The Effect of Opioid Policy on Prescriptions and Overdose Deaths

Motivation

In the late 1990s, pharmaceutical companies reassured the medical community that patients would not become addicted to prescription opioid pain relievers, and healthcare providers began to prescribe them at greater rates.[1] This misinformation led to the misuse of opioids, a category of highly addictive substances, and resulted in a tremendous rise in opioids addiction and overdose death.

As the Opioid Overdose Crisis becomes increasingly concerning, many states have taken actions to regulate opioid prescriptions in hope to lower the addiction rate and the overdose mortality rate due to the misuse of opioids. However, policy interventions are not guaranteed to be effective. While strict regulations on opioid prescriptions would have a direct impact on the amount of opioids prescribed by medical practitioners, reducing the risk of potential addiction, it is unclear that overdose mortality rate would decrease correspondingly. When they find it harder to get prescribed opioids, patients that have already become addicted to opioids are highly likely to obtain substitutions like heroin and fentanyl which are illicitly manufactured with high potency. Consuming these illegal substitutions without proper guidance from medical practitioners would lead to a huge increase in non-prescription opioids overdose deaths.

With these concerns in mind, we evaluate the effectiveness of policy interventions in Florida, Texas and Washington. While most of the states did not publish regulations until recent years, Texas, Florida, and Washington were the pioneers in regulating opioids abuse and they passed laws in 2007, 2010, 2012, respectively. In this project, we investigate the following research questions:

1. Does policy change on opioid drugs reduce the opioid prescriptions?
2. Does policy change on opioid drugs reduce the mortality rate?

Research Design

In this project, we thrive to estimate the effect of policy interventions on opioid prescriptions and drug overdose deaths using two methods: pre-post analysis and difference-in-difference analysis.

[1] Source: Opioid Overdose Crisis

The pre-post analysis takes the difference of opioids prescribed per capita and mortality rate before and after the policy effective year. For example, in Florida, if the mortality rate is 6 in 100,000 population before and 5 in 100,000 population after the policy effective year, the pre-post comparison would estimate policy intervention reduces the mortality rate by 1 in 100,000 population. The effectiveness of the policies cannot be obtained by just taking the difference between post-policy outcomes and pre-policy outcomes for the states of interest.

This is not reasonable because we do not have the counterfactual of these states -- the trend of outcomes had there been no policy enacted. For example, if we observe the drug overdose death per 100,000 population in a given county in Florida in 2003 is 16, and in 2015 (after the policy) is 5. By only comparing the pre-post data, we might falsely conclude that the policy decreases the mortality rate per 100,000 population by 11 people. In this process, we could ignore other national-level changes that could affect opioid prescription or mortality. For instance, the U.S. Coast Guard frequently patrols the South Pacific Ocean and the Caribbean Sea to curtail illicit narcotics before they reach the country, and the U.S. Customs and Border Protection implements strict custom examinations to prevent people from smuggling illegal opioids. These national actions have effects on *everyone* in the country. Therefore, we might overestimate the effect of the Florida policy if the number of drug overdose deaths in that county would have been 7 people had there been no policy. We overestimate the Florida policy because we attribute the impact of these national changes to the Florida policy. Similarly, we might underestimate the effect if the number of deaths is only 15 had there been no policy.

Since national-level changes affect every state, one solution for the lack of the counterfactual is to use other states as controls to estimate the trends of states of interest had there been no policy. This method is called the difference-in-difference analysis. Similar to the pre-post analysis, the difference-in-difference method also estimates the effects of the policies by taking the difference between after and before the policy. However, difference-in-difference takes a step further by comparing the difference with some control states. This approach, in theory, produced less biased estimates since we remove national-level effects when we take the difference between target states and control states. With that said, the validity of the difference-in-difference approach depends on the assumption: the trend of the control states must be the same as the states of interest before the policy interventions.

Data

A. Population Dataset

1. Summary

Since the population varies across different counties in the United States, it would be reasonable to normalize the amount of drug prescriptions and drug overdose deaths by population in each county. Therefore, we need the population data at county levels for all 49 states (except Alaska) from 2003 to 2015.

The data we find is from the U.S. Department of Energy Office of Scientific and Technical Information. It contains 3,144 observations and 23 columns and includes the intercensal estimates of the resident population from 2000 to 2019 for all counties from 50 states as well as Washington DC. Column 1 - 3 contains state, county, and FIPS code. Column 4 - 23 contains the population from 2000 to 2019.

2. Data Cleaning

Data preparation includes the following steps:

a. Since we decide to merge on county, state, and year, we exclude the unneeded FIPS code column.
b. We check for missing values and duplicated rows. No missing values and duplicated rows found.
c. Since we only need data from 2003 to 2015, we excluded column 2000 to 2002 and column 2016 to 2019.
d. We reshape data frames using pandas melt so each observation has four columns state, county, year, and population respectively.
e. We rename states to state abbreviations; and strip "county" from county names. For example, in the county column "durham" is used instead of "durham county"
f. Finally, we exclude observations from Alaska and Washington DC.

3. Summary Statistics

The cleaned population data contains 62,260 observations and 4 columns. Each row contains 4 columns: state, county, year, and population. Based on the average number of population for each year, we see a general increasing trend in population. More specifically, the average population increased from 89,778 in 2000 to 104,432 in 2019.

B. Opioids Prescriptions Dataset

1. Summary

This dataset released by *Washington Post* contains all prescribed opioid drug shipments in the United States from 2006 to 2013 with 42 variables. After carefully examining the dataset, we discover that the unit of observation is one opioid drug transaction, including reporter/buyer information, drug details, and transaction date.

2. Data Cleaning

From the data description, we realize for one transaction, there are distributors/manufacturers that shipped the opioid drugs and the pharmacies/practitioners that received the opioid drugs. Based on this information, we assume pharmacies/practitioners prescribed opioid drugs to patients locally and patients used these drugs within the county. Summing up, we select buyers' states and county information to match the state and county values in other datasets.

To calculate the total volume of opioids shipped per county per state per year, we first multiply the total active weight of the drug in the transaction in grams with its morphine milligram equivalent. The resulting variable weight describes the total weight of active ingredient in morphine milligram equivalent for the corresponding shipment.

The original dataset contains the date shipment that occurred in the month, day, year order in the integer type. We convert this variable into the date-time type and extract year information. We then group the weight variable by year by summing up the weight. As a result, we create a new variable year and the value of weight becomes the total weight of opioid drugs prescribed in the specified county.

3. Summary Statistics

The cleaned opioid prescriptions dataset has 20,874 observations with 4 variables: state, county, year, and weight of opioids prescribed. The unit of observation for the cleaned opioid prescriptions dataset is the total weight of opioid drugs prescribed for a certain county in a certain state (excluding Alaska) per year from 2006 to 2012. The average weight of opioid drugs shipped demonstrates an increasing trend. More specifically, the average opioid drug shipment weight increased from 25,217 mg in 2006 to 41,038 mg in 2012 with an average increase of 2,637 mg each year.

C. Vital Statistics Mortality Dataset

1. Summary

US Vital Statistics records data is used to obtain drug overdoses death. US Vital Statistics records include data on death in the United States on county levels by years.

National mortality data is provided from 2003 to 2015. In the data, seven categories of death causes are recorded on county levels: All other non-drug and non-alcohol causes, Drug poisonings (overdose) Unintentional (X40-X44), All other alcohol-induced causes, Drug poisonings (overdose) Suicide (X60-X64), Drug poisonings (overdose), Undetermined (Y10-Y14), All other drug-induced causes, and Alcohol poisonings (overdose) (X45, X65, Y15). Other information included in the datasets are county names, state, year, and the count of the death for each category in each county for a given year.

2. Data Cleaning

Since the mortality data is organized in the way that each file is the national mortality data in a given year, the cleaning process for this data includes reading in each file and dropping unrelated rows and columns. Furthermore, because we are only interested in drug overdose-related death, a subset is created by only including death statistics that relate to Drug poisonings (overdose) Unintentional (X40-X44). [2]

3. Summary Statistics

The resulting cleaned mortality data contains 7,573 observations on the 4 variables. The unit observation is the number of drug overdoses deaths for a given county in a given year ranging from 2003 to 2015. The 4 variables are year, state, county, and number of drug overdose deaths.

It is important to note that due to privacy considerations, the US Vital Statistics only report a given category of death cause for a county in a given year if the number of deaths is greater than 10. As a result, the number of observations for each year is not consistent. For example, in 2015, 781 counties reported drug overdose death; however, only 375 counties reported drug overdose death in 2003. Overall, there is a steadily increasing trend in the number of counties reporting drug overdose death from 2003.

Furthermore, the average drug overdose death also shows an increasing trend. The national average drug overdose deaths is 37.12 in 2003, and in 2015, the national average increased to 49.69.

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[2] There is one observation that had the value “Missing” -- this was dropped.

D. Merging

Prior to merging, we check the shape of these datasets and propose a structure for the final dataset based on the number of observations. For these three cleaned datasets, the population dataset has the most observations for both location (state and county) and time span (year). Opioid prescriptions dataset has a few missing values for some counties with a shorter time span. As mentioned above, a county would only appear in the mortality data, if that county had more than 10 cases of drug overdose death in a given year. As a result, the mortality dataset has the least observations for locations but a longer time span (2003 to 2015) compared to the opioid prescriptions dataset.

To deal with inconsistent dimensions across all three datasets, we consider the population dataset as the base dataset. Then, we merge the opioid prescriptions dataset on the population dataset to produce an intermediate dataframe. Finally, we merge the mortality dataset on the intermediate dataset to obtain the final outcome. Both steps are left merged on variables county, state, and year. The resulting final dataframe has the same number of rows as the population dataset with two additional columns which are the weight from the opioid prescription data and death from the mortality data.

E. Missing Value Handling

Since the merged dataset is based on the more comprehensive population dataset, the final dataset contained missing values due to the lack of data. Instead of dropping rows that contain missing values, we replace all missing observations with zeros.

The reason for this is that for the mortality dataset, the lack of observation for a given unit of observation is resulted from less than 10 drug overdose deaths being reported. Therefore, it is reasonable to assume the given unit of observation had zero drug overdose deaths. We argue that dropping all NA observations would overestimate the number of drug overdose deaths. Assuming zeros for the missing values will result in less biased estimations for mortality rates. We also fill in zeros for all missing values in the opioid prescription data. The reason for this is also the same as for the mortality data.

F. Final Data Summary

After filling in NAs, we calculate the opioid per capita[3] and mortality rate in the 100,000 population [4] for further analysis. Final merged dataset has 40469 observations with 5 variables: state, county, year, opioids prescribed per capita in morphine milligram equivalent and mortality rate in the 100,000 population. The unit of observation for the final merged dataset is opioid

[3] Opioids prescribed per capita = total weight of opioids/population
[4] Mortality rate in100,000 population = number of deaths/population*100,000

drugs prescribed in morphine milligram equivalent per capita and mortality rate in the 100,000 population for a certain county in a certain state per year from 2003 to 2015.

In our final dataframe, the average opioid per capita has an increasing trend where the average opioid per capita increased from 0.2232 mg in 2006 to 0.3676 mg in 2012. The average drug overdose mortality rate also increased significantly from 1.06 in 2003 to 4.13 in 2015.

Summary Statistics of the Final Dataset			
Year	**Average Population**	**Average Opioid per capita**[5]	**Average drug overdose death / 100k**
2003	92867.89	NA	1.06
2004	93737.35	NA	1.21
2005	94603.79	NA	1.44
2006	95512.98	0.22	1.86
2007	96470.03	0.25	2.08
2008	97364.81	0.28	2.26
2009	98203.80	0.30	2.23
2010	98939	0.33	2.79
2011	99655.76	0.36	3.11
2012	100385.19	0.37	2.98
2013	101079.43	NA	3.00
2014	101823.84	NA	3.67
2015	102576.25	NA	4.13

[5] The opioid dataset only ranges from 2006 to 2012.

Analysis & Interpretation

Control States

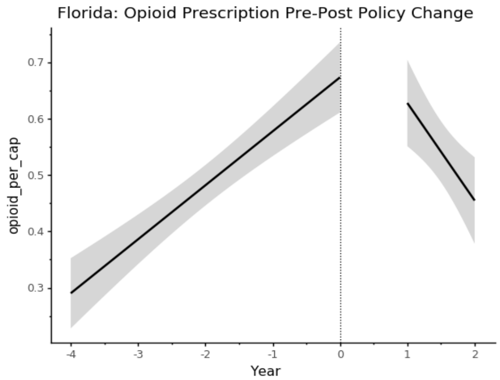
To choose control states that are reasonable for each of our states of interest, we first identify states that had regulations on opioid prescription before 2015. After research, we find Connecticut had opioid prescription regulations in 2012, therefore, it is excluded in the pool of control states. [6]

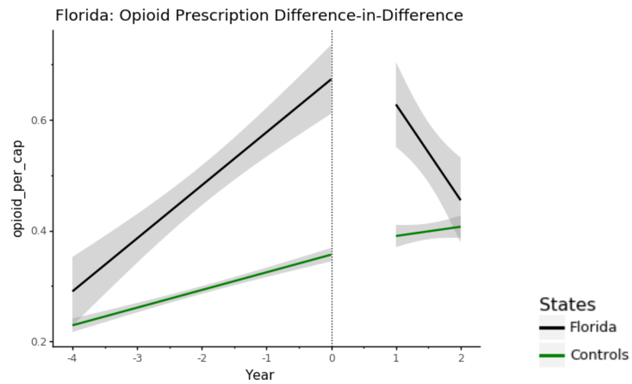
When choosing controls, we consider a number of factors that can potentially affect the "similarities" between the policy-change states and controls. First, we consider the geographic locations. We group all US states, excluding Alaska, into four geographic categories: West, South, Midwest, and Southeast based on the U.S. Census Bureau. We argue that states that are adjacent to each other have a higher probability of sharing similar trends in opioid prescription and drug overdoses deaths. Second, we consider state economic scales, particularly GDP per capita. We believe that states with similar economies tend to have similar trends. Finally, we plot the trends of opioid prescriptions and drug overdose deaths by each state to gauge the similarity of each state. Note, in this analysis, we define pre-policy period as all years before the year of the policy; and post-policy period as one year after the policy year.

A. Florida

Starting from 2010, there was a series of policy changes to regulate opioid prescriptions and ensure best practices in Florida. The Florida legislature required pain clinics using controlled substances to register with the state in 2010 and later prohibited physicians to dispense schedule II or III drugs from their offices in 2011. In 2012, the legislature demanded mandatory reporting to a prescription drug monitoring program from drug distributors[7]. For this project, we consider the policy effective year to be 2010.

[6] For more information in policy change in different states, see https://www.affirmhealth.com/blog/opioid-prescribing-guidelines-a-state-by-state-overview
[7] Source: Johnson, Paulozzi, Porucznik, Mack, and Herter, 2014.





In these two graphs, x-axis is the number of years before(-) or after(+) policy effective year. 0 indicates policy effective year 2010 in Florida. Y-axis is the weight of opioid drugs prescribed per capita, averaged across all counties in Florida or control states and estimated in morphine milligram equivalent. Estimated trends are bounded with 95% confidence intervals.

Florida Average Opioid Prescription per capita		
Year	**Control States**[8]	**Florida**
2006	0.2304	0.3198
2010 (Policy effective)	0.3601	0.7047
2012	0.4071	0.4549
2012-2006 difference	0.1767	0.1351
Diff-in-diff estimate[9]	-0.061	

Before the policy effective year 2010, there was a positive association between year and opioids per capita. However, the trend for opioids per capita in Florida reversed after the policy intervention. Opioids per capita increased steadily from 0.32 mg[10][11] in 2006 to 0.7 mg in 2010. After the policy intervention, opioids per capita decreased as time progressed and dropped to an

[8] The control states for Florida are Georgia, Maryland, North Carolina, Louisiana, Virgina, Alabama, Arizona, Mississippi, Oklahoma, South Carolina

[9] The difference-in-difference is calculated by {average(prescription per capita in Florida after policy) - average(prescription per capita in Florida before policy)} - {average(prescription per capita in controls after policy) - average(prescription per capita in controls before policy)}. All following difference-in-difference estimates are calculated this way. The averages are used in order to smooth out yearly shocks and fluctuation.

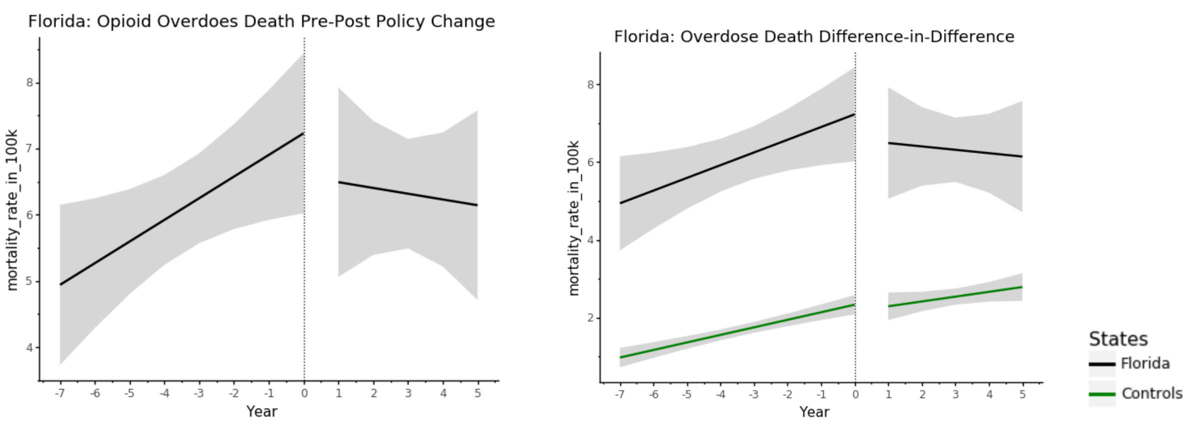
[10] For the specified state, this exact number of opioid per capita is the average across all counties with valid input within the state. For control states, we obtain opioid per capita for states first and then average across all states selected

[11] Opioid per capita measures are all in morphine milligram equivalent

average of 0.45 mg. Overall, from 2006 to 2012, opioids per capita in Florida increased by 0.14 mg and the policy intervention was effective based on the reversed trends.

From the Difference-in-Difference plot, we could see that for control states and Florida there was a positive correlation between year and opioids per capita before policy effective year 2010. Moreover, opioids per capita in control states did not increase as rapidly as in Florida as shown in the graph. The number increased from 0.23 mg in 2006 to 0.36 mg in 2010 for the control states. Note that the trends are not parallel, which would limit the analysis on the impact of policy intervention.

With policy intervention, Florida had a negative trend for opioid per capita whereas the trend continued to be positive for states without policy intervention. In 2012, the number of opioid per capita went up to 0.41 mg in control states. From 2006 to 2012, opioids per capita in control states increased by 0.18 mg -- 0.04 mg higher than the difference in Florida. To conclude, we estimate that policy intervention effectively decreased opioid per capita by 0.061 mg in Florida from 2006 to 2012.



In these two graphs, x-axis is the number of years before(-) or after(+) policy effective year. 0 indicates policy effective year 2010 in Florida. Y-axis is the mortality rate in the 100,000 population in Florida or control states. Estimated trends are bounded with 95% confidence intervals.

Florida Average Opioid Overdose Mortality per 100K		
Year	**Control states**	**Florida**
2003	0.7925	4.8811
2010 (Policy effective)	2.0264	7.1997

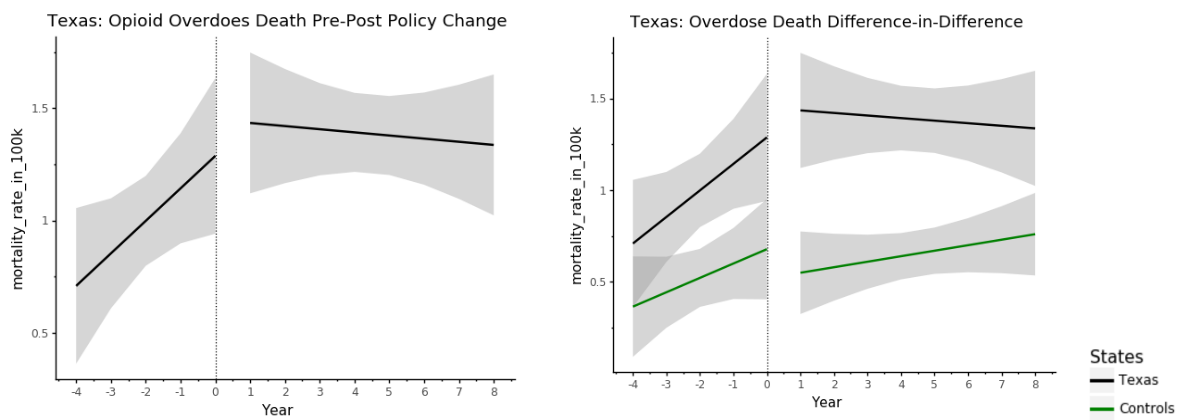
2015	2.8528	7.4167
2015-2003 difference	2.0603	2.5356
Diff-in-diff estimate	-0.654	

Similar to the trend displayed for opioid prescriptions, Florida experienced an increasing trend for drug overdoses death prior to the policy intervention in 2010. In 2003, the average mortality rate in Florida was 4.88 and it increased to 7.2 in 2010. One year after the policy went into effect, the mortality rate in Florida peaked in 2011 at 7.62. Following 2011, 2012 saw a sharp decrease. The mortality rate decreased by 21.6% to 5.03. From 2012 to 2014, the mortality rate increased slowly averaging at around 5.51. However, 2015 saw a sharp increase. The mortality rate back to pre-policy level at 7.41 (even higher). Whereas Florida experienced fluctuations in mortality rates, the control states overall displayed a steadily and consistently increasing trend. From the difference-in-difference plot, we see that control states experienced an increasing trend from 2003 to 2015. Overall, the average increase before and after the policy for Florida is 0.23[12] (from 6.09 to 6.31), and 0.88 (from 1.65 to 2.54) for control states.The resulting difference-in-difference estimate for the effectiveness of the policy on Florida's drug overdose deaths decreased by 0.654 from 2003 to 2015.

B. Texas

In 2007, the Texas Medical Board provided guidelines on treating pain with controlled substances, including performing a patient evaluation before prescribing opioids, obtaining informed consent, conducting periodic review of treatment and maintaining a complete medical record.[13] Therefore, we consider the policy effective year in Texas to be 2007.

[12] The average increase before and after policy is calculated by average(outcome after policy in Florida/control states) - average(outcome before policy in Florida/control states).
[13] Source: Texas Administrative Code



In these two graphs, x-axis is the number of years before(-) or after(+) policy effective year. 0 indicates policy effective year 2007 in Texas. Y-axis is the mortality rate in the 100,000 population in Texas or control states. Estimated trends are bounded with 95% confidence intervals.

Texas Average Opioid Overdose Mortality per 100K		
Year	**Control states[14]**	**Texas**
2003	0.3071	0.7431
2007(policy effective)	0.6045	1.0598
2015	0.8424	1.3973
2015-2003 difference	0.5353	0.6542
Diff-in-diff estimate	0.254	

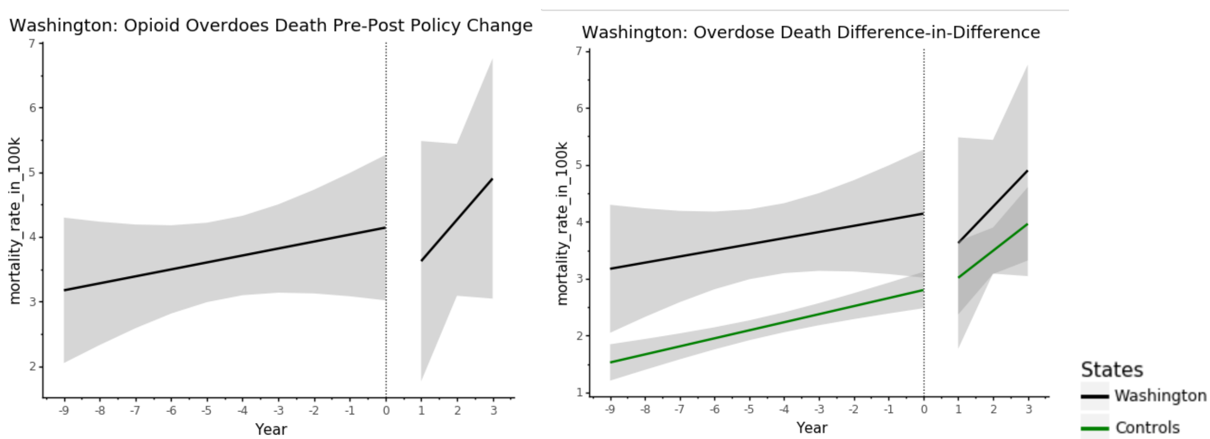
Both Texas and the control states saw an increase in opioid prescriptions from 2006 to 2012. The opioid prescriptions for Texas increased by 43.9% from 0.14 mg in 2003 to 0.20 mg in 2015. This is a comparatively smaller increase than that of the control states. The opioid prescriptions increased by 76.5% for control states from 0.17 mg in 2006 to 0.30 mg in 2012. Despite the increasing trend even after the policy went into effect in 2007, Texas actually increased less compared to control states. The average increase for Texas[15] before and after the policy is only 0.04 compared to 0.07 for control states. The difference-in-difference estimate for opioid prescription in Texas is -0.037. This suggests that the policy was effective in limiting the amount of opioids prescribed compared to control states.

[14] The control states for Texas are Kansas, Maine, Mississippi, Montana, South Dakota.
[15] This is calculated as average(prescription after policy for Texas) - average(prescription before policy for Texas).

In terms of drug overdoses death, Texas experienced fluctuations over the years. It first experienced a large increase in opioid overdose deaths from 2003 to one year prior the policy (2006). The opioid overdose death increased by 109% from 0.74 death per 100k people in 2003 to 1.55 in 2006. Then, the mortality dipped slightly in 2007 when the policy was in effect. However, it is important to note that the mortality in Texas increased one year after the policy went into effect. It peaked in 2010 at 1.54. Compared to 2007, this is a 45.7% increase in mortality. After 2010, the mortality in Texas displayed a gradual decreasing trend with some fluctuations. Overall, the average increase of drug overdoses deaths is 0.39 before and after the policy. Compared to Texas, control states have a more consistent increasing trend in mortality except for slight dips in 2011 and 2014. The average increase in drug overdoses death for control states before and after the policy is 0.133 which is smaller than that of Texas (0.387). The resulting difference-in-difference estimate for Texas is 0.254. This implies that overall the drug overdose deaths increased by 0.254 deaths per 100,000 population after the policy went into effect in Texas. However, it is imperative to point out that Texas experienced more fluctuations. Therefore, the estimates could be biased.

C. Washington

In 2011, the Washington Department of Health adopted rules regulating the prescribing of opioids for pain treatment, including setting mandatory consultation threshold for dosage, conducting periodic reviews on patients and documenting mandatory consultations.[16] In this report, we consider the policy effective year in Washington to be 2011.



In these two graphs, x-axis is the number of years before(-) or after(+) policy effective year. 0 indicates policy effective year 2012 in Washington. Y-axis is the mortality rate in the 100,000 population in Washington or control states. Estimated trends are bounded with 95% confidence intervals.

[16] Source: Washington State Permanent Rules

Washington Average Opioid Overdose Mortality per 100K		
Year	**Control States**[17]	**Washington**
2003	1.2460	2.2807
2012 (Policy effective)	2.5034	4.0843
2015	4.1600	4.8479
2015-2003 difference	2.9140	2.5672
Diff-in-diff estimate	-0.72	

In terms of opioid prescriptions, both Washington state and control states display a consistent increasing trend from 2006 to 2012. However, control states had a higher increase than control states. Washington increased by 26.5% from 0.30 mg in 2006 to 0.39 mg in 2012, whereas control states increased by 63.3% from 0.2 mg in 2006 to 0.33 mg in 2012. We could not assess how the policy might have affected opioid prescriptions after the policy because of the lack of the data after 2012.

In terms of drug overdoses death, both Washington and control states display an overall increasing trend from 2003 to 2015. Control states have a consistent increasing pattern -- the mortality rate increased each year gradually. The mortality rate increased by 133.5% from 2003 to 2015 for control states. For Washington, the mortality rate experienced more disturbances compared to controls. From 2003 to 2009, the mortality in Washington increased to more than double (from 2.28 to 4.49). However, in 2010, Washington experienced a sharp decrease to a similar level in 2003 (2.89). From 2010 to 2015, the mortality rate in Washington showed an increasing trend. It only showed a slight decrease one year after the policy (3.57 in 2013). Overall, Washington on average experienced a smaller increase in mortality rate after the policy compared to the control states. This average drug overdose death per 100K population before the policy is 3.66, compared to 4.26 after the policy in Washington. For control states, the mortality rate increased from 2.16 to 3.49 after the policy, resulting in 1.32 increase. Therefore, from our difference-in-difference analysis, we estimate that overall, the drug overdose deaths decreased by 0.72 deaths per 100,000 population after the policy went into effect.

[17] The control states for Washington are Maryland, Montana, North Carolina, Oregon, Wisconsin, Louisiana.

Conclusion

Policy intervention is effective in restricting the amount of opioids prescribed for Florida and Texas. The effect in Washington is inconclusive due to the lack of data. In Florida, the policy is noticeably effective. One year after the policy went into effect, the amount of opioid prescribed saw a steady decrease whereas control states increase consistently. In addition, the policy also seems to be effective in reducing drug overdose deaths in Florida. In Texas, our analysis shows that the amount of opioids prescribed increased after the policy. However, it was increasing at a smaller rate than that of control states. From the difference-in-difference estimation, we estimate that Texas policy decreased the amount of opioid prescribed by 0.037 mg. Signals are much unclear on the effects of government intervention on drug overdose deaths. Florida shows a decreasing trend in mortality one year after the policy, and the trend persisted for three years before we saw a sharp spike in 2015. Texas had large increases in mortality rates after the policy went into effect before experiencing a two-year decrease. After the short two-year period decreased, the mortality rate increased again and returned to a similar but lower level as the pre-policy period. In Washington, the mortality rates showed an overall increasing trend only showed a slight decrease one year after the policy and then quickly returned to the pre-policy period level and even higher.

We find the policies are generally effective in reducing the amount of the opioid prescriptions. This is a reasonable finding since most policies directly regulate opioids prescriptions, sales, and usages. We expect to see the policies have a direct impact on the amount of opioids prescribed. However, the effect of the policies on drug overdose deaths is less obvious. On one hand, reducing the amount of opioid prescribed should result in less drug overdose deaths since patients have less probability of becoming addicted. On the other hand, restricting the access to opioids could potentially turn already addicted patients to illegal drugs. Without medical professionals administering opioids, patients run a higher risk of overdosing and resulting in drug overdose deaths. In our analysis, we find Florida is relatively more successful in mitigating overdose deaths with mortality rates displaying a decreasing trend for a longer period. However, the signals are unclear. All three states experienced decreases in mortality in years following the policy, although he decreases seem to be transient. Following the short-term decrease, the increasing trend returned and mortality rates bounced back to pre-policy level and even higher, although Florida enjoyed a longer decreasing trend for about 3 years.

Referring back to the policy documents, we realize that Florida had the most comprehensive regulations on opioids prescriptions. From 2010 to 2012, the Florida legislature gradually added instructions and expanded to wholesale drug distributors. Furthermore, Florida created a monitoring program and a statewide task force to ensure the effective implementations. Compared to Florida, Texas and Washington only targeted physicians prescribing opioids with little response to address the violation of opioid regulations. In summary, our findings align with the detail of policy implementations.

In conclusion, our analysis shows that Florida is effective in reducing opioid prescriptions and mitigating drug overdose deaths. Texas and Washington are successful in restricting the amount of the opioid prescriptions. However, the effects of policies on drug overdose deaths in Texas and Washington are ambiguous, since the trend for both states fluctuates -- it generally decreases after the policy before it increases again. Therefore, we believe that a more rigorous analysis and longer time span are needed in order to extract more informative conclusions.

Appendix

Policy change year for each state:

https://www.affirmhealth.com/blog/opioid-prescribing-guidelines-a-state-by-state-overview
Region 1: Northeast
Division 1: New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont)
Connecticut(CT): 2012
https://portal.ct.gov/DPH/Health-Education-Management--Surveillance/The-Office-of-Injury-Prevention/Current-Laws-related-to-Opioids-Overdose-Prevention
Maine(ME): 2016
https://www.mainehealth.org/About/Health-Index-Initiative/Prescription-Drug-Abuse-and-Addiction/Limiting-the-Prescribing-of-Opioids
Massachusetts(MA) 2016
https://www.macep.org/chapter52
New Hampshire(NH):2017
https://www.nhms.org/resources/opioid
Rhode Island(RI):2017
https://health.ri.gov/healthcare/medicine/about/safeopioidprescribing/
Vermont(VT):2019
https://www.mitchell.com/mitchellnews/detail/lid/2095/vermont-adopts-opioid-prescribing-rule
Division 2: Mid-Atlantic (New Jersey, New York, and Pennsylvania)
Region 2: Midwest (Prior to June 1984, the Midwest Region was designated as the North Central Region.)
Division 3: East North Central (Illinois, Indiana, Michigan, Ohio, and Wisconsin)
Illinois: 2019
https://www.dph.illinois.gov/opioids/prevention
Indiana:2017
https://www.in.gov/isdh/28027.htm
Michigan: 2018
https://www.michigan.gov/documents/lara/LARA_DHHS_Opioid_Laws_FAQ_05-02-2018_622175_7.pdf
Ohio:2018

https://med.ohio.gov/Overview-Regulations-for-Chronic-and-Subacute-Opioid-Prescriptions
Wisconsin:2015
https://docs.legis.wisconsin.gov/misc/lrb/lrb_reports/lrb_reports_2_6.pdf
Division 4: West North Central (Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota)
Iowa:2018
https://governor.iowa.gov/2018/05/gov-reynolds-signs-bipartisan-opioid-bill-into-law
Kansas: 2021
https://www.nacds.org/news/kansas-e-prescribing-law-as-critical-step-in-opioid-abuse-prevention/
Minnesota: 2015
https://www.house.leg.state.mn.us/hrd/pubs/opioidreg.pdf
Missouri: not found
Nebraska: 2018
https://www.nebmed.org/about/news/new-nebraska-laws-regarding-opiates-prescribing-and-continuing-ed
North Dakota: 2018
https://www.drugabuse.gov/drug-topics/opioids/opioid-summaries-by-state/north-dakota-opioid-involved-deaths-related-harms
South Dakota:2018
https://www.drugabuse.gov/drug-topics/opioids/opioid-summaries-by-state/south-dakota-opioid-involved-deaths-related-harms
Region 3: South
Division 5: South Atlantic (Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, District of Columbia, and West Virginia)
Delaware - 2015
https://dprfiles.delaware.gov/controlledsubstances/20-DE-Reg-564-01-01-17.pdf
Georgia - 2017
https://www.district4health.org/services/community-health/opioid-abuse-prevention/
Maryland - 2017
https://bha.health.maryland.gov/OVERDOSE_PREVENTION/Pages/Index.aspx
North Carolina - 2017
https://www.ncbon.com/vdownloads/strengthen-opioid-misuse-prevention.pdf
South Carolina - 2017
https://scdhec.gov/sites/default/files/media/document/Opioid_Prescription_in_South_Carolina_Oct-2018.pdf
Virginia - 2017
https://townhall.virginia.gov/l/ViewXML.cfm?textid=11462
West Virginia - 2018
http://drphilipfisher.com/statutes/A_Guide_to_WV_State_Opioid_Prescribing_Policies.pdf
https://oig.hhs.gov/oas/reports/region3/31803302_Factsheet.pdf
https://www.virginiachiropractic.org/page/OpoidReductionAct
Division 6: East South Central (Alabama, Kentucky, Mississippi, and Tennessee)
Alabama - 2016
https://oig.hhs.gov/oas/reports/region4/41900125_Factsheet.pdf
Kentucky - 2018
https://www.affirmhealth.com/blog/legislative-update-kentucky
Mississippi - 2018
https://www.msafp.org/wp-content/uploads/2018/01/msbml-summary-january2018.pdf
Tennessee - 2018
https://www.affirmhealth.com/blog/legislative-update-tennessee
Division 7: West South Central (Arkansas, Louisiana, Oklahoma, and Texas)
Arkansas - 2017

https://www.arkmed.org/news/2017/08/asmb-proposes-new-amended-rules/
Louisiana - 2017
https://www.louisianahealthconnect.com/newsroom/2017-23--opioid-prescription-policy-update.html
Oklahoma - 2019
https://www.painweek.org/media/news/new-law-oklahoma-limits-initial-opioid-dose
Region 4: West
Division 8: Mountain (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming)
Arizona - 2018
https://azdhs.gov/audiences/clinicians/index.php#clinical-guidelines-and-references-rx-guidelines
Colorado - 2016
https://www.cdph.ca.gov/Programs/CCDPHP/DCDIC/SACB/CDPH%20Document%20Library/Prescription%20Drug%20Overdose%20Program/CAOpioidPreventionStrategies4.17.pdf
Idaho - 2019
https://gov.idaho.gov/wp-content/uploads/sites/74/2019/06/eo-2019-09.pdf
Montana - 2019
https://www.mtpr.org/post/id-now-required-pick-opioid-painkillers-montana
Nevada - 2015
https://oig.hhs.gov/oas/reports/region9/91801004_Factsheet.pdf
New Mexico - 2019
https://www.nmhealth.org/go/opioid/
Utah - 2017
https://oig.hhs.gov/oas/reports/region7/71805115_Factsheet.pdf
Wyoming - 2019
https://www.wyoleg.gov/Legislation/2019/SF0046
Division 9: Pacific (Alaska, California, Hawaii, Oregon, and Washington)
California:*2018*
https://www.lacare.org/tl/node/26859
Hawaii: 2018
https://www.hawaiiopioid.org/pharmacists/
Oregon - 2018
https://www.allcarehealth.com/media/3415/acute-prescribing-guidelines.pdf