Estimating the Impact of Opioid Control Policies: Data Science Report

Emma Wang, Pragya Raghuvanshi, Lorna Aine & Eric Rios Soderman

December, 12, 2022

Motivation

The opioid crisis plagued the United States in the mid 1990s and has since continued in a series of overlapping waves. More than 932,000 people in the country have been killed since 1999, within which the number of opioid deaths has increased eightfold, according to the Centres for Disease Control and Prevention (CDC). The country witnessed three distinct waves of increasing opioid deaths caused by prescription opioids, heroin, and synthetic opioids such as fentanyl. Opioids are a class of drugs that are used as prescription pain relievers, and can provide effective pain management when taken as directed. However, these prescription drugs are misused and abused leading to overuse, addiction and mortality. According to the Centers for Disease Control and Prevention (CDC), prescription opioid–related overdose deaths increased sharply during 1999 to 2010 in the United States alongside increased opioid prescription. Even though these prescription opioids are legally available and have vaste clinical applications, they can also be procured and distributed illegally. This misuse of prescription opioids fuels the opioid epidemic as the abuse of these leaves the users being habitual or even addicted to the use of illicit opioids like fentanyl and heroin. To curb this drug menace, many states have put up several laws and policies in place.

The primary objective of this analysis was to examine the effectiveness of interventions in the states' opioid policies in lowering the volume of opioid prescriptions and rate of drug overdose mortality.
In this analysis, we sought to answer:

- Does the implementation of a policy on opioid drugs reduce the number of opioid prescriptions?
- Does the implementation of a policy on opioid drugs reduce the mortality rate due to drug overdose?

In this analysis we focused on the interventions implemented in Florida, Washington and Texas. Florida implemented several policy changes in 2010, as part of Operation Pill Nation, carried out numerous statewide clinic raids on facilities that did not adhere to the best practices for the prescription of opioids. Both the regulation of wholesale drug distributors and the formation of a statewide task force were the results of these processes (DEA, 2011). In Texas, the medical board established a thorough procedure in 2007 that included patient assessment, consent-seeking, periodic reviews of opioid treatments, and periodic reviews of the patients' opioid treatments (Texas Medical Board, 2007). Finally, in Washington, changes in 2012 included the addition of specialized consultations for patients who needed doses of opioids greater than 120 mg/day and a greater emphasis on recording these special consultations. (Department of Health, 2011).

For the comparative aspect of our analysis of each policy intervention, the data from a state where a policy was enacted (base state) was compared to data from a group of states where fewer restrictions or no policies were put into effect. These were chosen based on having a similar proportion for elderly population as the base state.The rationale behind this is that the elderly population undergoes more medical procedures, and as a result, opioids are frequently prescribed (Harbaugh, 2019). This enabled us to compare the number of opioid prescriptions and overdose deaths in our base states, where a policy change has occurred, to the control states, where a policy change has not occurred.

Research design

For this problem, we asked how effective was the opioid policy in restricting the amount of opioids prescribed and in decreasing the mortality rate due to drug overdose?

- **H0**: Policy enactment on opioid drugs does not significantly reduce opioid prescriptions and opioid related deaths (drug overdose).

- **H1**: Policy enactment on opioid drugs does significantly reduce opioid prescriptions and opioid related deaths (drug overdose).

We used the effect of opioid drug regulations on the amount of opioid prescribed (in mg) per capita and drug overdose deaths per capita to answer the question using the following methods:

- **Pre-post analysis**: This method illustrated the change in opioids shipment and overdose deaths data pre and post policy implementation. It included a pre- and post-model graph for the state with the policy change with a goal to see if the plotted outcome continued to rise or drop after the year of intervention. An ideal effectiveness of the policy would depict a fall in the outcome of interest and a rise otherwise.

Additionally, while a pre-post analysis is a simpler and straightforward approach to estimating causal effects, it was not sufficient in itself to conclude this analysis as the changes in the drug overdose deaths and the opioid shipment could be attributed to multiple factors, necessitating the use of more comparative analysis of the effects of policy change on the base state and the control states.

- **Difference in difference analysis**: This is a regression technique performed to compare the state with the policy intervention, known as the treatment state, with the counterfactual states undergoing no policy change. This state should follow a similar trend to the treatment state under consideration prior to the policy change. The idea is to create a parallel universe for the base state where the policy change has not taken place, and compare it with the reality where the policy has been put in place. This helped us better gauge the effectiveness of policy in a conclusive manner as compared to the earlier approach of pre-post analysis. The difference-in-difference graphs depict the differences in trends between the treated and untreated states over factors of opioid shipment and drug overdose per capita respectively.

- **Visualization:** This technique involves representing data visually, using graphs, and charts. For this analysis we used graphs to illustrate the trends before and after policy change and the model fit to show the differences in trends and volatility around them.

Data

FIPS Dataset

In order to make the analysis consistent and prevent additional type or merging errors, we needed to obtain all the counties' unique FIPS codes by using the FIPS dataset. They were the ideal choice because county names are shared across multiple states, unlike their FIPS codes, and the names of the counties themselves are prone to cause errors when merging, especially if the datasets to be merged have different spellings of the same name. One such case was the "saint johns county" of the opioids dataset, which was different from the FIPS dataset's "*st. johns county*". This was the core objective behind obtaining the FIPS dataset, getting our opioids dataset's counties their respective FIPS codes, which was a success.

Overdose Dataset

To assess the effect of policy on overdose deaths, we shall use the US Vital Statistics dataset (that includes underlying causes of death from 2003-2015 in the US), which includes our variable of interest, drug overdose deaths. The unit of observation for this dataset is the total annual number of drug overdose deaths per county.
While cleaning the data, it is important to note that, since the files included multiple causes of death, the data was filtered to keep only the deaths that were due to drug overdoses, identified under the D-1 through D-4 categories. Within this metric, although not every drug belongs to the class of opioids, it acts as our closest proxy to detect opioid related deaths. In addition, there were 20 missing values for some of Arkansaw's counties (Prince of Wales-Outer Ketchikan Census Area, Skagway-Hoonah-Angoon Census Area, Wrangell-Petersburg Census Area) and some of Virginia's counties (Bedford City and Clifton Forge City), so those records had to be removed from the dataset. Furthermore, when the amount of deaths are below a threshold of 10, they can be grouped under another category or the number is simply not reported, resulting in more missingness. Lastly, some records of death also lacked causes of death, rendering inaccessible to the study.

County Populations Datasets

To make the result comparable between counties and states, we needed to calculate the average opioids prescribed and drug overdose deaths per capita. To do this, we needed to divide the total weight of opioids prescribed and the drug overdose deaths by the county population, respectively. For this reason, we obtained two county population datasets. The first one covered the years from 2006 to 2014 (United States Census Bureau, 2016), and the second covered the years from 2003 to 2005 when a missingness of death values arose for the Texas subset, which will be discussed in its own section. The resulting unit of observation would be the number of residents per county.

Opioids Shipment Dataset

To assess the effect of policy on opioids prescriptions, we shall use the opioid shipment data set. The Washington Post published the opioid shipment data set as part of their study on the rise of deaths caused by increasing opioid prescription shipments, which contains information on all shipments of prescription opioid drugs made in the US between 2006 and 2014, and it was obtained through a Freedom of Information Act (FOIA) request to the US Drug Enforcement Agency (Drug Enforcement Administration, 2011). This will serve as our data set to derive opioid prescription data. From this data set, the following variables will be used:

- The buyer state, which is the state of the entity receiving shipments from the reporter.
- The buyer county, which is the county of the entity receiving shipments from the reporter.
- The date of the transaction, which is the date the shipment occurred.
- The weight of the drug in grams during the transaction.
- The conversion factor to calculate a drug's morphine milligram equivalent in milligrams

By obtaining the product of the drug’s weight in grams and its morphine equivalents, we will use this data set to estimate the total amount of drugs prescribed in grams. Given that morphine is one of the commonly prescribed opioids, we shall use the product of those two variables to describe the total amount of morphine prescribed in grams, to make the amounts of the different opioids shipped more comparable. The total amount of morphine prescribed in grams per county, per state, and per year constitutes the final observational unit in this dataset after the cleaning process.

Final Merged Dataset

The final working dataset was a merged dataset formed by combining the opioid shipments dataset, the FIPS dataset, the overdose deaths and the county population datasets. The final dataset’s unit of observation was the annual, total weight of opioids prescribed per capita and annual, total number of deaths caused by drug overdoses per capita per county.

Control States and Subsetting

The selection criteria for control states was based on similarity of proportion of elderly population as the treatment states. A data set containing the age distribution across all states was used to compare the proportion of population that was 65 and above in the treatment states and any states within a 0.1% less or more range were taken as control states.

The data was divided into three main subsets, where each was a treatment state accompanied by its control states. One of the issues was missingness across a county level, where counties in the opioid shipment data had recorded information, yet no county name despite having a recorded state. For example, Louisiana was the most prominent state with this issue in our subsets, and a few of its counties were dropped as a result. Consequently, we recognize the impact this has in our data, which is why we had more than 3 control states in the subset.

Data Missingness and Analysis Scope

One of the challenges we ran into was the Texas missing population in the year prior to 2006. additional population dataset (which is the population dataset from Census) to cover the years from 2003 to 2005 and add that information into that subset. To further address the data quality issues across all datasets we analyzed complete and missing data sets for each of the subsets and found that at respective population thresholds across all the states in the subset above which there existed complete data for all the variables of interest.The subsets were further subsetted by the population threshold and this curved out a very specific scope for the analysis performed in this report. The analysis carried out in this data represents Texas and its corresponding control states counties with population above 19,286, Florida its corresponding control states counties with populations above 40,008 and Washington and its corresponding control states counties with populations above 67,791.

Treatment State	**Control States**
Florida	West Virginia, Delaware, Hawaii, Pennsylvania, New Hampshire, South Carolina, and New Mexico.
Washington	Maryland, Oklahoma, Indiana, Idaho, Minnesota, Nebraska, Nevada and Virginia.
Texas	Colorado, Utah, Georgia, California, North Dakota, Illinois, Maryland and Oklahoma.

Table 1: Control States for difference-in difference analysis

Summary statistics for data

The table below throws light on the descriptive statistics of the dataset in consideration. We probe the central tendency, the spread in the values and any skewness present in the dataset for all treatment and control states.

State	Year for policy change	Mean	Median	Min	Max
Florida	Pre 2010	15.71	15.88	14.09	17.21
	Post 2010	13.76	13.51	12.59	15.44
Control States for Florida	Pre 2010	14.63	13.28	6.26	28.75
	Post 2010	20.26	17.40	10.15	42.75
Texas	Pre 2007	8.94	8.86	8.15	9.93
	Post 2007	9.88	9.96	8.13	10.84
Control States for Texas	Pre 2007	12.06	12.11	5.32	19.39
	Post 2007	14.05	13.15	7.41	21.33
Washington	Pre 2012	13.62	13.81	12.69	14.29
	Post 2012	13.37	13.37	13.32	13.42
Control States for Washington	Pre 2012	11.86	10.95	4.15	23.86
	Post 2012	14.32	14.79	5.52	22.85

Table 2: Summary Statistics for Treatment and Control States for Overdose Mortality Rates (measured per 100,000)

From the summary statistics for the mortality rates we can see that for Florida, post the policy enactment in 2010, the mean mortality rate (measured in 100,000) dropped from 15.71 to 13.76. The minimum and maximum value of mortality rates also fall indicating a possible positive impact of the policy change on the statistics. For Texas, however, we see a minimal increase in mean mortality rates after 2007, from 8.94 to 9.88, when the policy comes into effect. We can also check for median, maximum and minimum values which somehow show a similar trend. Again, for Washington, it is seen that the mean mortality rate decreases minutely across 2012 from 13.62 to 13.37 per 100,000 population. In all the states, median value is almost equal to the mean, inferring that there is no noticeable skewness in the data.

Opioid Shipment per cap(in gm)

State	Year for policy change	Mean	Median	Min	Max
Florida	Pre 2010	0.34	0.33	0.21	0.53
	Post 2010	0.23	0.18	0.14	0.41
Control States for Florida	Pre 2010	0.20	0.17	0.06	0.42
	Post 2010	0.28	0.23	0.068	0.65
Washington	Pre 2012	0.14	0.14	0.13	0.15
	Post 2012	0.12	0.12	0.12	0.12
Control States for Washington	Pre 2012	0.15	0.15	0.07	0.32
	Post 2012	0.16	0.17	0.073	0.26

Table 3: Summary Statistics for Treatment and Control States for Opioid Shipment per capita (measured in gram)

The table above shows statistics for the mean opioid shipment per capita in grams across Florida, Washington and their control states. It can be seen that there is a clear decrease in the mean shipment for Florida post the policy change in 2010. A similar decrease is found in minimum and maximum amount of shipments across 2010. The takeaway from the statistics of both the metrics of Florida is that there is a possibility that the policy enactment was able to curb the opioid epidemic for Florida. We can also see that in the control states where there is no policy change has taken place, the mean shipment of opioid increases. For Washington, the mean value of the shipment witnessed a minute change across the year of policy change. Again, there is no noticeable skewness in the data for the opioid shipment per capita.

The results from the data analysis performed using the summary statistics show that the regulations put in force to curb the opioid prescriptions and mortality rate may be indeed effective. This will further be probed in our statistical analysis using pre-post and difference in difference methodologies.

Analysis

Assumptions

The following assumptions are made in the analysis for the effectiveness of policy enactments on curbing opioid prescriptions and overdose deaths:

1. We make an assumption that the criteria for choosing constant states based on a similar proportion of elderly population as the treatment states, with the hope to result

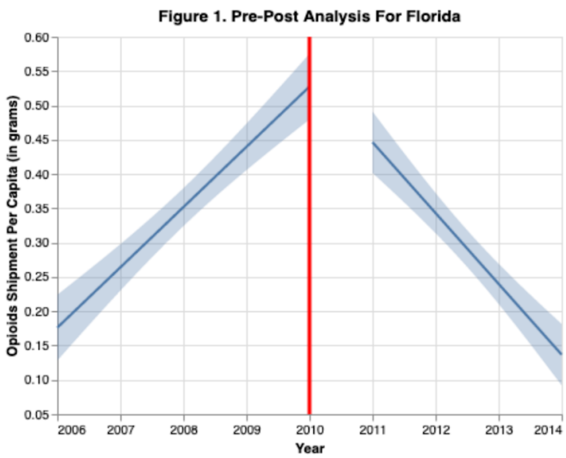
in a parallel trend between the treatment and control states prior to the policy change. This ensures that for the difference in difference approach we can analyze the difference in treatment states where policy change has taken place and treatment states in a parallel universe where it has not, as the control states are assumed equivalent to the treatment states with no policy change.

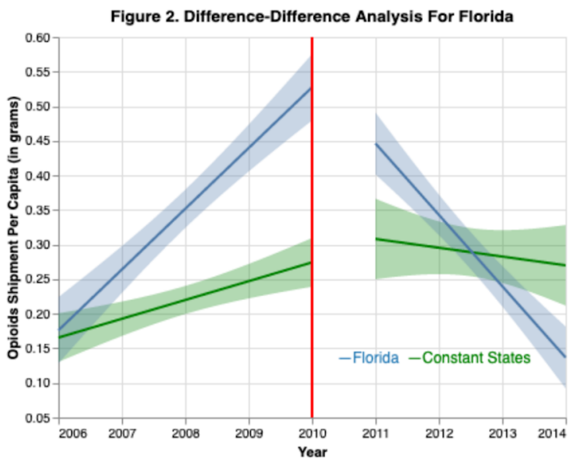
2. We also conclude that the policy enacted by the State to regulate opioids has been effective based on the two metrics, overdose deaths and opioids shipment per capita. This leaves room to probe other metrics that may be influential in determining the efficacy of the policies.
3. The expected behavior for the control states is that these metrics continue to increase post the year of policy change in treatment state, which we can attribute to the absence of policy regulation. However, our analysis is inept in handling the states where these metrics decrease post the year in consideration.

For all the following graphs, the green lines and error bands represent the metrics for the control states, while the blue lines and error bands represent our treatment state in consideration.

Florida

<u>Opioids shipment per cap</u>





In this graph, the base state is Florida and the constant states include West Virginia, Delaware, Hawaii, Pennsylvania, New Hampshire, South Carolina and New Mexico

Analyzing the pre-post graph regarding Opioids shipment per capita for Florida, it can be observed that there is a rising trend in the opioid shipment per capita prior to 2010, when the policy was not in effect. With a value of 0.17 gm per capita in 2006, the shipment peaked in 2010 to the value of 0.53 gm per capita. However, post the policy intervention, a sharp decline is witnessed in the shipments influx, with the value dropping to 0.13 gm per capita in 2014. The results from the pre-post analysis are simple, but not conclusive enough to suggest that the major reason for the decreasing trend in the shipments per cap can be attributed only to the policy interventions in Florida. Therefore, difference-in-difference analysis is performed with other control states that had a similar trend pre policy intervention and no policy change unlike Florida, as comparisons with them can serve to better gauge the effectiveness of policy implementation in Florida. The control states used for Florida are West Virginia, Delaware, Hawaii, Pennsylvania, New Hampshire, South Carolina, and New Mexico. From the difference-in-difference regression conducted on the treatment and control states, we can see whether or not the control states witness a similar decline in opioid shipment per capita. It is noted that for the control states the shipment per cap value in 2010 is 0.27 gram per capita, rising from 0.16 gram in 2006, which remains rather stagnant at 0.27 gram in 2014, the year for policy change in Florida. The resulting difference in difference estimator is calculated as the difference in average opioid shipment per capita in Florida, our treatment state, before and after the policy change, minus the difference in average opioid shipment per capita in control States before and after policy change.

Policy Change	**Average opioid shipment per capita in Florida (in gm)**	**Average opioid shipment per capita in Control States (in gm)**
Pre 2010	0.352	0.219
Post 2010	0.292	0.289
Difference(post-pre)	-0.0602	0.069
DID = Difference (Florida-Control States)	-0.129	

Table 4: Difference in Difference estimator for Florida for Opioid Shipment per capita (measured in gram)

As you can see from Table 4, the estimated difference-in-difference of -0.13 suggests that the opioid shipment per capita in Florida decreased more than that in Control States from 2006 to 2014. This indicates the effectiveness of policy in drug overdose deaths. Hence, we can conclude that the policy change in Florida was indeed effective in curbing the shipment per capita. Since shipments directly relate to the demand of opioid in a State, which is indeed a result of opioid prescriptions, we can say that the force of law was indeed influential in reducing the volume of opioid prescription.

Drug overdose death

Figure 3. Pre-Post Analysis For Florida

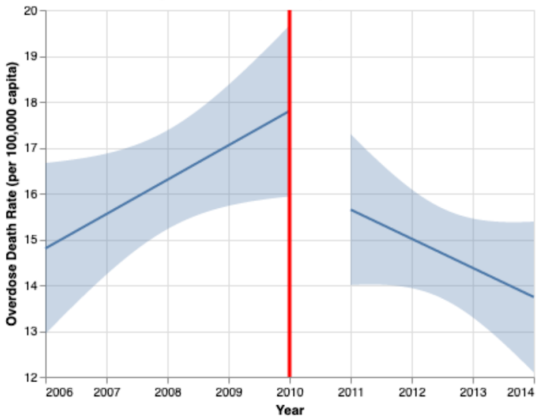
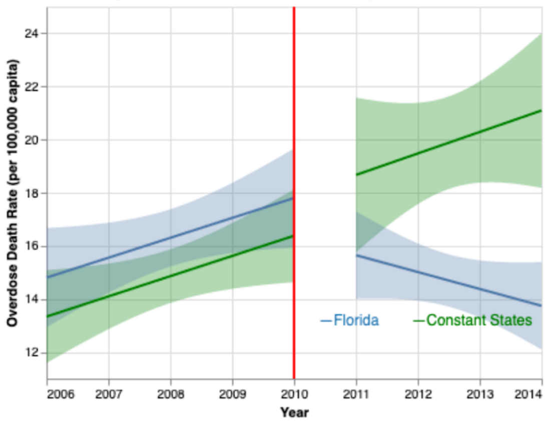


Figure 4. Difference-Diference Analysis For Florida



In this graph, the base state is Florida and the constant states include West Virginia, Delaware, Hawaii, Pennsylvania, New Hampshire, South Carolina and New Mexico

From the drug overdose death graph measured per 100,000 population, Florida's pre-post analysis depicts that death rates rose steadily from 14.9 to 17.8. Peaking in 2010, there is a sharp decline, to 13.8 in 2014. Adding to the pre- post graph, in the difference-in-difference analysis we can observe that the death rate for the control states continues to increase even post 2010. From a value of 16.4 in 2010 to 21 in 2014 we can observe a steady increase in the death rate. The resulting difference in difference estimator is calculated as the difference in average overdose death rate in Florida, our treatment state, before and after the policy change, minus the difference in average overdose death rate in control States before and after policy change.

Policy Change	Average Overdose death rate in Florida	Average Overdose death rate in Control States
Pre 2010	16.299	14.856
Post 2010	14.694	19.879
Difference(post-pre)	-1.605	5.024
DID = Difference (Florida-Control States)	-6.63	

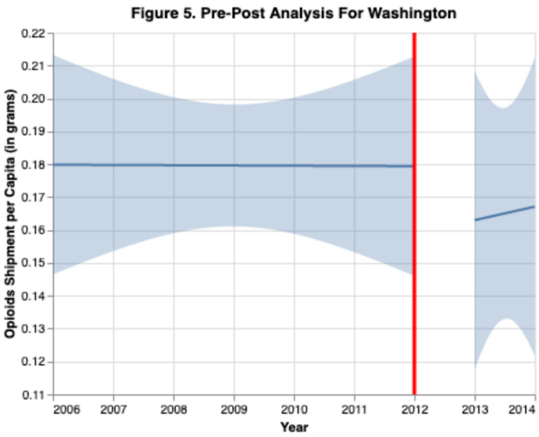
Table 5: Difference in Difference estimator for Florida for Average Overdose death rate (measured per 100,000)

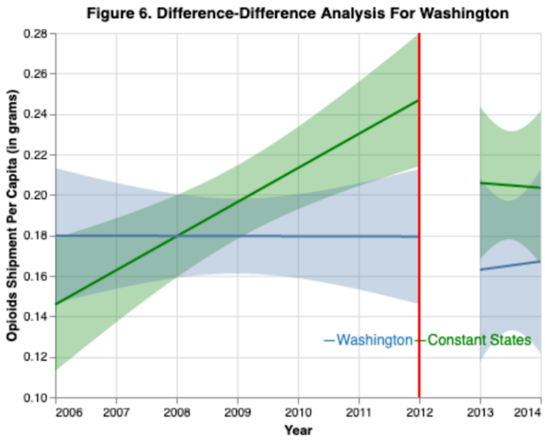
From Table 5, we can see that the estimated difference-in-difference has a value of -6.63, implying that the death rate in Florida decreased more than the death rates in Control States. This indicates the effectiveness of policy in drug overdose deaths.

Therefore, the two metrics we used, opioid prescriptions and death due to overdose, both witness a decreasing trend corroborating that the policy enactment was indeed fruitful. To conclude, we reject the hypothesis H0 and retain H1, that is, policy enactment on opioid drugs does significantly reduce opioid prescriptions and opioid related deaths (drug overdose).

Washington

<u>Opioids shipment per cap</u>





In this graph, the base state is Washington and the constant states include Maryland, Oklahoma, Indiana, Idaho, Minnesota, Nebraska, Nevada, Virginia.

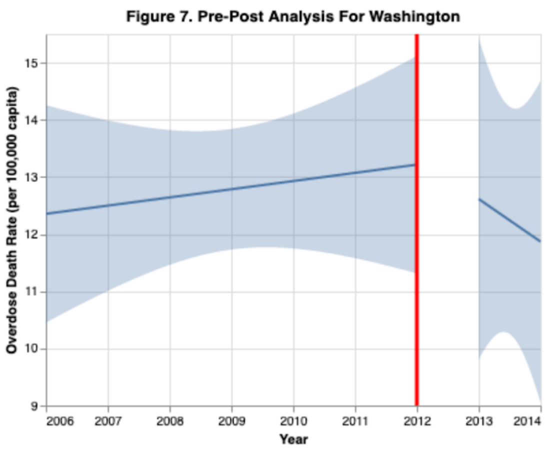
For Washington, we perform a pre-post comparison in the opioid shipment per capita with respect to the year 2012, when the policy came into effect in the state. The pre-post analysis for Washington depicts a relatively stagnant value in the opioid shipment per capita with around 0.18 gm per capita from 2006 to 2012. For the period ensuing 2012, the year for the policy enactment, the opioid shipment sees a slight decline and has a value of 0.17 gm per cap in 2014. We further probe into the analysis by performing a difference in difference between the treatment state and the control states. The control states chosen for Washington are Maryland, Oklahoma, Indiana, Idaho, Minnesota, Nebraska, Nevada and Virginia.

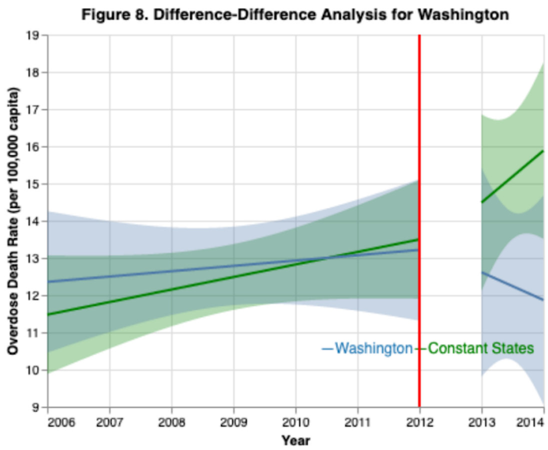
Policy Change	Average opioid shipment per capita in Washington(in gm)	Average opioid shipment per capita in Control States(in gm)
Pre 2012	0.179	0.196
Post 2012	0.165	0.205
Difference (post-pre)	-0.0146	0.0083
DID = Difference (Washington-Control States)	-0.023	

Table 6: Difference in Difference estimator for Washington for Opioid Shipment per capita (measured in gram)

From the table above, the estimated difference-in-difference of -0.023 suggests that the opioid shipment per capita in Washington saw a higher decrease than that observed in Control States from 2006 to 2014. This implies that the policy in place in Washington and absent in Control States has been effective in curbing the influx of the opioid shipments. However, studying the pre-policy period in the difference-in-difference analysis we can see that the control states do not have a parallel trend with Washington, which indicates that the assumption of difference-and-difference analysis is not met. In other words, it fails to create a parallel universe for Washington where there is no policy enacted in 2012. Since it fails to meet our assumption, the findings from the difference in difference are not very conclusive in nature.

Drug overdose death





In this graph, the base state is Washington and the constant states include Maryland, Oklahoma, Indiana, Idaho, Minnesota, Nebraska, Nevada, Virginia.

For the drug mortality rate(measured in 100,000), we see that in the pre-policy period there is an increment in rate from around 12.5 to 13.2 . Post the policy change in 2012, we see a steady and sharp decline to roughly 11.8 in 2014. The results from the pre-post analysis show that the policy change may have been effective in curbing the mortality rates. We confirm our findings by conducting difference in difference regression on control and treatment states.

Policy Change	Average Overdose death rate in Washington	Average Overdose death rate in Control States
Pre 2012	12.784	12.485
Post 2012	12.242	15.184
Difference (post-pre)	-0.543	2.699
DID = Difference (Washington-Control States)	-3.24	

Table 7: Difference in Difference estimator for Washington for Average Overdose death rate (measured per 100,000)

From Table 7, we can see that the estimated difference-in-difference has a value of -3.24 implying that the average death rate in Washington decreased more than that in Control States from 2006 to 2014. While the difference in difference regression analysis suggests that the policy in Washington has indeed been effective in decreasing the overdose death rates post 2012, we still have to be cautious as the parallel universe was not perfectly created prior to the policy change.

Overall, from the pre-post analysis of the opioid shipment per capita for Washington, we can see that the policy may have been effective. Also, from the drug mortality rate analysis, it can be said that the policy put in place in 2012 was effective. Therefore, it can be concluded that, for Washington, we reject hypothesis H0 and retain H1. In short, policy enactment in Washington to regulate opioid drugs does reduce opioid prescriptions and opioid related deaths (drug overdose).

Texas

<u>Drug overdose death</u>

Figure 9. Pre-Post Analysis For Texas

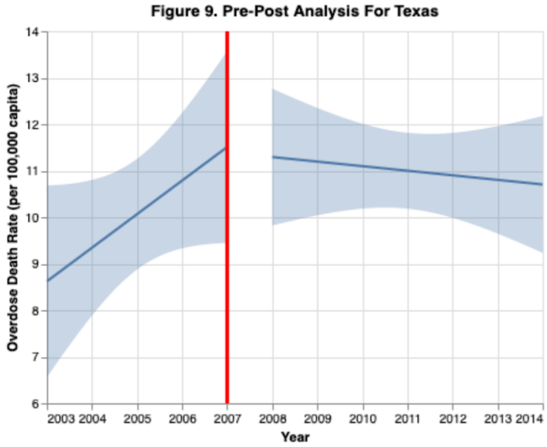
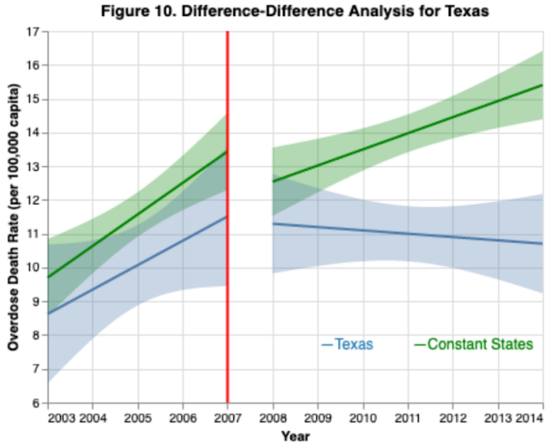


Figure 10. Difference-Difference Analysis for Texas



In this graph, the base state is Texas and the constant states include Colorado, Utah, Georgia, California, North Dakota, Illinois, Louisiana , Maryland and Oklahoma

For Texas, we probe the effectiveness of the policy change which took place in 2007. From the pre-post analysis, it can be seen that the mortality rate (measured per 100,000) rises from 8.8 in 2003 and peaks at 11.5 in 2007 when the policy is not in place. However, we see a decline post the policy change to a value of 10.8 in 2014. To corroborate our findings and ensure whether the decrease in mortality rate is in fact an outcome of the policy effectiveness, we conduct the difference-in-difference analysis. The states chosen as control states for Texas are Colorado, Utah and Georgia, California, North Dakota, Illinois, Maryland and Oklahoma. We see a somewhat parallel trend between the control and treatment states, which depicts that our assumption is met. For the control states, the mortality rate rose from 9.8 in 2003 to 13.5 in 2007. Post 2007, we see a decline in the mortality rate for Texas while there is a steady increase in our control states' mortality rate. The death rate depreciates to a value of 10.8 in 2014 for Texas; on the other hand, for the control states, it continues to rise to around 15.5.

Policy Change	Average Overdose death rate in Texas	Average Overdose death rate in Control States
Pre 2007	10.066	11.568
Post 2007	11.000	13.970
Difference (post-pre)	0.934	2.403
DID = Difference (Texas-Control States)	-1.469	

Table 8: Difference in Difference estimator for Texas for Average Overdose death rate (measured per 100,000)

Lastly, from the above table, we can calculate this difference in difference estimate from 2003 to 2014 between the control and treatment states, which has a value of -1.469 which shows that the death rates decreased more in Texas than the control states implying the effectiveness of the policy change. The difference in difference regression conducted on overdose death rate shows that the policy enactment in Texas has been effective. Therefore, we can conclude that the state was indeed effective in minimizing the overdose mortality rate by implementing a regulatory policy. To conclude, we reject the hypothesis H0 and retain H1, which is that the policy enactment on opioid drugs in Texas does significantly reduce overdose death rate caused by opioids.

Conclusion and Discussion

To conclude, we can say that, in regards, for Florida and Texas, the regulatory policy put into effect regarding opioid restriction has been successful. For both, we can see a decreasing trend in the mortality rate metrics after the policy change period. Also, the difference-in-difference coefficient estimates indicate that the policy enactment is effective in reducing the mortality due to drug overdoses. For Washington, however, our assumptions are not met, and we fail to create a parallel universe where control states are equivalent to a pre-policy Washington. As for the most salient finding, Florida has the most significant change with an estimated difference of a death rate of 6.63 per 100,000 people (followed by Washington's 3.24 and Texas's 1.47), and we can conclusively suggest that the policy enactment is effective in Florida, based on both the coefficients and the fact that a parallel universe of control states successfully created a Florida from a pre-policy period.

As for the policy effect on opioids prescription per capita, we can see that, according to the difference in difference estimate, the impact on Washington is present and trivial, with only a 0.023 gram difference after the policy enactment. Nonetheless, it is not conclusive enough to suggest that the policy regulation led to decrease in opioid shipment per capita due to the presence of non parallel trends from the control states prior to policy change. As for Washington's overdose death rates, where the difference in difference returns a coefficient estimate of -3.24, indicating a reduction in opioid overdose mortality after policy change, while we cannot fully confirm that the reduction is attributed to the policy given the not perfectly parallel trend prior the policy change period.

Finally, to expound upon the difficulty of the causal inference analysis, it, in and of itself, is hard to implement. For a given state, we want to ensure that, in the world with opioid policy enactment, overdose death rates and opioid prescription rates are decreasing, and, in the world without opioids policy enactment, the trend of the overdose death rates and opioid prescription rates for that state would remain the same or increase. This magical parallel can never happen; however, there are strategies to make the inferential process more valuable, which pushes us to examine the limitations of the study.

Given that the period we have is from 2006 to 2014 (only Texas has the 2003 - 2014 time frame), the difference between pre-policy and post-policy is hard to compare, especially for Washington, which has a policy change in 2012 with only 2-years of examination available for a post-policy period. Secondly, the selection criteria for constant states is only based on the elderly population proportion, so the criteria itself may be too arbitrary to conclude that the states themselves have similar characteristics in their opioids shipments. Additionally, our population datasets have two different sources, meaning that both of their population metrics may have been estimated with slightly, similar or very different criteria, which could potentially introduce some inconsistencies in our analysis. Thus, to extract more informative conclusions, a more rigorous criteria in constant states selection and longer time span are needed for further study.

Bibliography

United States Census Bureau (2016). Population Counties for 2000-2006. Retrieved from https://www2.census.gov/programs-surveys/popest/datasets/2000-2006/counties/totals/co-est2006-alldata.csv

Harbaugh, C. (2019). Older Adults' Perceptions of Opioids-Related Policies And What They Mean for Pain Treatment. Health Affairs Forefront. Retrieved from https://www.healthaffairs.org/do/10.1377/forefront.20190415.123669/full/

CDC. Understanding the Epidemic Retrieved from https://www.cdc.gov/opioids/basics/epidemic.html

Davis, C. State-by-State Summary of Opioid Prescribing Regulations and Guidelines. The Network for Public Health Law. Retrieved from https://www.azdhs.gov/documents/prevention/womens-childrens-health/injury-prevention/opioid-prevention/appendix-b-state-by-state-summary.pdf

K. F. F. (2019). *Population Distribution by Age*. KFF. Retrieved November 28, 2022, from https://www.kff.org/other/state-indicator/distribution-by-age/?currentTimeframe=1&selectedDistributions=65&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D

W. P. (2019). *arcos-api/population_counties20062014.csv*. WPInvestigative/arcos-api. Retrieved November 28, 2022, from https://github.com/wpinvestigative/arcos-api/blob/master/data/pop_counties_20062014.csv

Department of Health. (2011, May 24). WSR 11-12-025. Retrieved from https://apps.leg.wa.gov/documents/laws/wsr/2011/12/11-12-025.htm

Drug Enforcement Administration (DEA). (2011, February 24). DEA-Led Operation Pill Nation Targets Rogue Pain Clinics In South Florida. Retrieved from https://www.dea.gov/press-releases/2011/02/24/dea-led-operation-pill-nation-targets-rogue-pain-clinics-south-florida

Texas Medical Board. (2007, January 4). Minimum Requirements for the Treatment of Chronic Pain. Retrieved from https://texreg.sos.state.tx.us/public/readtac$ext.TacPage?sl=R&app=9&p_dir=&p_rloc=&p_tloc=&p_ploc=&pg=1&p_tac=&ti=22&pt=9&ch=170&rl=3

The Washington Post. (2019, July 16). Drilling into the DEA's Pain Pill Database. Retrieved from https://www.washingtonpost.com/graphics/2019/investigations/dea-pain-pill-database/

Estimating the Impact of Opioid Control Policies: Policy Recommendation Report

Emma Wang, Pragya Raghuvanshi, Lorna Aine & Eric Rios Soderman
December, 12, 2022

Motivation

It has been over a decade since the CDC declared an epidemic of prescription painkiller overdoses and drugs like Oxycontin (a brand-name version of oxycodone) and related semi-synthetic opioids like Hydrocodone (CDC, 2022). In a bid to avert this crisis, many US states have adopted legal restrictions on the ability of medical professionals to prescribe or dispense opioids for pain in the hopes of combating over prescription and, as a result, reducing shipments of these drugs. For this report, we examine the effectiveness of these policies by comparing the rates of drug overdose deaths and opioid shipments before and after policy changes for Texas in 2007 (Texas Medical Board, 2007), Florida in 2010 (Clinics In South Florida, 2011), and Washington in 2011 (Department of Health, 2011), and comparing them to the same metrics in states with little or no policy change to determine the size of the effect of the policy change under examination.

Methodology

Analysis Methods

To assess the impact of opioid regulation in the aforementioned states, we used pre-post analysis and difference-in-difference analysis to compare overdose deaths and shipments between 2003 and 2014, contrasting a sufficient amount of years before and after the policy change for our given state of interest and its corresponding comparison group of states to gauge the impact of a policy. In a pre-post analysis, we verify if there was a change in the amount of overdose deaths or opioid shipment numbers, comparing the results before and after the year of the policy's implementation. Furthermore, we conducted further study with a difference-in-differences analysis. Holding the overdose mortalities and the opioid shipment amounts as the main metrics, the purpose of the difference-in-difference analysis is to compare the policy's effect on these metrics for a given state to the effect of having a less stringent policy or a "quasi-policy" or no policy approach on these metrics. This analysis also serves to isolate the weight of a policy's effect from the effects from external factors, such as a manufacturing shortage of these opioids affecting shipments. These analyses helped us make sure that the reduction in opioids prescription and overdose death rate, if any, is caused by the policy enaction.

Data

For the shipment data, we used The Washington Post's opioid prescriptions data (obtained from the DEA through a Freedom of Information Act) to ascertain the amount of opioids prescribed, which was available at a monthly level from 2006 to 2014 (The Washington Post, 2019). For the mortalities, the US Vital Statistics records provided us with information on drug overdose deaths for each county in the United States. To account for the population of each county, we used population and FIPS code county data from the Washington Post from 2006 to 2014 and the government census data from 2000 to 2006 (United States Census Bureau, 2016). As for missingness in the data, our main challenges were removing nameless counties, and counties with missing causes of death numbers of drug overdose deaths and missing population amounts. After handling these hurdles, we were finally able to calculate the opioids shipments per capita and the overdose deaths per capita, and we also had the information required to analyze our treatment and control states. As for the control states, they were chosen because their elderly population proportions were similar to those of the treatment states, and this information also came from a dataset including these measures (K.F.F., 2019). The reasoning behind this choice of criteria is that the elderly population has more medical surgeries and is prescribed opioids; and this is an avenue that could lead to opioid supply to the general public. This allowed us to compare opioid prescriptions and overdose deaths in our treatment states, where policy changes had occurred, to those in control states, where no such changes had occurred.

Scope

To form a more composite dataset with consistent data, we first identified the counties in the treatment and control groups that met a population threshold above which all the data was available. For Texas and its corresponding control states the analysis covered the effects of drug overdose between 2003 and 2014 for counties with a population above 19,286.

For Florida, Washington and their respective control states, the analysis covered the effects of opioid shipment and drug overdose deaths between 2006 and 2014 for counties with populations above 40,008 and 67,791 respectively. These thresholds also formed a scope for the analysis findings in this report.

Analysis

Florida

Effect of Policy on opioid shipments

From the pre-post analysis below, we observed a rise in opioid shipment before the policy was enacted, which began its fall after 2010. The opioid shipments increased from 0.17g per capita to 0.53g per capita, from 2006 to 2010, and then lessened to 0.13g per capita by 2014. For the difference in difference estimation, we also see a parallel trend (when the lines do not intersect) between Florida and its control states (West Virginia, Vermont, Delaware, Hawaii, Montana, Pennsylvania, New Hampshire, South Carolina, and New Mexico) before 2010, and, after 2010, the overall trend falls for Florida while it continues to rise for the control states. This serves as the first of two indicators that the policy to regulate pain clinics and drug distributors in 2010 was effective in curbing the opioids shipment rates.

Figure 1. Pre-Post Analysis For Florida

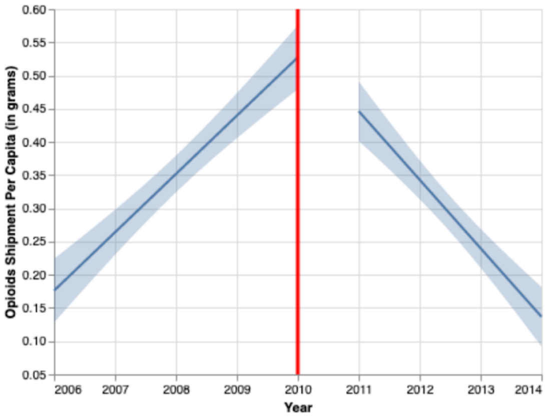
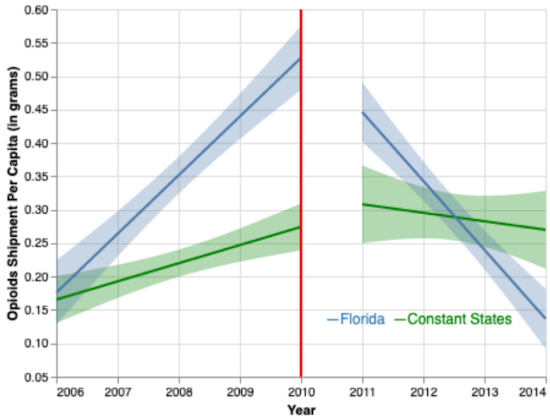


Figure 2. Difference-Difference Analysis For Florida



In this graph, the base state is Florida and the constant states include West Virginia, Delaware, Hawaii, Pennsylvania, New Hampshire, South Carolina and New Mexico

Effects of Policy on Drug Overdose deaths

Figure 3. Pre-Post Analysis For Florida

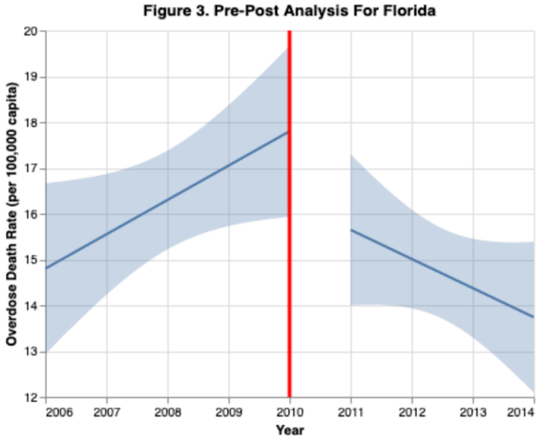
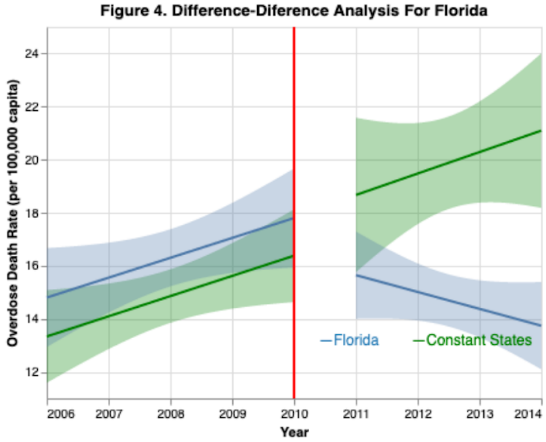


Figure 4. Difference-Diference Analysis For Florida



In this graph, the base state is Florida and the constant states include West Virginia, Delaware, Hawaii, Pennsylvania, New Hampshire, South Carolina and New Mexico

From the pre-post analysis above, we observed a rise in overdose death rates (measured per 100,000 capita) before the policy was enacted, which began a quite drastic fall after 2010, the year in which the regulations were administered. Prior to that year, overdose deaths were at 14.9 (per 100,000 capita) in 2006, and by 2010, they had risen to 17.8 and fell to 13.8 in 2014. From the difference in difference, we see a parallel trend between Florida and its control states before 2010, and after that, the trend splinters. The overdose death rates plummet for Florida, while they ascend for the control states. Therefore, Florida's policy to regulate pain clinics and drug distributors in 2010 was effective in diminishing the opioid menace in terms of mortalities due to opioids overdose.

Washington

Effect of Policy on opioid shipments

Figure 5. Pre-Post Analysis For Washington

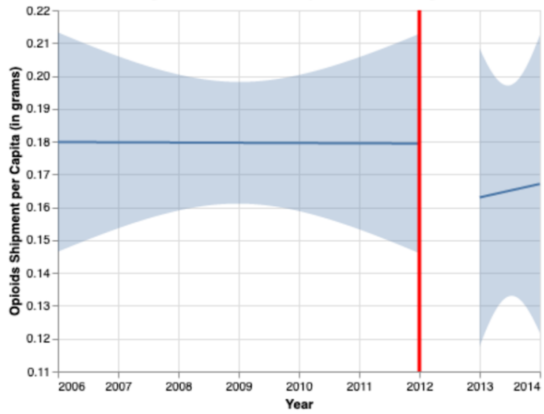
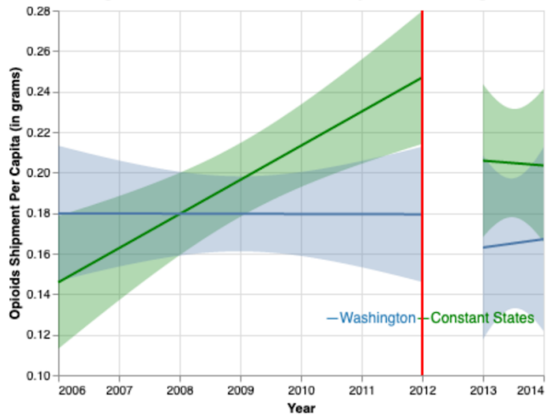


Figure 6. Difference-Difference Analysis For Washington



In this graph, the base state is Washington and the constant states include Maryland, Oklahoma, Indiana, Idaho, Minnesota, Nebraska, Nevada, Virginia.

According to the Washington pre-post analysis, we discovered that opioids shipments were relatively stagnant, capping at 0.18 gm from 2006 to 2012, and decreased slightly towards 0.17 gm from 2013 to 2014 after the implementation of regulations. However, the difference-in-difference analysis also exhibits a similar trend, but it does not conclusively confirm whether the slight decline in opioid shipment after 2012 was due exclusively to the policy change. The reason is a clear absence of a parallel relationship between the opioid shipment rates in Washington and its control states prior to 2012, a condition that has to be satisfied in order to lend validity to the results of the analysis.

Effects of Policy on Drug Overdose deaths

Figure 7. Pre-Post Analysis For Washington

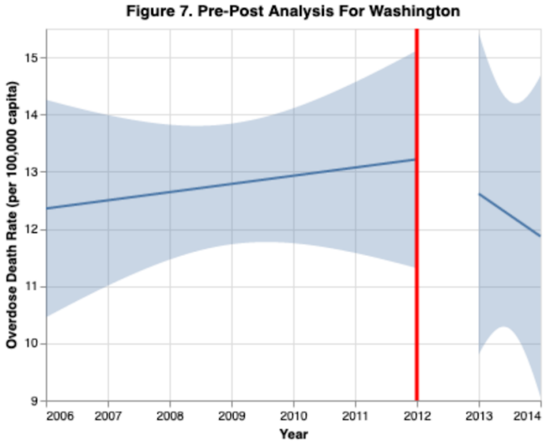
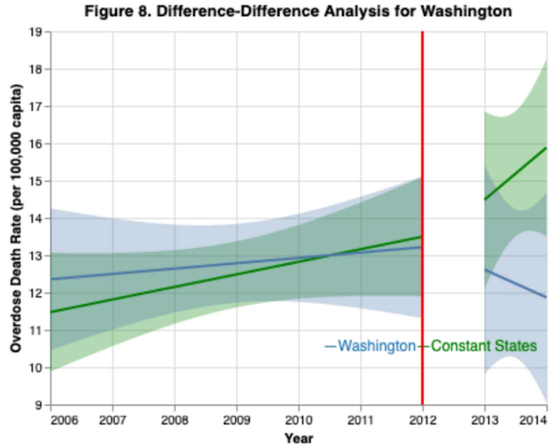


Figure 8. Difference-Difference Analysis for Washington



In this graph, the base state is Washington and the constant states include Maryland, Oklahoma, Indiana, Idaho, Minnesota, Nebraska, Nevada, Virginia.

Based on the Washington pre-post analysis, overdose deaths increased slightly from 2006 to 2012, and when the regulations were implemented, they experienced a sharp decline from 2013 to 2014. In addition, the difference-in-difference analysis confirmed the same trend. This leads us to theorize that the policy was effective in reducing deaths due to opioids overdose; however, we have to be cautious due to the lack of parallel trends seen between Washington and its comparison states.

Texas

Effects of Policy on Drug Overdose deaths

Figure 9. Pre-Post Analysis For Texas

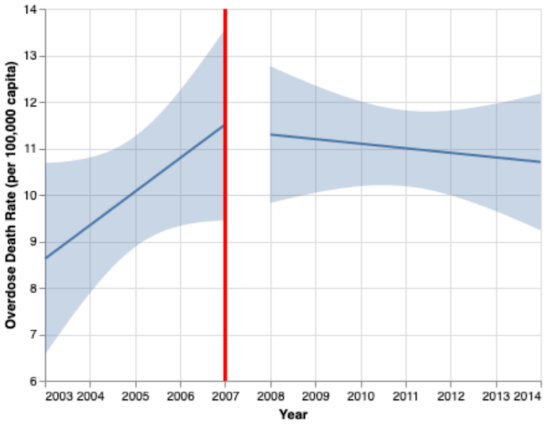
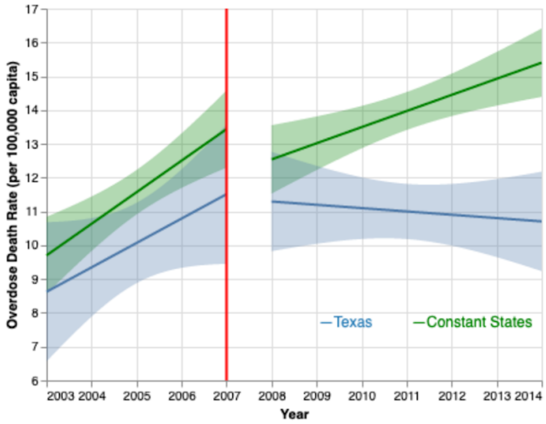


Figure 10. Difference-Difference Analysis for Texas



In this graph, the base state is Texas and the constant states include Colorado, Utah, Georgia, California, North Dakota, Illinois, Louisiana , Maryland and Oklahoma

From the pre-post analysis, we see a spike in overdose deaths that morphs into a steady drop after 2007, when the policy was enacted. In that year, the overdose death rate peaked at 11.5 and, after the policy, then fell to 10.8 by 2014. Moreover, the difference in difference also validates a parallel trend between Texas and its control states (Colorado, Utah and Georgia, California, North Dakota, Illinois, Maryland and Oklahoma) before 2007. After that year, the trend for Texas experiences a sharp decline, while the control states mortality rates continue ascending as they did previously. Therefore, the policy, established by the Texas Medical Board in 2007, entailing a detailed procedure involving patient assessment and periodic reviews seems to be effective in mitigating the impact of the opioids mortality rate.

Limitations

First and foremost, this analysis only took into account counties above the population thresholds of 19,286 for Texas and its control states, 40,008 for Florida and its control states and 67,791, for Washington and its control states. This was due to the missingness of overdose deaths data in smaller communities, a dynamic that was introduced by how the US Vital Statistics data was recorded, therefore the results described above were not representative of the entire states' data.

Another limitation of this analysis is that it did not tackle Texas's opioids shipment and an extended period after Washington's policy enactment. For the former, there was only one year of shipment data for Texas before the policy change, which would also force one year of comparison data after the policy change, both not enough to interpret and understand trends in a meaningful capacity. For the latter, Washington's issue is that the data after the policy change was available for just two years, weakening a bit of the long term interpretability that is ideal and recommended for these types of analyses.

As with any study that involves selection criteria, each method has its flaws and benefits. The choice of control states based only on the proportion of the elderly who need opioid prescriptions was not entirely representative of other metrics of that subpopulation, which could have been added to our criteria. Another option may have been to consider other communities in addition to the elderly population.

Conclusion

When considering the pre-post analysis graphs, for Florida and Texas, we can see a decreasing trend in the overdose deaths and opioid shipment metrics after the policy change period. The policies implemented by Texas and Florida were effective in curbing the overdose and opioid shipment rates; however, we fail to conclude on the effect of Washington's policy, as the aforementioned assumptions were not met. For Washington, we did not succeed in mirroring a world where ideal control states are present.

From the difference-in-difference analysis graphs, Florida exhibits a drastic drop in shipment and deaths from drug overdoses, which indicates the drug policy compared to Texas.
For Washington, even though there was a decline, it is hard to conclude that the policy change was successful given the assumptions were not met.

A closer look at the policies across the three states reveals that the Washington and Texas policies targeted patients while the policy in Florida targeted the clinics. This could explain the difference in the resulting measurements of the analysis, with Florida showing more promising results.

A future recommendation would be to expand the control state selection criteria for a few reasons. The selection criteria for constant states is only based on the elderly population proportion, so that criteria alone may not be representative enough to gauge the characteristics necessary to best identify control states for our given treatment states. Furthermore, changing our criteria can better help us create a parallel universe for states where it was not possible and to also obtain comprehensive states data for the outcomes of interest to have a full analysis of the effects of the policy, even for the counties below the population thresholds. Additionally, for future analysis, we may want to look at different treatment states with more data available in terms of the range of years that we can examine, in addition to states with other unique and different policy changes.

Bibliography

United States Census Bureau (2016). Population Counties for 2000-2006. Retrieved from https://www2.census.gov/programs-surveys/popest/datasets/2000-2006/counties/totals/co-est2006-alldata.csv

Harbaugh, C. (2019). Older Adults' Perceptions of Opioids-Related Policies And What They Mean for Pain Treatment. Health Affairs Forefront. Retrieved from https://www.healthaffairs.org/do/10.1377/forefront.20190415.123669/full/

CDC. Understanding the Epidemic Retrieved from https://www.cdc.gov/opioids/basics/epidemic.html

Davis, C. State-by-State Summary of Opioid Prescribing Regulations and Guidelines. The Network for Public Health Law. Retrieved from https://www.azdhs.gov/documents/prevention/womens-childrens-health/injury-prevention/opioid-prevention/appendix-b-state-by-state-summary.pdf

K. F. F. (2019). *Population Distribution by Age*. KFF. Retrieved November 28, 2022, from https://www.kff.org/other/state-indicator/distribution-by-age/?currentTimeframe=1&selectedDistributions=65&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D

W. P. (2019). *arcos-api/population_counties20062014.csv*. WPInvestigative/arcos-api. Retrieved November 28, 2022, from https://github.com/wpinvestigative/arcos-api/blob/master/data/pop_counties_20062014.csv

Department of Health. (2011, May 24). WSR 11-12-025. Retrieved from https://apps.leg.wa.gov/documents/laws/wsr/2011/12/11-12-025.htm

Drug Enforcement Administration (DEA). (2011, February 24). DEA-Led Operation Pill Nation Targets Rogue Pain Clinics In South Florida. Retrieved from https://www.dea.gov/press-releases/2011/02/24/dea-led-operation-pill-nation-targets-rogue-pain-clinics-south-florida

Texas Medical Board. (2007, January 4). Minimum Requirements for the Treatment of Chronic Pain. Retrieved from https://texreg.sos.state.tx.us/public/readtac$ext.TacPage?sl=R&app=9&p_dir=&p_rloc=&p_tloc=&p_ploc=&pg=1&p_tac=&ti=22&pt=9&ch=170&rl=3

The Washington Post. (2019, July 16). Drilling into the DEA's Pain Pill Database. Retrieved from https://www.washingtonpost.com/graphics/2019/investigations/dea-pain-pill-database/