Estimating the Impact of Opioid Control Policies: Data Science Report

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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 1999–2010 in the United States in parallel with increased opioid prescribing. 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 is to examine the effectiveness of interventions in the states' opioid policies in lowering the volume of opioid prescriptions and rate of drug overdose mortality.
We seek 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?

For the treatment states, 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 dosages of opioids greater than 120 mg/day and a greater emphasis on recording these special consultations. (Department of Health, 2011).

For the difference in difference analysis that will be described later, the strategy for choosing counterfactual states is filtering the states based on population distribution by age. The counter states are chosen such that they have a similar proportion for elderly population as the base states. The rationale behind this is that the elderly population undergo more medical surgeries and are prescribed opioids as a follow up (Harbaugh, 2019). This will allow us to map the opioid prescription and death due to overdose in our base states where policy change has taken place with the control states where there has been no policy intervention.

Motivation for the research design

For this problem, we ask how effective is 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 shall use 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 would include a pre- and post-model graph for the state under consideration, that is, the state with the policy change in areas of opioid shipment and drug overdose per capita respectively.

- A difference in difference analysis: This is a graphical model comparing the state under consideration, that is, the state with policy intervention, with the counterfactual states undergoing no policy change. This state should follow a similar trend to the state under consideration prior to the policy change. The difference-in-difference graphs will depict the differences in trends between the treated and untreated states over factors of opioid shipment and drug overdose per capita respectively.

- Visualization: The analysis will be shown using a linear regression model fit to show the differences in trends and volatility around them.

Datasets

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 the 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 is the core objective behind obtaining the FIPS dataset.

This was the crux of the challenge, given that our opioids dataset possessed county names, but not FIPS codes. This forced us to merge the opioids and the FIPS datasets on county names and states. The FIPS county records were lowercased, but we then discovered that they did not always have the word "county" in them. The "county" string was removed and newly inserted to a string, and these county naming issues were present and treated in the opioids dataset. Lastly, the columns of the FIPS dataset were renamed for ease of merging; the states were in identical two-letter formats across the two datasets, and the datasets were finally merged on the counties and states. The observational unit for this merged dataset is the FIPS code per county and per state.

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. In this data set, all of the files across the years were joined together into one dataframe. Then the county and state, which were together in one string, were split into two respective columns, and the county string was lowercased and had the word "county" aggregated to it, an identical process like the one seen in the prior dataset. Lastly, the deaths were converted to decimals.

After the cleaning, we get the "number of overdose deaths" in each county over the years 2006–2015 by filtering 'Drug/Alcohol Induced Cause' = drug/alcohol-induced poisoning is the unintentional cause. The dataset is then grouped or aggregated on the FIPS code and year. After this step is completed, we have the required FIPS, Year, and total sum of the overdose deaths as columns. The final unit of observation is the number of drug overdose deaths per year. This data will be merged with the opioids data set to obtain the total amount of morphine prescribed in grams and the number of drug overdoses per county, per state, and per year.

Opioids Prescriptions 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:

- BUYER_STATE, which is the state of the entity receiving shipments from the reporter.
- BUYER_COUNTY, which is the county of the entity receiving shipments from the reporter.
- TRANSACTION_DATE, which is the date the shipment occurred.
- CALC_BASE_WT_IN_GM, which is the total active weight of the drug in the transaction, in grams
- MME_Conversion_Factor, which is a drug's morphine milligram equivalent in milligrams

By obtaining the product of "CALC BASE WT IN GM" and the "MME Conversion Factor", 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 help the amounts of the different opioids shipped 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.

As for the data wrangling process required to complete this series of steps, it is only fitting to highlight the sheer difficulty of maneuvering around this dataset. With rows, the memory footprint is very large, which imposes a penalty when running multiple merges with this dataset. Although the weight of this issue will be addressed later, the relevant piece of this section is how we took only those select columns to help the process finish more quickly. In addition, we chunked the dataset as it was loaded in our computers, and we filtered what rows to keep in the final, opioids shipment dataframe, only if the states of those rows were from our pool of treatment and control states. To create this pool, we used the constant state selection function to generate the constant states for each treatment state respectively (as explained in the motivation).

After this chunking process, the next step was to convert the dates to a usable format. In their current state, they were 7 to 8 numeric characters. There were only 7 if the date under observation lacked a “0” at the beginning of the string, such as “3102006” when contrasted to “03102006”. The numbers in the transaction date column were first converted into strings. The strings were then processed with a helper function to identify the number of characters in that string, concatenated with a “0” at the beginning of the string only if said string had 7 characters, formatted to have slashes within the string i.e. “ 08/12/2007” , extracted into a transaction year column to get the digits of the years, and finally converted into a date object. At the end of this process, the dataset had a transaction date column formatted as a date and a transaction year column as an integer. The last two steps were creating an “opioids shipment in grams” column by calculating the product between "CALC BASE WT IN GM" and the "MME Conversion Factor" and cleaning the county name column in an identical manner, as was done with the prior two datasets. At this point, the dataset became ready to merge with the others.

County Populations Datasets

To make the result comparable between each county and state, 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. From the population dataset, we required three variables: FIPS, year, and population. The resulting unit of observation would be the number of residents per county.

Two county population datasets were utilized. 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 merging issue arose. These datasets needed no cleaning and were ready for merging.

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 had the following variables : FIPS, buyer state, buyer county, transaction year, transaction date, total weight of opioids prescribed per capita, and drug overdose deaths per capita. The units of observation are the total weight of opioids prescribed per capita and drug overdose deaths per capita per state per year.

The data wrangling process for these merges was unanimously the most difficult and taxing. The gamut of issues span every possibility, beyond simple errors, and still continue to challenge us, even while this report is being written. The painful nexus of this arduous process was the memory footprint of the opioids shipment data during and after the merges. It frequently crashed our computers, and we implemented chunking and creating multiple intermediate files to avoid repeating so much work. Besides these details, we will also explain the steps that we followed to complete the merges themselves.

The first merge was between the opioids data and the FIPS data, where they were joined on buyer states and counties, and the purpose of this merge was to attach the FIPS codes to our opioid shipments dataset, since those codes are much more reliable than using county names for merges. Although successful at the end, it did not work well at the beginning because many of our counties did not have FIPS codes, due to different naming conventions across the two datasets, which were referenced previously. After the first merge, the second and third merges were successful due to having a corresponding FIPS codes per county, and they were completed by uniting the first merged dataset with the population dataset of 2006 to 2014 to get the populations per county per year and the overdose deaths dataset to get the deaths per county per year. During and after the merges, unnecessary columns were dropped to reduce memory consumption. At the end of the merges, the null values in the counties section were removed from the final merged dataset. Then this dataset was split into three different csv files for each control state and its treatment states.

Subsets

Subsets of control states and the treatment states. Texas, in particular, was the most difficult subset because our population dataset capped at the oldest year of 2006, but we needed more overdose death years. Therefore, we had to find an additional population dataset (which is the population dataset from Census) to cover the years from 2003 to 2005 and merge that information into that subset, which was accomplished by using the FIPS codes and years. After this issue was solved, the difference and difference analysis was ready to be conducted. Before performing pre-post analysis and difference and difference analysis, the datasets needed two columns “policy”, which indicates if the year is pre-policy (coded as 0) or post-policy (coded as 1) and the “state”, which indicates whether the state is a control state (coded as 0) or treatment state (coded as 1).

Control States for each Treatment State

Selection Criteria : control states with a similar proportion of elderly population as the treatment states.

Treatment State	Control States
Florida	West Virginia, Vermont, Delaware, Hawaii, Montana, Pennsylvania, New Hampshire, South Carolina, and New Mexico.
Washington	Maryland, Oklahoma, Indiana, Idaho, Minnesota, Nebraska, Nevada and Virginia.
Texas	Colorado, Utah and 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	14.22	14.36	12.68	15.33
	Post 2010	12.62	12.40	11.41	14.27
Control States for Florida	Pre 2010	8.356	8.13	0.0	19.51
	Post 2010	12.22	10.64	1.54	24.91
Texas	Pre 2007	9.24	7.66	0.18	45.52
	Post 2007	11.25	9.93	0.10	51.85
Control States for Texas	Pre 2007	7.89	6.77	0.56	42.74
	Post 2007	8.67	8.35	0.43	35.14
Washington	Pre 2012	12.18	12.36	11.21	12.84
	Post 2012	11.95	11.95	11.89	12.02
Control States for Washington	Pre 2012	9.16	8.29	2.139	24.91
	Post 2012	12.11	12.25	2.47	24.057

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, prior to the policy enactment in 2010, the mean mortality rate (measured in 100,000) is 14.22. Post 2010, the mean mortality rate dropped to 12.62. We can also see that there is a decrease in both minimum and maximum mortality rates for Florida post 2010. For Texas, however, we see an increase in mean mortality rates after 2007, from 9.24 to 11.25, when the policy comes into effect. Again, for Washington, it is seen that the mean mortality rate decreases minutely across 2012 from 12.18 to 11.95 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	0.70	0.65	0.42	1.08
	Post 2010	0.52	0.44	0.36	0.81
Control States for Florida	Pre 2010	0.36	0.33	0.19	0.62
	Post 2010	0.45	0.43	0.26	0.69
Washington	Pre 2012	0.36	0.37	0.31	0.38
	Post 2012	0.35	0.35	0.35	0.36
Control States for Washington	Pre 2012	0.39	0.38	0.14	0.74
	Post 2012	0.44	0.40	0.21	0.68

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 by 2.6% in the mean shipment volume post policy change from 0.70 to 0.52 per cap in gm. We can also see that in the control states where no policy change has taken place, the mean shipment of opioid increases from 0.36 to 0.45 per cap in gm. For Washington, the mean value of the shipment witnessed a minute change from 0.36 gm per cap to 0.35 gm per cap.

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

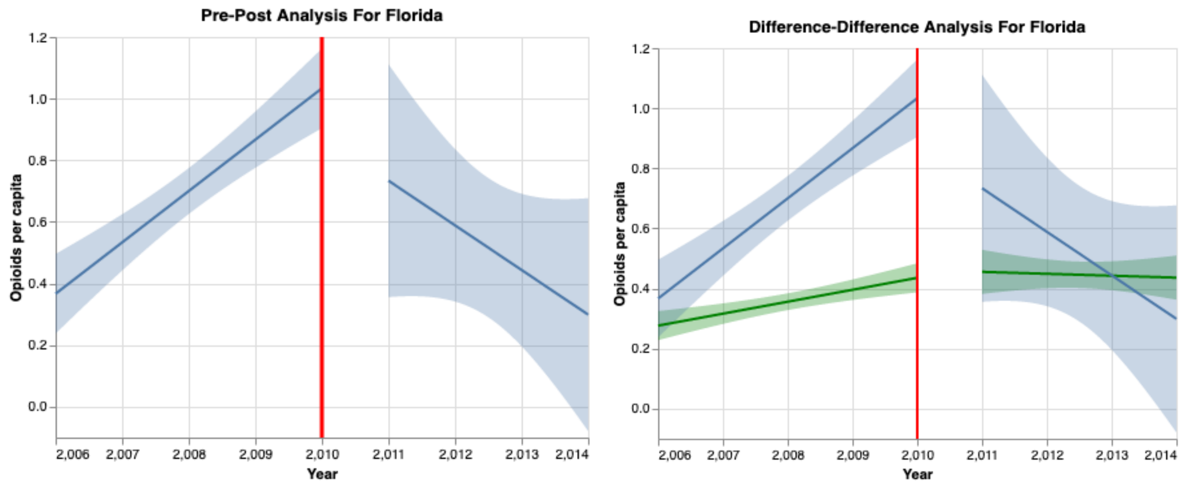
The following assumptions are made in the analysis for the effectiveness of policy enactments on curbing opioid prescriptions and overdose deaths:

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, that is, 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.

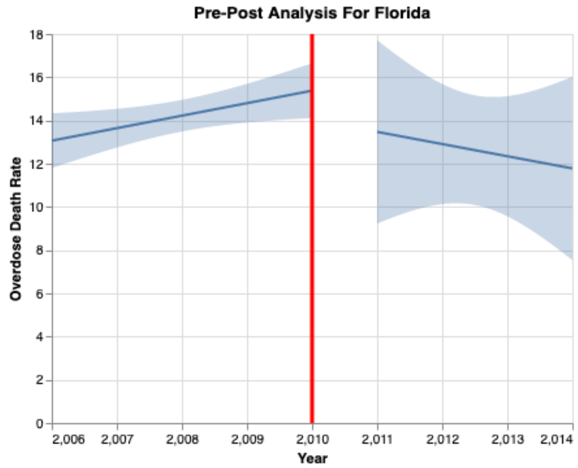
Florida

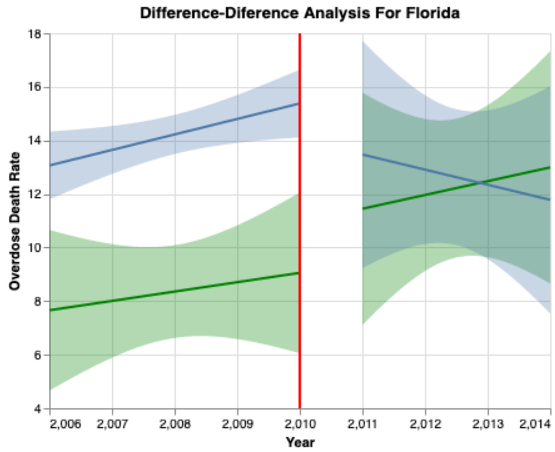
Opioids shipment per cap



Analyzing the pre post graph regarding Opioids 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 0.4 gm per capita in 2006, the shipment peaked in 2010 to the value of 1.15 gm per capita. However, post the policy intervention, a sharp decline is witnessed in the shipments influx, with the value dropping Therefore, difference-in-difference analysis is performed to compare Florida 0.3 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. With other control states that had no policy change, their presence as comparisons can serve to better gauge the effectiveness of policy implementation in Florida. The control states used for Florida are West Virginia, Vermont, Delaware, Hawaii, Montana, Pennsylvania, New Hampshire, South Carolina, and New Mexico. From the diff-in-diff 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 0.4 gm per capita, which witnesses a rather stagnant or extremely slow decline post 2010, the year for policy change in Florida. The resulting difference-in-difference estimate for the effectiveness of the policy change in 2010 on opioids per capita in Florida increased by 0.0619 (treatment: 0.008 - constant : -0.053) from 2006 to 2014. 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



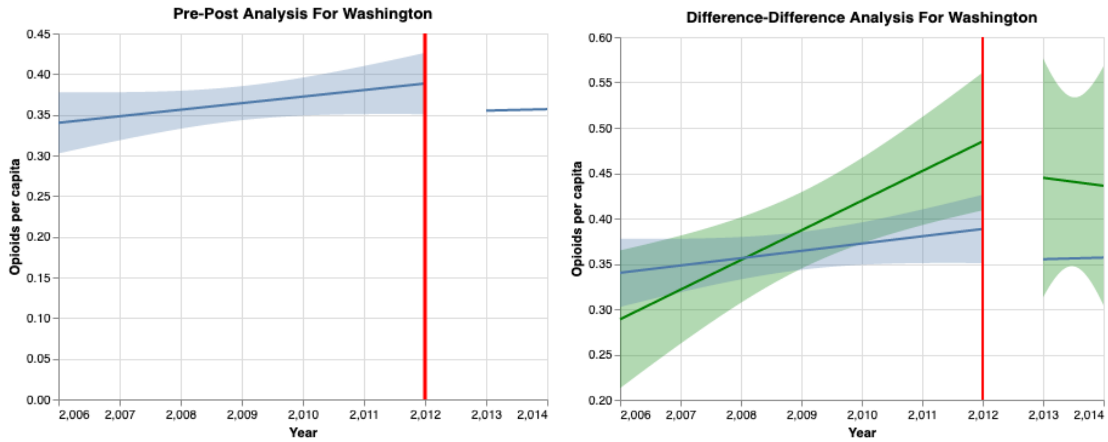


From the drug overdose death graph measured per 100,000 population, Florida's pre-post analysis depicts that death rates rose steadily from .013% to .015%. Peaking in 2010, there is a continuous decline, to .012%. Adding to the pre- post graph, in the difference-in-difference analysis we can observe that the death rate for the control states continues to increase even post 2010. From a value of .009% in 2010 to .013% in 2014 we can observe a steady increase. The resulting difference-in-difference estimate for the effectiveness of the policy on drug overdose deaths in Florida increased by 3.19 (treatment = 0.24 - constant= -2.95) from 2006 to 2014. This, again reinforces the fact that policy change in Florida was indeed effective in bringing down the death rates.

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 accept H1, that is, policy enactment on opioid drugs does significantly reduce opioid prescriptions and opioid related deaths (drug overdose).

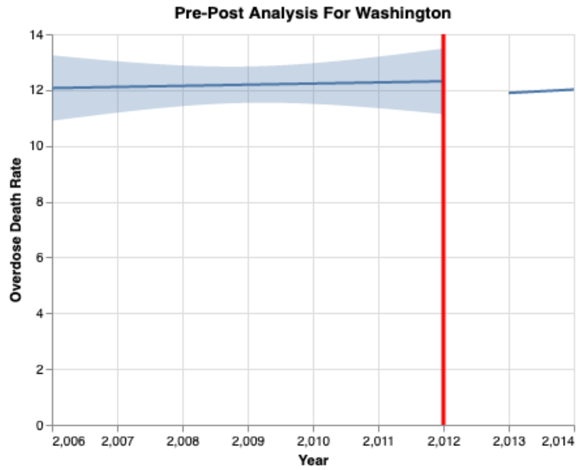
Washington

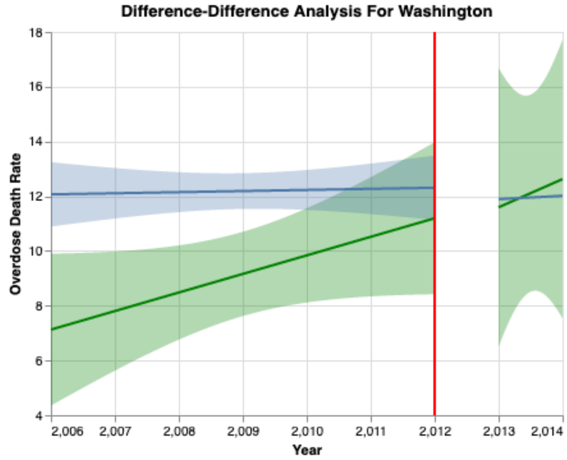
<u>Opioids shipment per cap</u>



For Washington, we perform a pre post comparison with respect to the year 2012, when the policy came into effect in the state. The pre-post analysis for Washington depicts a very slow rising trend in the opioid shipment per capita with around 0.35 gm per capita in 2006 to 0.4 gm per cap in 2012. Observing the pre post graph for the treatment state, Washington, prior to 2012, we can see that there is a slow rising trend in opioid shipment from 0.35 gm per capita in 2006 to 0.4 gm per capita in 2012. For the period ensuing 2012, the year for the policy enactment, we see a stagnancy of volume of opioid shipment around 0.35 gm per cap. We further probe into the analysis by performing a difference in difference between the base state and the control states. The control states chosen for Washington are Maryland, Oklahoma, Indiana, Idaho, Minnesota, Nebraska, Nevada and Virginia. The difference-in-difference estimate for the effectiveness of the policy enacted in 2012 on opioids shipment per capita in Washington increased by 0.273 (treatment: 0.18 - constant:-0.09) from 2006 to 2014. 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 conclusive in nature.

Drug overdose death



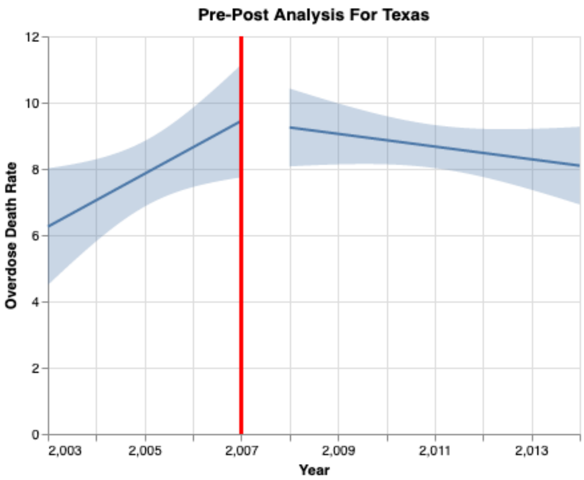


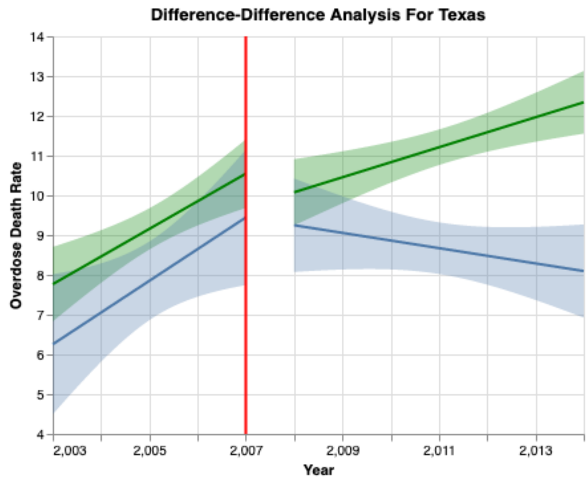
For the drug mortality rate(measured in 100,000), we see that in the pre-policy period there is a very minute increment in rate from around .012% to .0125% . Post the policy change in 2012, we again see a very minute decline to about .012% in 2014, which is not conclusive enough in itself to gauge whether or not the policy was effective. Hence, we conduct difference in difference regression on control and treatment states. The resulting difference-in-difference estimate for the effectiveness of the policy on drug overdose deaths in Washington increased by 5.458 (treatment = 1.59 - constant= -3.86) from 2006 to 2014. Although it can be observed that the mortality rate for the control states continues to rise and stagnates for Washington, we can also see that the control states do not have a perfect parallel trend with respect to Washington in the pre policy change period, that is prior to 2012. This shows that our assumption for difference in difference to create an equivalent for our treatment state is not met. Hence, the findings are not significant.

As both the metrics fail to meet the assumptions, it can be concluded that for Washington, we reject hypothesis H1 and retain H0, that is, policy enactment in Washington to regulate opioid drugs does not significantly reduce opioid prescriptions and opioid related deaths (drug overdose).

Texas

<u>Drug overdose death</u>





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 .006% in 2003 and peaks at .009% in 2007 when the policy is not in place. However, we see a decline post the policy change to a value of .008% 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 is somewhat similar to our state in consideration, Texas. There is a rise from .08% in 2003 to .011% in 2007. Post 2007, we see a decline in the mortality rate for Texas while there is a steady increase in the mortality rate for our control states. The death rate depreciates to a value of .08% in 2014 for Texas, on the other hand, for the control states it continues to rise to around .013%. So, we calculate this difference in difference estimate from 2003 to 2014 between the control and treatment states which increases by 1.23 (treatment = -0.780 - constant = -2.01). The difference in difference regression conducted on opioid shipment per capita shows that the policy enactment in Texas to curb the shipment influx has been effective. Therefore, we can conclude that the State was indeed effective in bringing down the prescription of opioids by putting a regulatory policy in place. To conclude, we reject the hypothesis H0 and accept H1, that is, policy enactment on opioid drugs does significantly reduce opioid prescriptions.

Conclusion and Discussion

To conclude, we can say that for Florida and Texas, the 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, difference-in-difference coefficient estimates indicate that the policy enactment is effective in reducing the "drug overdose mortality". For Washington, however, our assumptions are not met and we fail to create a parallel universe where control states are equivalent to the Washington pre-policy period. Even though, Washington has the most significant change with an estimated difference of around 5.46 death rate per 100,000 people, followed by Florida 3.19 and Texas 1.23, we cannot conclusively suggest that the policy enactment is effective as we fail to create a parallel universe where control states are equivalent to the Washington 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 Florida though trivial, with only 0.062 gram difference after the policy enactment, is conclusive enough to suggest that the policy regulation led to decrease in opioid shipment per capita. For Washington, again even though the difference in difference returns a higher coefficient estimate of 0.28 gram, we cannot say that our findings are conclusive enough to say that policy is successful..

Finally, to touch upon the difficulty of the causal inference analysis, it is in itself hard to implement, given that we want to ensure that in the world with opioid policy enactment, overdose death rate and opioid prescription is decreasing and in the world without opioids policy enactment, overdose death rate and opioid prescription would stay the same. This magical parallel can never happen, however, there are always things we can do to make the inferential process more valued. This takes us to look at the limitations in the study. Given that the period we have is from 2006 to 2014 (only Texas has 2003 - 2014 time frame), the difference between pre-policy and post-policy is hard to compare especially for Washington that has policy change in 2012, and thus only 2-years for post-policy period. Secondly, the selection criteria is only based on the elderly population proportion, which would be too arbitrary to conclude that they have similar opioid characteristics. Additionally, our population datasets have two different sources, meaning that it is possible they use different criteria to calculate the population estimates and potentially making our analysis inconsistent. Thus, to extract more informative conclusions, a more rigorous criteria in constant states selection and longer time span are needed.

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

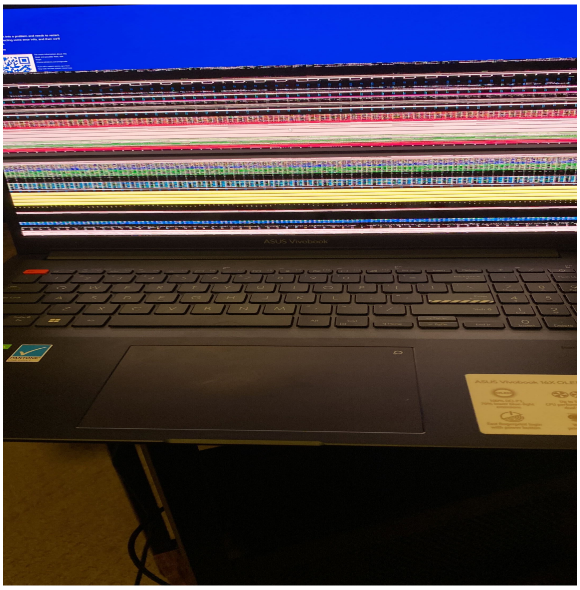
Drug Enforcement Administration (DEA). (2011, February 24). DEA-Led Operation Pill Nation Targets Rogue Pain Clinics In South Florida. Retrieved from https://www.dea.gov/press-releases/2011/02/24/dea-led-operation-pill-nation-targets-rogue-pain-clinics-south-florida

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/

Appendix

Visuals of Challenges



Estimating the Impact of Opioid Control Policies: Policy Recommendation Report

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Motivation

The United States is currently dealing with one of the worst drug epidemics in its history. It has been over a decade after the CDC declared epidemic of prescription painkiller overdoses and drugs like Oxycontin (a brand-name version of oxycodone) and related semi-synthetic opioids like Hydrocodone are still a leading cause of overdoses and deaths. According to the National Institute on Drug Abuse, opioids are a class of drugs that include the illegal drug heroin, synthetic opioids such as fentanyl, and pain relievers available legally by prescription such as oxycodone, hydrocodone, codeine and morphine.

Although access to opioids could be attributed to a variety of factors, in this report, we shall examine how the over prescription of legal pain medications and their distribution form the major foundation of the opioid supply chain to the public in this epidemic. The United States Department of Health and Human Services (DHSS) issued a public health alert on opioid addiction and dependence especially for patients who take opioids for an extended period of time as a pain relief medication. Opioid shipment, on the other hand, plays a significant role in this, with The Washington Post reporting that 500 million transactions from 2006 to 2014 from the DEA's database analyzing oxycodone and hydrocodone shipments to pharmacies created a virtual opioid belt of more than 90 counties across the US, with 18 of the top 20 counties ranked by per capita prescription opioid deaths nationwide.

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 prescription and, as a result, reducing shipment in an attempt to avert this crisis.

In 2007, the Texas Medical Board adopted regulations with regards to treating pain with controlled substances including performing a patient evaluation before prescribing opioids and reviewing prescription data and history related to the patient contained in the state's prescription drug monitoring program (PDMP).

In 2010, Florida was home to 98 of the 100 U.S. physicians who dispensed the highest quantities of oxycodone directly from "pain" clinics. The Florida legislature combated this by requiring pain clinics to register with the state by January 4, 2010. Mandatory dispenser reporting to the newly established prescription drug monitoring program began in September 2011. Finally, in 2012, the legislature expanded regulation of wholesale drug distributors.

In 2011, the Washington Department of Health adopted a rule regulating the prescribing of opioids for pain treatment. Mandatory consultation threshold for adults was set to 120 mg of MED per day (oral) and recommended that a practitioner could not prescribe more than an average MED of 120 mg without either the patient demonstrating improvement in function or without first obtaining a consultation from a pain management expert.

In this report, we examined the effect of these policy changes on the opioids shipment and overdose deaths due to opioids in the states of Texas, Florida, and Washington by comparing the rates of each of these factors before and after policy changes and comparing them to the events in states with little or no policy change to determine the size of the effect of policy change.

Methodology

Analysis Methods

To assess the impact of opioid regulation in the aforementioned states, we used two analysis methods, pre-post analysis and difference-in-difference analysis, to compare overdose deaths and shipments between 2003 and 2014, contrasting the years before and after the policy change. In the pre-post analysis, we looked to see if there was a difference in overdose deaths or opioid shipment numbers based on the year the policy was implemented.The goal here was to see if policy implementations influenced overdose deaths or opioid shipment numbers after the implementation year, as a no policy effect plot would show an increase in overdose deaths and opioid shipment numbers after the implementation year, whereas a policy effect plot would show a decrease in overdose deaths and opioid shipment numbers in the same time frame. Furthermore, we conducted a difference-in-differences analysis to isolate the causal effect of the policy from factors other than the treatment that may be affecting our interest in overdose and shipment changes; for example, a manufacturing shortage of these opioids affecting shipment numbers would result in a reduction in prescriptions and, as a result, a decrease in overdose deaths across the country. It is important to differentiate between this type of effect and the effect of the actual policy, which reduces shipments and, as a result, overdose deaths. However, we needed to compare this effect between states that changed their policies and those that did not. We compared each state with a policy change to those with less stringent changes or no changes at all. We assessed the impact of policy in that state using a pre-post analysis and compared the control and treatment groups.

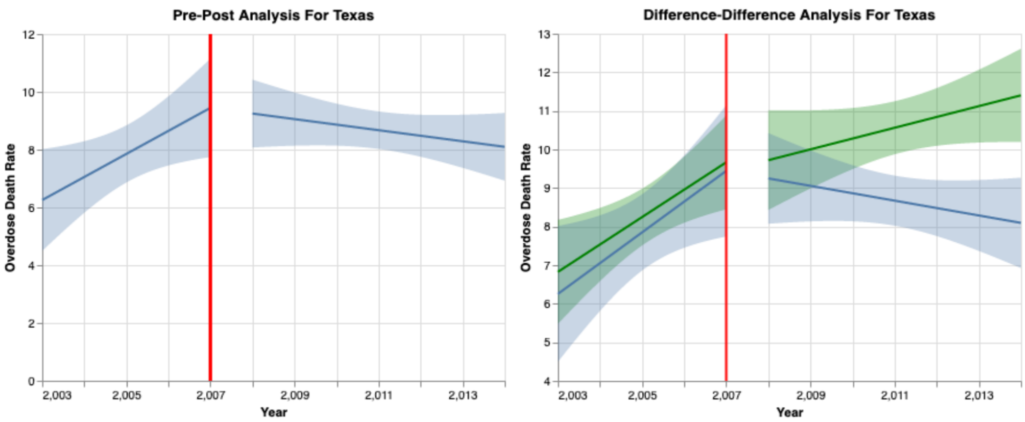
Data

We used The Washington Post's Opioid Prescriptions to obtain the amount of opioids prescribed, which was available in the data at the monthly level from 2006 to 2015. The US Vital Statistics records provided us with information on opioid overdose deaths in each county in the United States. To account for the population of each county, we used data from the Washington Post from 2006 to 2014 and the government census data from 2000 to 2006. We were able to calculate shipments per capita and deaths per capita for each county for the respective years using this data. The control states were chosen because their elderly population proportions were similar to those of the treatment states. The reasoning behind this is that the elderly population has more medical surgeries and is prescribed opioids; 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.

Analysis

Texas

Effects of Policy on Drug Overdose deaths



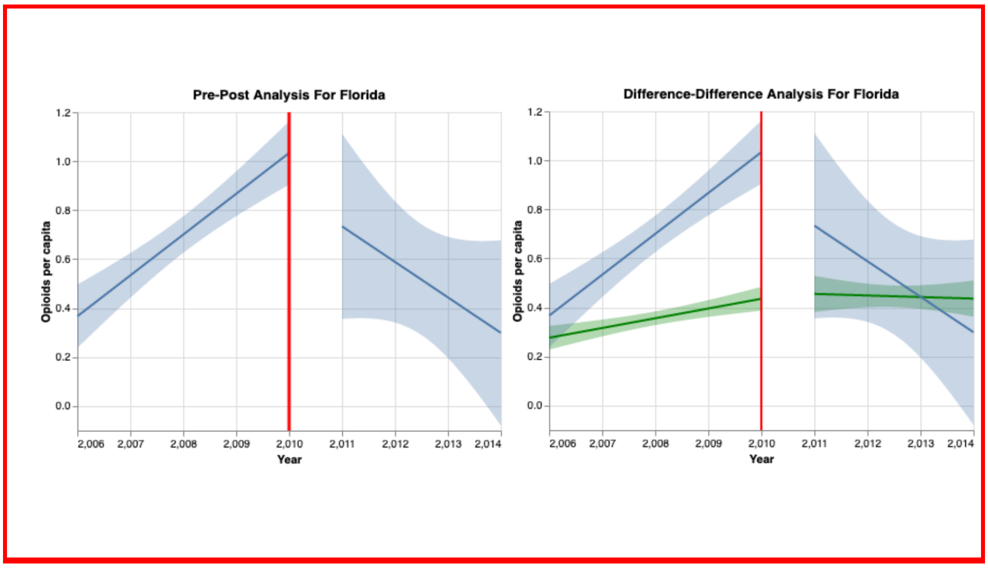
From the pre post analysis we see a rise in overdose deaths that starts to fall after 2007 when the policy is enacted.
From the difference in difference we see a parallel trend between Texas and the control states Colorado, Utah and Georgia, California, North Dakota, Illinois, Maryland and Oklahoma

before 2007 and after that, the trend started to fall for Texas while it continues to rise for the control states.
Looking at the Texas pre-post analysis, we noticed that drug overdose deaths increased from 2003 to 2007, when the regulations went into effect. From 2003 to 2006, death rates increased from 0.06% to 0.09%, then fell to 0.08% in2014. When we consider the difference in difference analysis, we see that after the policy was implemented, Texas overdose death rates began to fall while those in the control state continued to rise, despite the fact that both groups had a parallel trend prior to 2007.

Florida

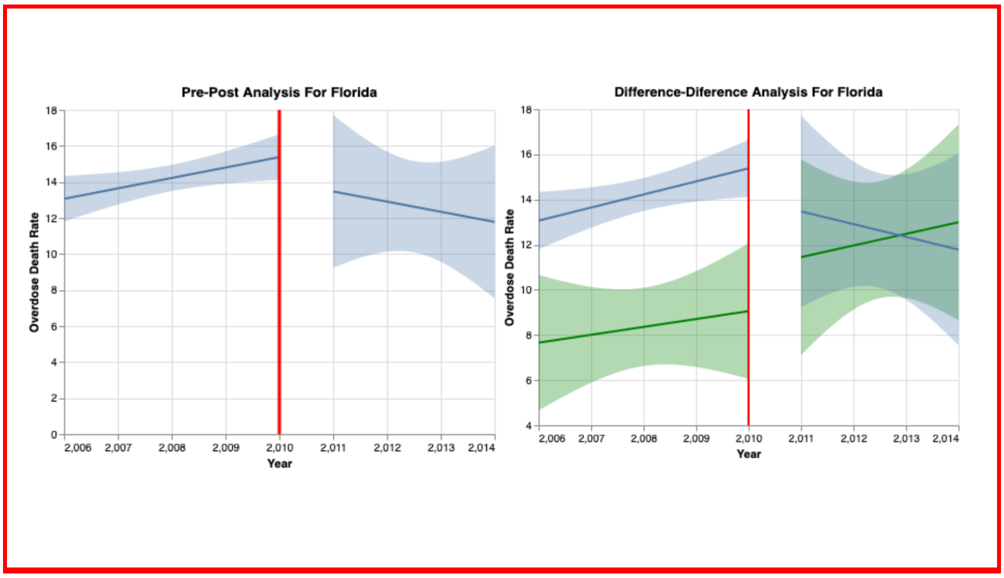
Effect of Policy on opioid shipments

From the pre post analysis below, we observed a rise in opioid shipment before the policy was enacted that started to fall after 2010.
From the difference in difference we see a parallel trend between Florida and the control states West Virginia, Vermont, Delaware, Hawaii, Montana, Pennsylvania, New Hampshire, South Carolina, and New Mexico before 2010 and after that, the trend starts to fall for Florida while it continues to rise for the control states.



Based on the Florida pre-post analysis, we discovered that opioid shipment increased dramatically from 2006 to 2010, when the regulations went into effect. The opioid shipment increased from 0.4g per capita to 1.15g per capita from 2006 to 2010, then fell to 0.3g per capita in 2014. When we look at the difference in difference analysis, we can see that after the policy was implemented, Florida opioid shipments drastically fell while the same metric rose in control states, despite the fact that both groups had a parallel trend prior to 2010.

Effects of Policy on Drug Overdose deaths

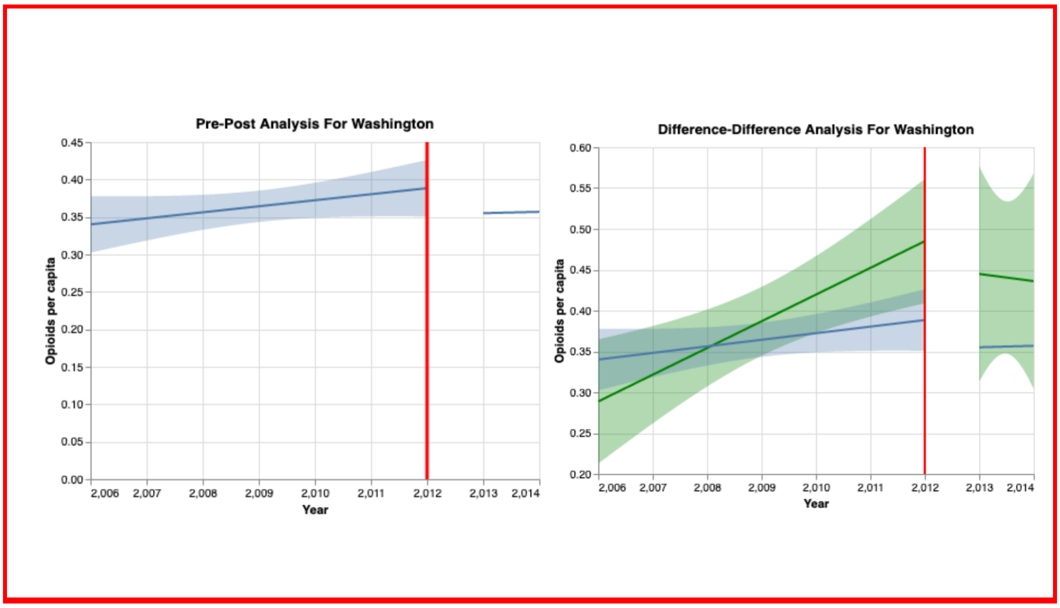


From the pre post analysis below, we observed a rise in opioid shipment before the policy was enacted that started to fall after 2010.
From the difference in difference we see a parallel trend between Florida and the control states West Virginia, Vermont, Delaware, Hawaii, Montana, Pennsylvania, New Hampshire, South Carolina, and New Mexico before 2010 and after that, the trend starts to fall for Florida while it continues to rise for the control states.

According to the Florida pre-post analysis, drug overdose deaths increased between 2006 and 2010, when the regulations went into effect. Overdose deaths were at 0.13% in 2006, and by 2010, they had risen to 0.15% and fell to 0.012% in 2014. Using a difference in difference analysis, we can see that after the policy was implemented, Florida overdose death rates began to fall dramatically, while those in the control state continued to rise, despite the fact that both groups had a parallel trend prior to 2010.

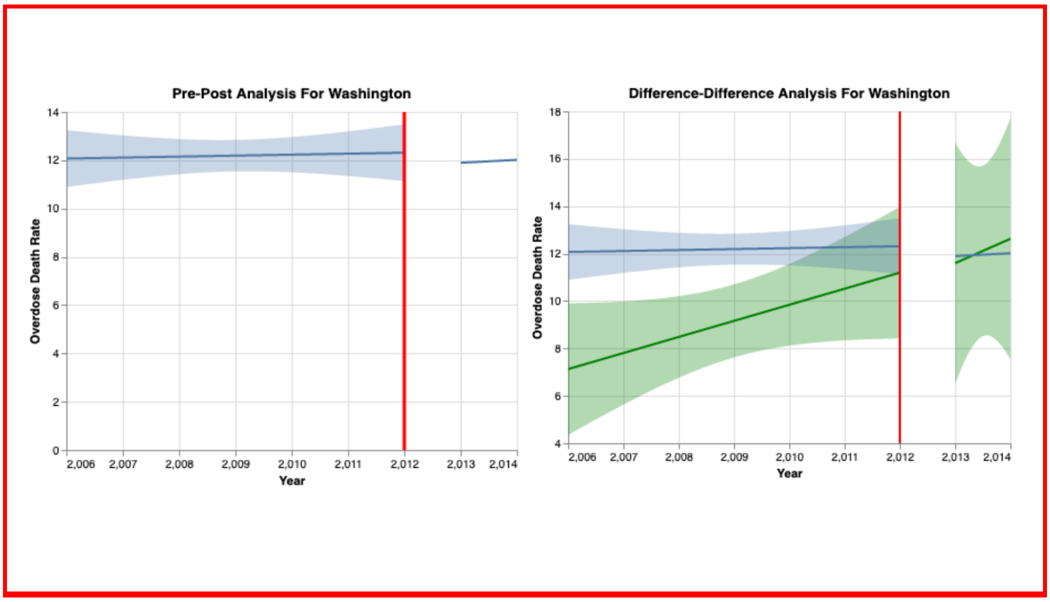
Washington

Effect of Policy on opioid shipments



According to the Washington pre-post analysis, we discovered that opioid shipment slightly increased from 2006 to 2012, when the regulations were implemented, and decreased from 2013 to 2014. However, the difference-in-difference analysis does not confirm whether the decline in opioid shipment after 2012 was due to the prior policy because there was no parallel relationship between the opioid shipments in Washington and the control states prior to 2012.

Effects of Policy on Drug Overdose deaths



Based on the Washington pre-post analysis, overdose deaths increased slightly from 2006 to 2012, and when the regulations were implemented, they nearly did not decrease from 2013 to 2014. However, because there was no parallel relationship between opioid overdose deaths in Washington and the control states prior to 2012, the difference-in-difference analysis cannot confirm whether the decline in overdose deaths after 2012 was due to the prior policy.

Limitations

First and foremost, as with any study that involves selection criteria, each method has its flaws and benefits. The flaws with this method was looking only at the proportion of the elderly who need opioid prescriptions. There may have been other metrics of that subpopulation we could have added to our criteria or other communities to have considered.

Another limitation was how not all of our treatment states met the assumptions for our control states, with the exception of Florida. That may have shed light on potential inefficiencies underlying the selection criteria (although this also could have happened with other types of selection criteria). Furthermore, the assumption itself is very difficult to satisfy, since the control states need to have a trend parallel to the given treatment state. Also, we can never be completely sure that, if the difference-in-difference analysis showed there was an improvement, that there were no other factors present that created the given result.

Conclusion

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 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 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. As for future recommendations, we might opt for different selection criteria to find more or different control states, and, therefore, conduct further analyses.