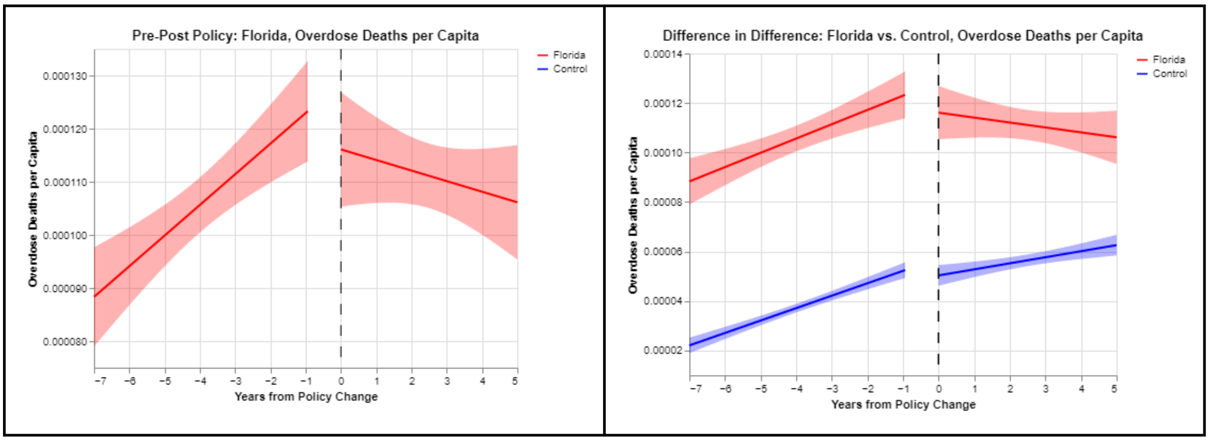
Left: Before/After Analysis. Right: State Comparison.

In terms of reducing the amount of opioids per capita present in the state, these plots demonstrate that the 2010 policy change in Florida was effective. Judging purely off the left plot for Florida, it is clear that in the years after the policy change was implemented, the trend for shipment of opioids completely flipped trajectories. In other words, it appears that in the years leading up to 2010 in Florida, the amount of opioids per capita were increasing steadily, however, in the years after 2010, the amount of opioids per capita started to steadily decline instead.

The plot on the right puts our findings from the left plot into context, using the additional states of Georgia, Alabama, Mississippi, and South Carolina. We assume the trend in Florida should be the same as Georgia, Alabama, Mississippi, and South Carolina had there's no policy implementation. However, this comparison reveals a clear difference between trends in Florida and in other states in the post-policy years, reaffirming that the change in trends was specific to Florida and not due to unconfounded national, regional, or cultural factors.

2) Florida: Overdose deaths per Capita

[Figure 2. Analysis of Overdose deaths data for Florida]



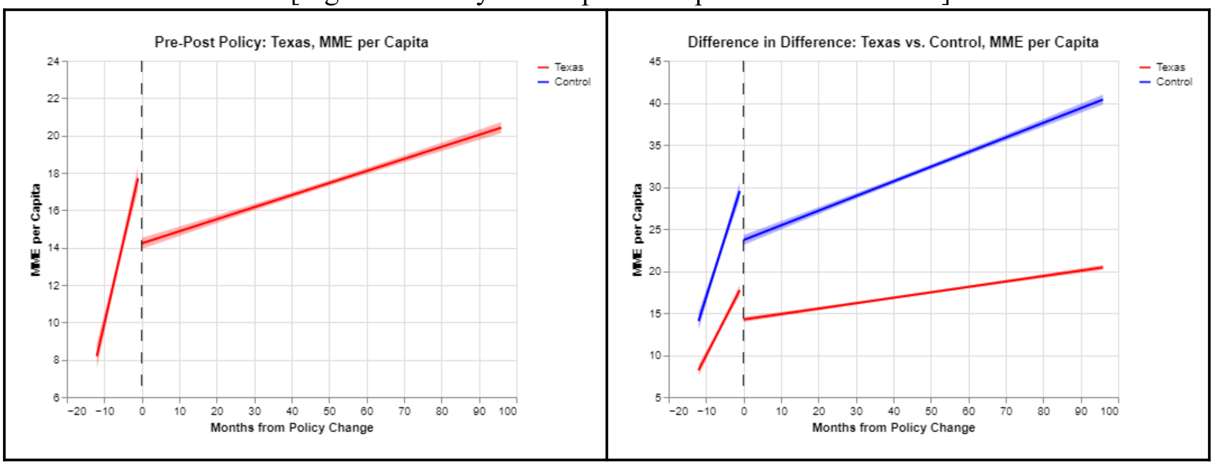
Left: Before/After Analysis. Right: State Comparison

The 2010 Florida policy change also appears to be effective when it comes to reducing the amount of overdose deaths per capita. The left plot shows that although overdose deaths per capita were steadily increasing before the change in 2010, once the change occurred, they began to show a decreasing trend.

The State Comparison plot on the right reaffirms what we learned from the left plot, showing that in states similar to Florida where there was no policy change, overdose deaths continue to have an increasing trend.

3) Texas: MME per Capita (Monthly)

[Figure 3. Analysis of Opioids shipment data for Texas]

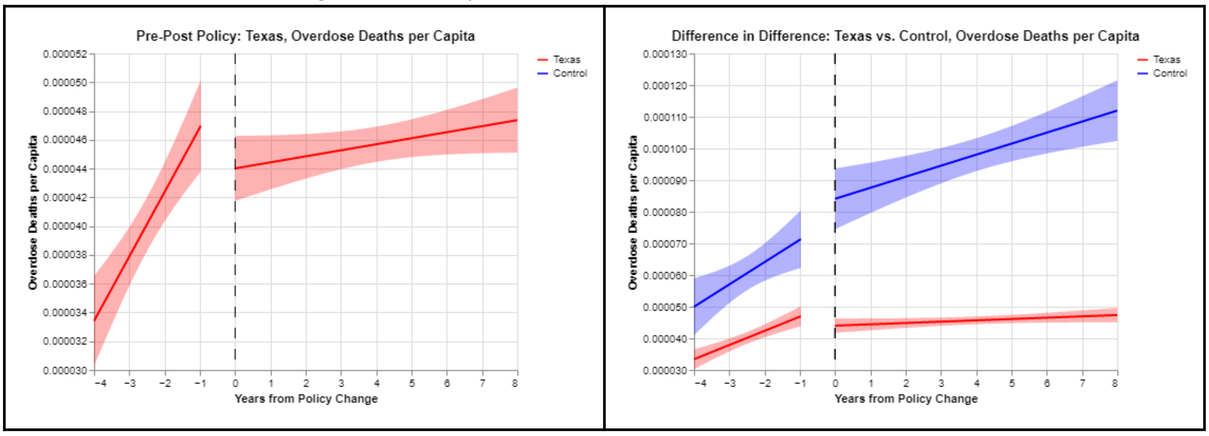


Left: Before/After Analysis. Right: State Comparison

As we only have one year of data before the policy implementation for Texas, we conduct the analysis on a monthly basis here. These plots evaluating the effects of the 2007 Texas policy change on opioids per capita differ from our Florida plots, as these plots seem to demonstrate a less effective change. Our plot from our Before/After Analysis on the left shows that in the months leading up to the policy change, the amount of opioids per capita were steadily increasing, similarly to Florida. Yet, unlike Florida, in the months following the policy change in Texas, this increasing trend does not change to a decreasing one. However, even though the trend in the months after the policy implementation does not completely change directions, the line does appear to flatten a bit, indicating that the Texas policy at least worked to slow down opioid use. Our State Comparison plot on the right validates this, as our trend line from Texas does look flatter compared to the trend line from our geographically similar states: Louisiana, Oklahoma, and New Mexico.

4) Texas: Overdose deaths per Capita

[Figure 4. Analysis of Overdose deaths data for Texas]

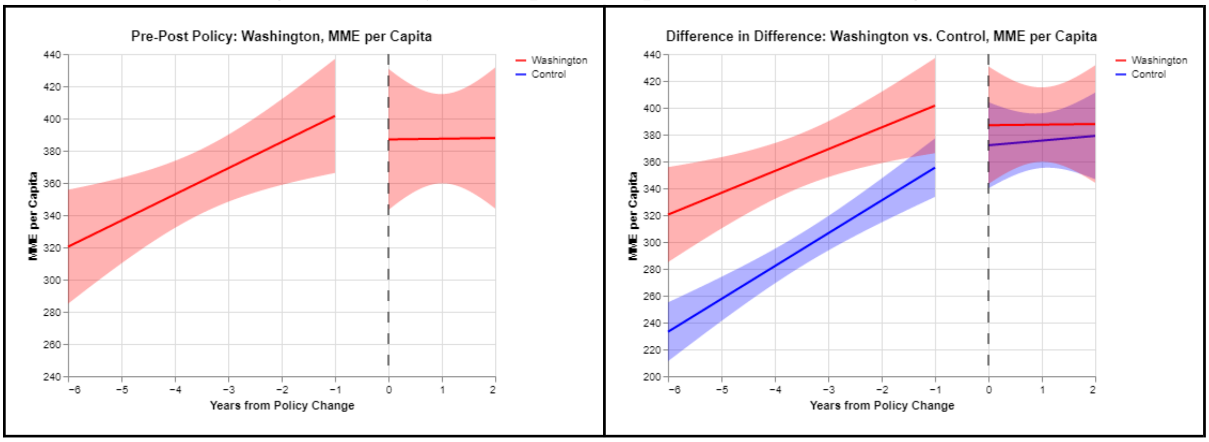


Left: Before/After Analysis. Right: State Comparison

Our plots examining the impact of the 2007 Texas policy change on overdose deaths show similar results to what we found when examining this policy with the opioids per capita metric. The left plot shows that in the months after the policy was implemented, overdose deaths continue to increase, yet not as steeply. The plot on the right confirms that the trend for overdose deaths in Texas in the months following the policy change is much flatter compared to geographically similar states, suggesting a mildly successful policy change.

5) Washington: MME per Capita

[Figure 5. Analysis of Opioids shipment data for Washington]

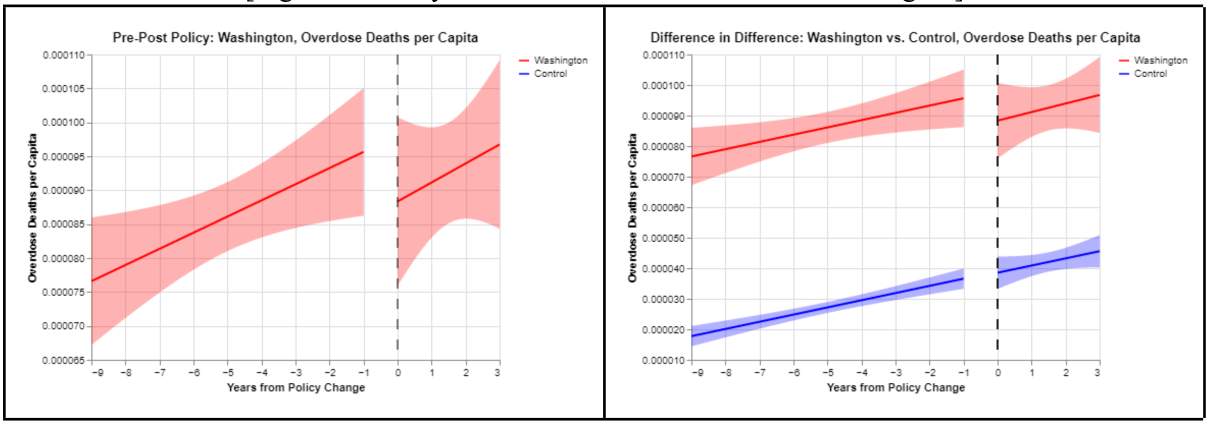


Left: Before/After Analysis. Right: State Comparison

These plots show that the 2012 Washington policy change had a similar effect to the Texas policy change on opioids per capita, in that the 2012 Washington policy also appears to have flattened the opioids per capita trend line, suggesting a slightly effective policy change. However, the plot on the right suggests that some of this flattening we see could be due to unconfounded national, regional, or cultural factors, as our geographically similar states (Montana, Oregon, and Idaho) also show a flattening in the trend line for opioids per capita in the years after the policy change. Yet, even so, Washington's line still seems to flatten more. Regardless, it is clear by these plots that Florida still seems to have the most effective policy change so far.

6) Washington: Overdose deaths per Capita

[Figure 6. Analysis of Overdose deaths data for Washington]



Left: Before/After Analysis. Right: State Comparison

Finally, we have these plots examining the effects of the 2012 Washington policy change on overdose deaths. These plots reveal that this policy did not have much of an effect on overdose deaths per capita at all. On the left, we see that in the years before the policy change, overdose deaths per capita were increasing at a steady rate. In the years after the policy change, although the mean value decreased a little bit, they continue to increase at almost the same rate. On the right, we compare this Before/After analysis to our geographically similar states, and see very little difference in the overdose death trends. These results suggest that even though Washington's policy change might have done something to slow down the increasing quantities of opioids per capita in the state, the policy was not effective in reducing overdose deaths.

Ⅵ. Conclusion

In conclusion, when it comes to creating successful opioid policies in reducing overdose deaths and opioids per capita, the 2010 Florida Policy change is one to look up to. Florida's policy on opioids was a strict crackdown on pain clinics and physicians prescribing the drug, and according to our plots, it was very effective. The 2007 Texas policy is the second most successful one, resulting in the change to a milder increasing trend (almost flat), yet is not strictly decreasing and is not as effective as Florida. In comparison, the 2012 Washington policy almost had no effect on the control of opioid shipments and overdose deaths. It's probably due to looser policy measures in Texas and Washington, explaining the slower change in these states.