Estimating the Impact of Opioid Control Policies

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Introduction

In the past 10 years, opiate abuse has become a leading health epidemic in the United States, killing more people every year since 1999. This is representative of the current healthcare system in the United States, that emphasizes quick and simplistic answers to complex physical and mental health needs. This in turn is apart of what has led to mass overprescription of opioids. Due to the addictive nature of opioids, this overprescription can lead to an increase in overdose deaths. Patients may overdose on these legally sourced opiates or may switch to non-prescription opioids such as heroin and fentanyl to feed their addiction. This issue that arises is that likelihood of overdosing on these illegal opioids is far higher than prescribed prescription drugs, due to their higher strength. By analyzing mortality and opioid shipment data to states where policy changes were and were not enacted, this paper provides suggests that within a state, restrictive policy changes are effective in reducing drug-related deaths.

1. Motivation of this Study

The motivation of this study is to evaluate the effectiveness of different policy changes intended to limit the overprescription of opioids and the mortality of drug related overdoses. The theory is that by limiting the access of opioids, the possibility that patients will become addicted decreases. This in turn, leads to a reduction in those who overdose on legal opioids and those who turn to illegally sourced opioids, which are much easier to overdose on, due to their variation in strength. A reduction in those overdosing will hopefully decrease mortality rates of future patients.

2. The Motivation for the Research Design being Used

To begin with, a pre-post comparison, measurements are taken before and after the treatment. In this situation, mortality rates before and after the policy change in Florida will be measured to see if the policy change resulted in a decline in opioid shipments and mortality. Although simple to produce and interpret, it is not without its problems. The issue that arises is that if there was some unknown external factors that contributed to the decline of mortality that was not related to policy change, then one could misattribute the policy change as the driver of the decreased mortality rather than the external factor.

To remedy this, a difference-in-difference approach is used. This is a statistical technique that is commonly used in economics and in the social sciences that mimics an experimental research design where the regression calculates the effect of a treatment on an outcome by comparing the average change over time for the treatment group compared to the control group. This statistical approach reduces the concern of extraneous factors. For example, one extraneous factor that one might overlook could be DEA raids that limit the overall supply illicit substances. If a pre-post comparison was used, one could misattribute the decline of opioids to the policy change, rather than the DEA raids.

3. Data Details and Data Construction

The main source of the data for this analysis is the shipments of prescription opioids in the United States, which was provided by the Washington Post for years 2006 to 2012. The data was originally provided by the DEA Automation of Reports and Consolidated Orders System (ARCOS), but was released due to the Freedom of Information Act (FOIA). This dataset includes information on shipments of oxycodone and hydrocodone pills, which comprises roughly 75% of all opioids sent to pharmacies at the county level for all 50 states.

The following columns were used from the ARCOS dataset: BUYER_COUNTY, TRANSACTION_DATE, CALC_BASE_WT_IN_GM, MME_CONVERSION_FACTOR, BUYER_STATE. The last 4 digits of transaction date were extracted to create a column with the year. CALC_BASE_WT_IN_GM was multiplied by the MME_CONVERSION_FACTOR to obtain a column with the morphine gram equivalent (MGE), and the previously mentioned two columns were dropped. MGE was converted to Morphine Milligram Equivalent (MME) by multiplying the column by 1000 to convert to milligrams. BUYER_COUNTY, BUYER_STATE were renamed to County and State. Rows were grouped by County, Year, and State and the MME was summed to give MME in each county in each year. MME is used as a unit to standardize the strength of an opioid relative to the opioid strength of morphine.

The second data set used in the analysis was the US Vital Statistics records, which includes data on every death in the United States between 2003 and 2015. By filtering the US Vital Statistics record for deaths only related to drug overdose, we can examine how MME is related to number of drug-related deaths in a county by merging these two datasets together. However, if a single cause of death category is less than 10 for a given county in a given year, the death count does not appear in the data, which could alter the overall results of our analysis. Zeros were imputed for these values in order to account for the potentially missing data. This assumption has to be kept in mind when looking at the end results, as our model will likely display a more conservative representation of the actual mortality. Rows were grouped by County Code, Year, and State.

When merging the US Vital Statistics records with the ARCOS data for an individual state, names of counties were compared. Proper names were looked up and fixed in the US Vital Statistics records file. The two files were merged on County, Year, and State with a left join. This was validated to be 1 to 1.

Lastly, a population dataset sourced from the US Census provided population figures at the county and state level. This will be used to calculate deaths per capita at the county and state level. The downloaded raw population data set, Annual Population Estimates (2018 PEP, PEPANNRES), contains US census population data from 2003 to 2018.

The first intermediate dataset was fetched by merging population dataset onto the already merged mortality-ARCOS data set on County, Year, and State. This resulted in a county-level data set containing the MME, deaths, and population per county, with the time scope from 2006 to 2012.

Another intermediate dataset we made is county-level drug induced mortality data combined with the population dataset. This yields to a data set with a broader time scope (from 2003 to 2015) which is helpful for extracting yearly trends in target and control states with higher confidence level.

The following states were used as control states: PA, OH, IN, IL, GA. These states were chosen because of their similar population sizes to the test sets(FL, WA, TX).

4. Statistics Summary of Dataset

State	No. of Counties With 0 Deaths	Number of Counties	Zero Death (%)
FL	421	871	48.33
TX	2872	3302	86.97
WA	309	507	60.94
PA	438	871	50.29
OH	732	1144	63.97
IN	939	1196	78.51
IL	1120	1326	84.50
GA	1759	2067	85.10
Total	8590	11284	76.13

Figure 4.2: Summary of Summed Zero-Value Mortality Records

by State (2003 - 2015)

Table 2 displays a precis of the percentage of counties, grouped by states, where a 0 value is present for drug/alcohol related deaths between 2003-2015. States with the highest amount of 0 values are Texas, Georgia, and Illinois. This is shown to demonstrate that the 0 imputed for drug/alcohol related deaths under 10, which do not appear in the mortality data, may serve as a potential bias. Deaths are likely to be underestimated for all states, but even more for those with the highest ‘Zero Death’ percentages. Interestingly enough, Florida counties displayed the least amount of zero values, further exemplifying how drastic the opiate problem is in Florida.

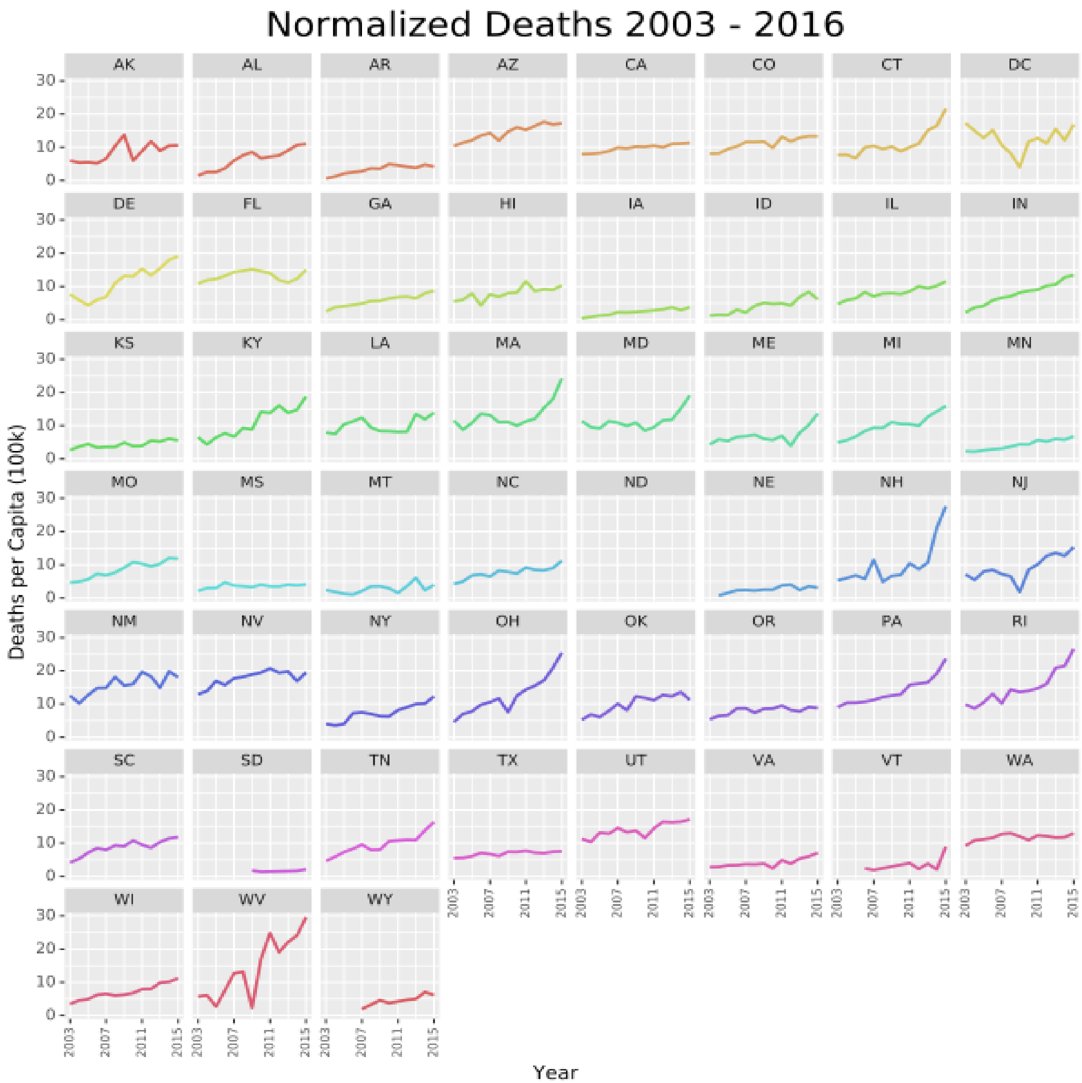

Figure 4.2: Mortality Normalized by Population/State

By plotting the normalized deaths by year using the Mortality dataset, we can see which states might be potential control states or treatment states based on the gradient of the line. The idea is that states that have some sort of inflection point and downward trend have enacted a policy change, while states that have a consistent trend would be control states. One state of notice is North Dakota which does not have trend line. This is because the mortalities are so low for that state, that there are few data for the state. The "State-by-State Summary of Opioid Prescribing Regulations and Guidelines" was used to confirm whether or not the chosen states indeed had a policy change.

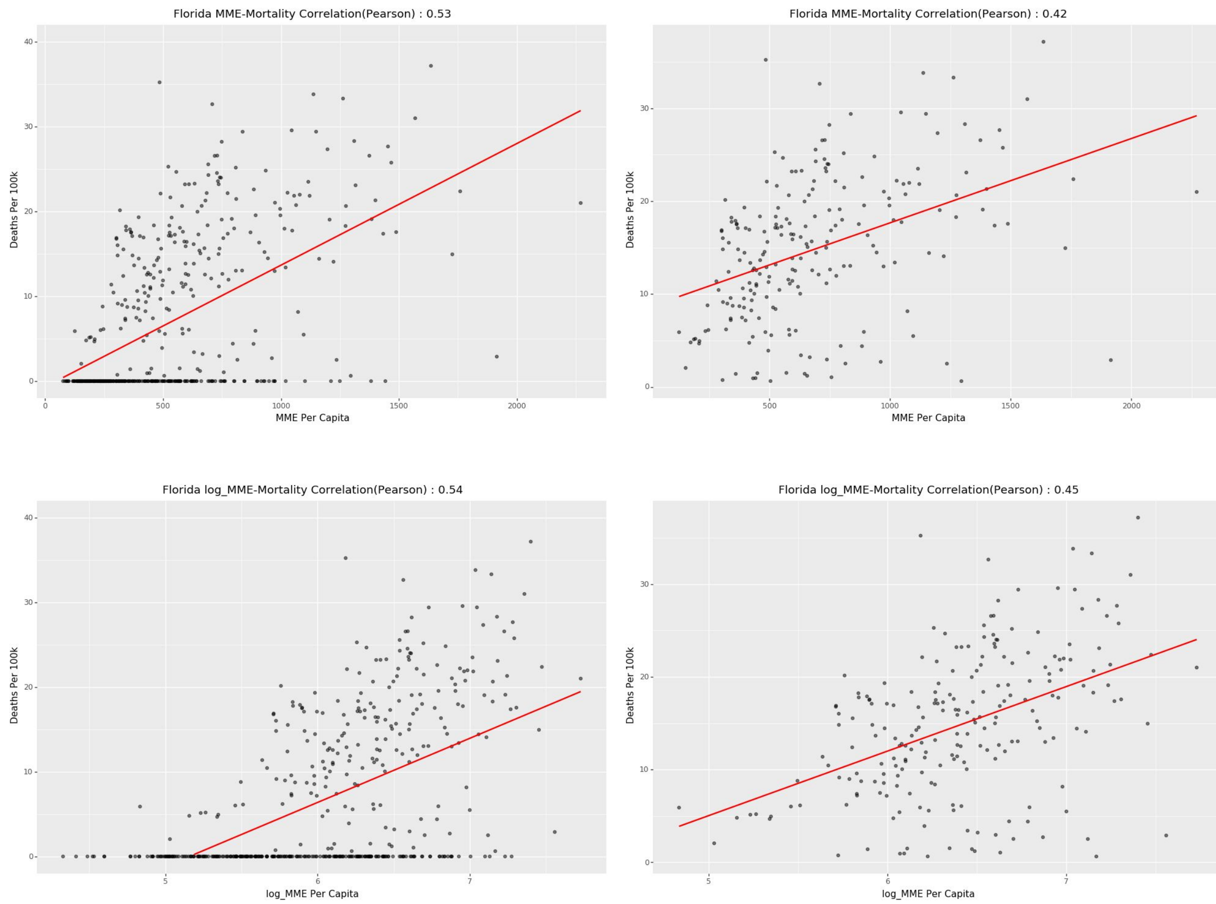

Figure 4.3: Florida MME-Mortality Correlation (Pearson)

Upper-left: MME with zeros imputed; **Upper-right:** MME without zeros imputed

Lower-left: Log MME with zeros imputed; **Lower-right:** Log MME without zeros imputed

To understand the relationship between mortality and MME, a correlation between the two was taken, and we can see a relatively high linear correlation between drug shipment and mortality among Florida. When accounting for zeros in the data, the pearson correlation was 0.53, and when not accounting for the zeros, the pearson correlation was 0.42. To see if transformations could improve the correlation, we applied a log transformation to MME. After the application, we see that there was only a marginal improvement and that it was unnecessary to continue the analysis using transformed variables.

5. Analysis

5.1 Pre-Post Analysis

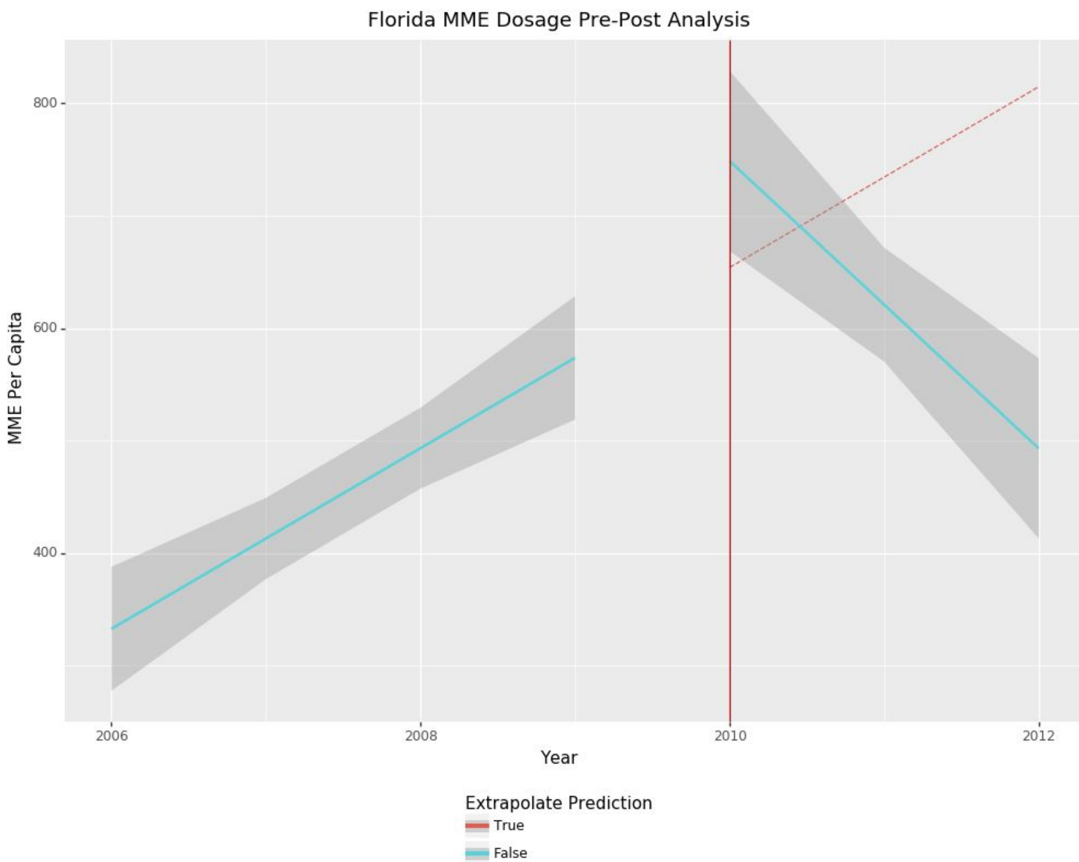

Figure 5.1: Pre-Post Florida MME

(95% Confidence Intervals)

Analyzing Florida MME per capita, we see that after the policy change was enacted, indicated by the red line, the amount of MME that was shipped into Florida dropped year over year. In 2012, the amount of MME being shipped into Florida was actually more than was actually less than what was seen in 2009, based on the Pre-Post regressions.

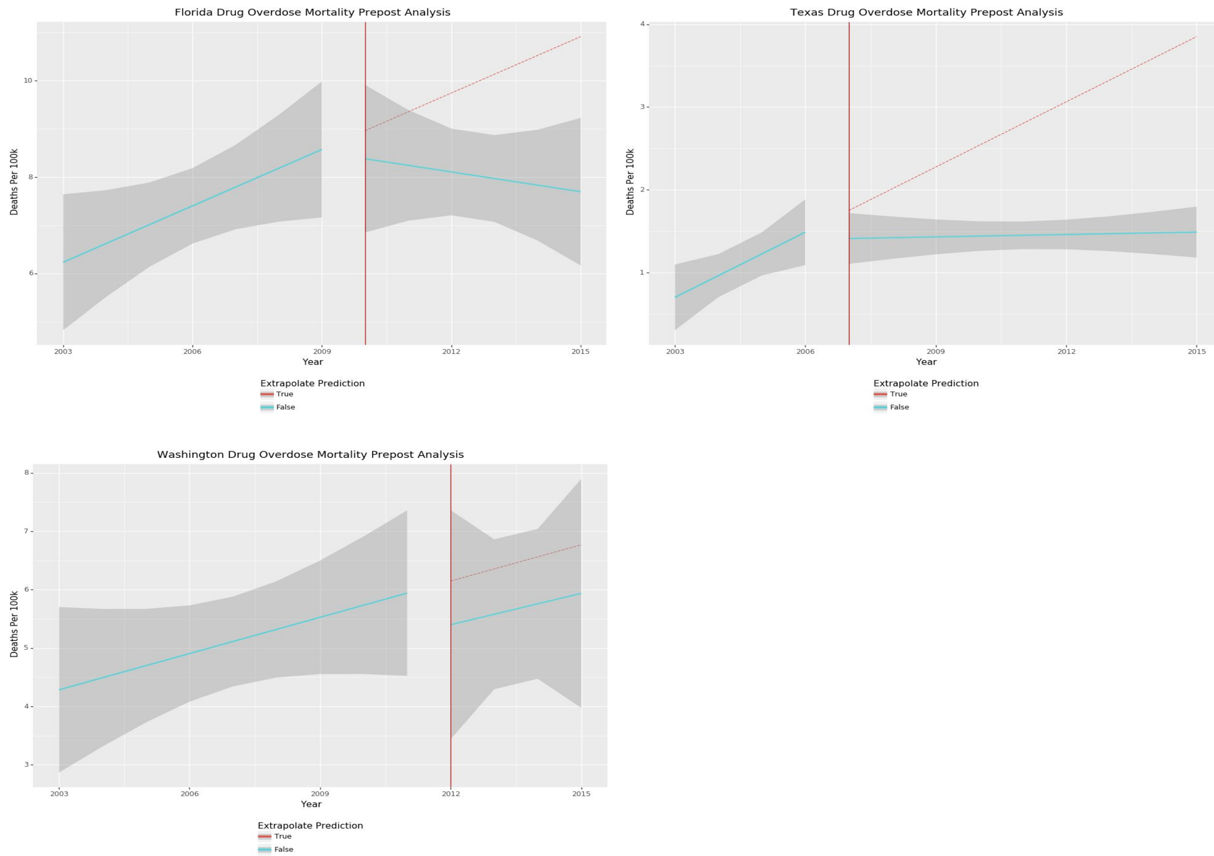

Figure 5.2: Pre-Post Analysis - Mortality

(95% Confidence Intervals)

Upper-left: Florida; **Upper-right:** Texas

Lower-left: Washington

When observing the pre-post analysis for Florida (Fig 5.1 & 5.2), it appears that the policy change was effective in reducing MME/capita and drug overdose/capita. The downward gradient line indicates that the mortality after 2010 has decreased year over year. Texas was somewhat successful at reducing deaths. After the Texas policy change in 2007, the rate of deaths flatlines, indicating that mortality stays consistent throughout the years. However, Washington policy change did not have a similar level of success in terms of deaths. This is due to the downshifted post-treatment line that has a similar slope as the pre-treatment line, indicating that the rate of deaths is still the same. Upon further investigation, we see that the Washington Department of Health had more relaxed policy changes on the prescription of opioids for pain treatment compared to other states with policy changes. For example, it was recommended that a practitioner not prescribe more than an average of 120 mg morphine equivalents per day (MED) without either the patient demonstrating improvement in function or without first obtaining a consultation from a pain management expert. 120 MED is already an extremely high dosage, and at that level, risk of overdose and addiction substantially increases (CDC 2019). For addicts, it would be easy to feign discomfort/pain in order to have the practitioner sign off for pain medication.

5.2 Difference-in-Difference Analysis

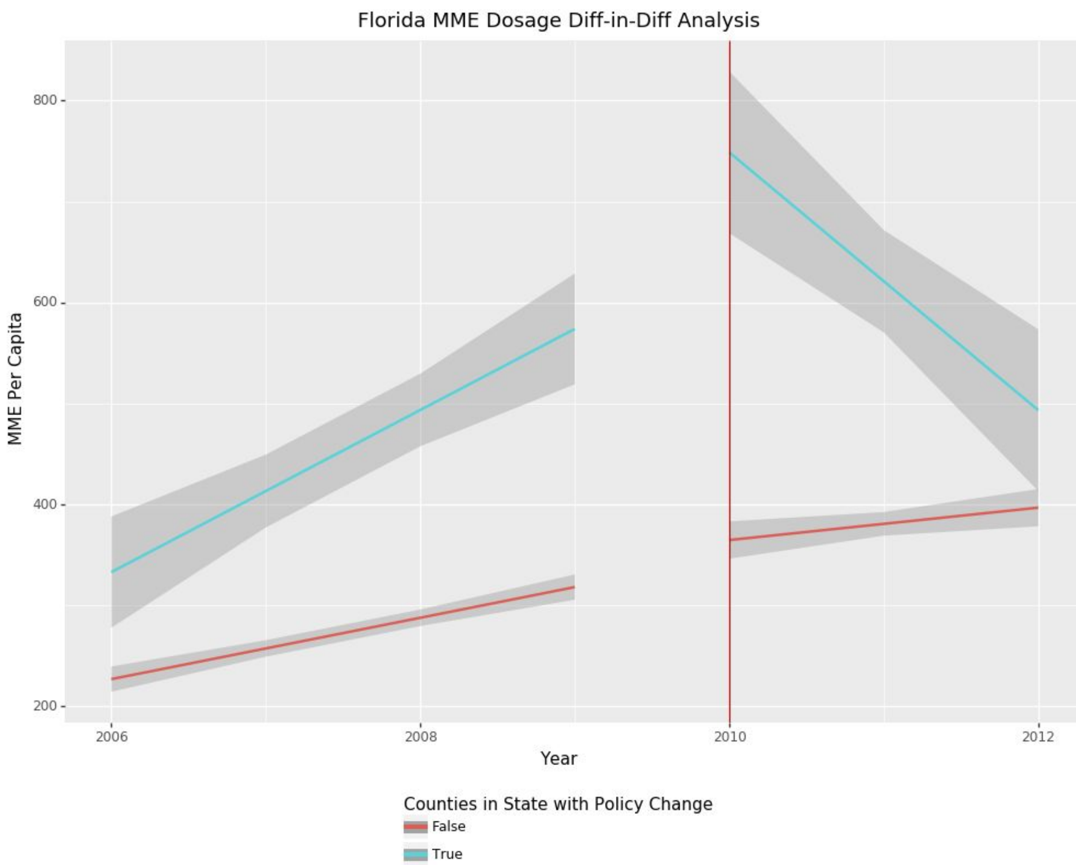

Figure 5.5: Diff in Diff - Florida MME

(95% Confidence Intervals)

Evaluating the MME Dosage Difference-in-Difference comparing Florida to the control states, we see that that enacting a policy change did indeed have a controlled effect on the amount of opioids that were brought in. Initially, Florida, on average had a much higher MME per capita compared to the control states. However, after the policy implementation, MME per capita dropped significantly compared to the steady increase of MME per capita for the control states.

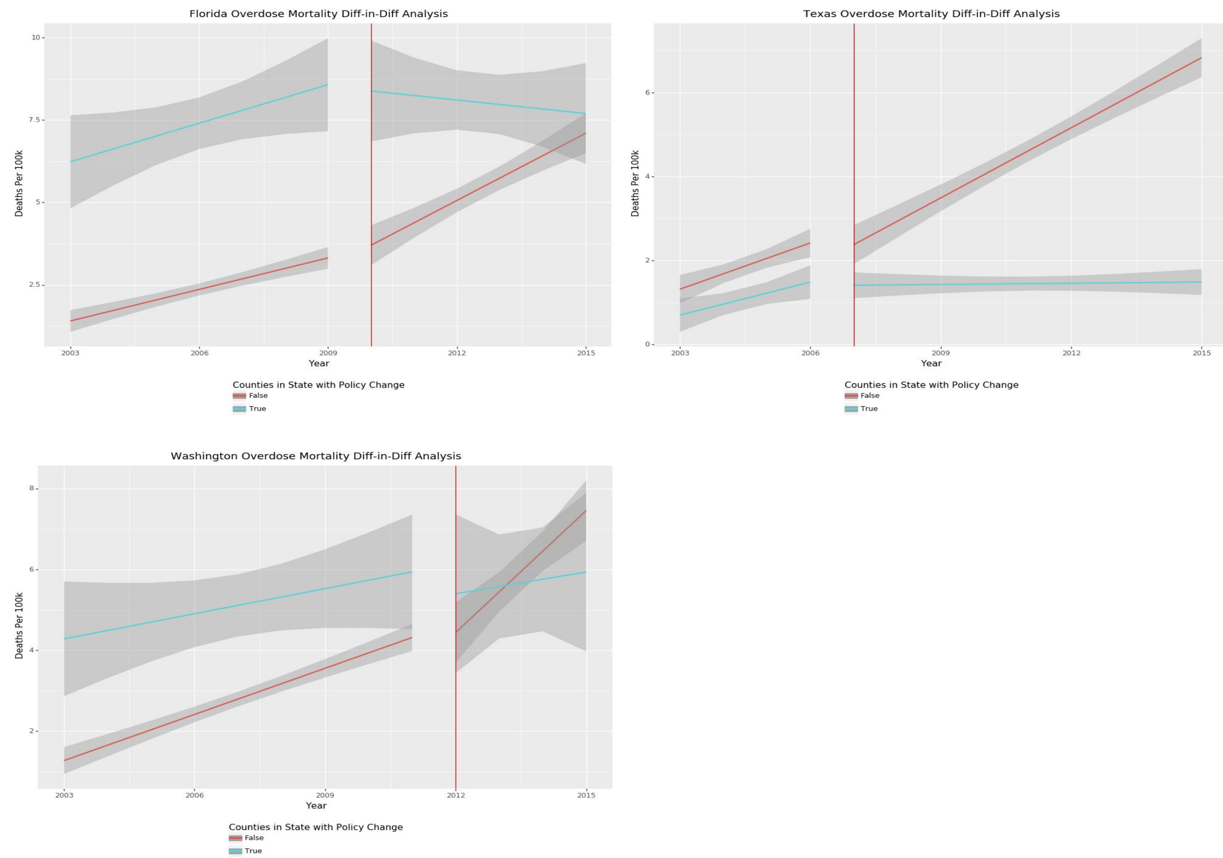

Figure 5.6: Diff in Diff - Mortality

(95% Confidence Intervals)

Upper-left: Florida; **Upper-right:**Texas

Lower-left:Washington

Similarly above, we compare mortalities through Difference-in-Difference regressions. Starting with Florida, we see similar results before. Prior to the policy implementation, Florida had above average deaths compared to the controls. But after the policy was introduced, the number of deaths decreased noticeably while deaths in non-policy states continued to increase. For Texas we see that the number of deaths has decreased noticeably since the policy introduction in 2007. Similar to the Texas pre/post analysis for mortality, we see that the rate of deaths flatlined after the introduction, but compared to states that did not have a policy change. Lastly for Washington, again the results for the policy change are similar to the pre/post analysis where the line was downshifted and the slope remained the same. But when compared to the control states, it seems that the policy change was successful as the slope is flatter compared to the control states, indicating that the rate of deaths is lower.

6. Interpretation and Conclusion

6.1 Comparison of policy changes effectiveness in three states

Policy changes differ in their actions in the three states that were investigated. As a result, the mortality records in each state and drug shipment volume in Florida appears to be affected after the policy changes were imposed.

However, it's worth mentioning that at least part of the mortality prediction in Florida and Washington lies within the 95% confidence interval, indicating that (1): the observations in these two states varies significantly, some counties may have drastic drug overdose induced mortality rate, (2) the trends after the policy change are not strictly linear, i.e. there may be more changes regarding opioid prescription regulation in post years. Since all the predictions of Washington mortality the effectiveness of policy change in Washington is not statistically significant.

Additionally, in difference-in-difference analysis, we see that all the three states have a significant inhibition in drug induced mortality rate compared to control states. The 95% confidence intervals of both MME and Mortality regressions in comparison states have thinner width than those in Florida and Washington states, this may be due to either (1) more observations in comparison states (2) more centered observations distribution.

Therefore, we draw the conclusion that any kind of policy change at all, would be beneficial in saving lives and reducing the amount of opiates prescribed.

6.2 Limitations of Analysis

6.2.1 Assumptions on missing values

As is shown in Table 2, the proportion of missing values in mortality is relatively large, especially in Texas, Illinois, and Georgia, which contain over 80% records of no mortality. Therefore, our analysis is biased and leans more on the conservititve side.

6.2.2 Assumptions on drug shipment dataset

Hydrocodone and oxycodone make up 75% of the opiates being shipped in the United States. The other 25% is not accounted for in our analysis, which might affect the overall results. Stronger opioids such as oxymorphone and hydromorphone have MMEs of 3 and 4, respectively (CDC, 2019). Since these prescribed pills are stronger, they are likely to be more dangerous for users, specifically recreational users, which may not be able to accurately gauge the dose they are taking. In addition, we do not have data for looking at illegal opioids shipped into each state or county. Since illegal opioids are generally stronger and vary in strength more, users are more prone to overdosing. Illegal opioids are also more likely to be injected intravenously by addicts, which increases the bioavailability of the drug, making it stronger, and potentially more dangerous.

6.2.3 Limitations on quantitative analysis support

Although the representation of pre-post analyses and difference-in-difference analyses are clear and illustrative, few quantitative calculations are conducted in this study. To better support the results in statistical points of view, future endeavors on quantitative analysis in these aspects can be considered:

1. Proportional changes of MME and drug induced mortality before and after the policy change year
2. Differential proportional changes in between target and comparison states before and after the policy change year
3. Comprehensive statistical significance tests on policy changes

Citations:

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