Estimating the Efficacy of Opioid Control Policies

Technical Analysis Report

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Abstract

The past two decades in America witnessed a significant increase in rates of opioid prescription and, subsequently, opioid addiction. Among the many side effects of this addiction trend is a rapid increase in unintentional overdose fatalities as addicts turn to other sources to fulfill their dependencies. Beginning in the mid-2000s, states across the U.S. started to fight back against the growing epidemic trend through policy and regulation. This report examines the impact of those actions in Texas, Florida, and Washington counties with over 250,000 residents. Two analytical techniques are leveraged to investigate data measuring opioid shipments as a proxy for prescriptions and unintentional overdose fatalities. The findings support the approaches taken in Florida and, to a degree, Texas but do not find Washington's policies effective.

Introduction

Over the last two decades, the use and abuse of prescription opioids have skyrocketed in the United States, leading to an increase in opioid addiction. The rise in prescription and addiction rates has had other windfall effects, such as increased drug overdose deaths. Deaths from non-prescription or unregulated opioids such as heroin and fentanyl have increased as people addicted to prescription opioids turn to illegal markets to sustain their addiction post-treatment. This trend has become an increasingly common topic of debate in political arenas, with many proposed and attempted policy solutions.

In this analysis, we evaluate the efficacy of policies in three designated states designed to limit opioid prescriptions. Since the impact of these policies may not be apparent under the influence of multiple factors, we will assess the effectiveness of policy initiatives by examining the effect on opioid prescriptions and drug overdose fatalities. The specific states and policy changes we will evaluate are:

1. Texas (Effective January 2007): The Texas Medical Board adopted regulations concerning treating pain with controlled substances. The guidelines significantly increased the burden of proof on providers before and during opioid treatments. These new regulations were intended to limit the number of new prescriptions and therefore depress addiction rates in the future. Noteworthy changes included:
    - Performing a patient evaluation before prescribing opioids (including reviewing prescription data and history)
    - Obtaining informed consent from the patients
    - Conduct a periodic review of the opioid treatment
    - Maintain a complete medical record of the patient's treatment

2. Florida (Effective February 2010): Florida was home to 98 of the top 100 clinics in the U.S. for oxycodone prescription rates before 2010. The Florida state legislature then began a series of steps that aggressively targeted pain clinics and opioid prescriptions. Those steps included:
    - A requirement that pain clinics treating pain with controlled substances register with the state by January 4, 2010
    - A partnership with the Drug Enforcement Administration and various Florida law enforcement agencies on Operation Pill Nation beginning in February 2010
    - Expansions of pain clinic regulations throughout late 2010
    - DEA-Law enforcement raids of select pain clinics for failure to comply with policies in February 2011

3. Washington State (Effective January 2012): Similar to the state of Texas, Washington took action in 2012 to increase the requirements on providers before and after prescribing opioids. This state took a slightly different approach by providing prescription dose guidelines. Noteworthy parts of this policy included:
    - Requirements to annually review patient cases with doses up to 40mg/day
    - Mandatory consultation threshold of 120mg/day
    - Consultation with pain management specialists if the 120mg/day threshold is exceeded
    - Recommendation to not exceed the 120mg/day threshold without specific behavioral improvements in the patient.

Before analyzing these policies, it is essential to note that these state policies did not build upon each other; they are unique in their jurisdictions and timelines. This aspect of the analysis allows for each state and procedure to be examined individually, and the results or merits of those policies are considered as such.

Research Design

Overview

Our interest in examining mortality as well as opioid prescriptions comes from the fact that while restricting access to opioids may reduce the likelihood that future patients will end up addicted to opioids, it may drive already addicted patients to turn to alternative forms of opioids, be those illegally purchased prescription drugs, heroin, or fentanyl. This possibility is deeply troubling because the likelihood of overdosing on these illegal drugs is much higher than on monitored prescription drugs, as drug users can't know the strength and potency of illicit drugs. We will attempt to measure the effect of the described policy changes in Florida, Texas, and Washington by examining (a) opioid drug prescriptions and (b) mortality from drug overdoses. Specifically, we will only analyze fatalities due to unintentional overdose. We will only investigate deaths from drug overdoses in Texas due to a shortage in opioid prescription data. To study the effectiveness of these policies, we will use two analytical tools, pre-post analysis and difference-in-difference analysis.

Methods

Our analysis is limited to counties in the United States with over 250,000 residents. The team chose this threshold due to issues with missingness in our data, specifically in the mortality occurrences data from the CDC. While we assess that this might limit the transferability of this analysis to other populations, we see that risk as minimal. After significant analysis and comparison with multiple means for conducting this research, we found little significance in the deviations from what is presented here. We believe this analysis presents the best findings from the data, and we further elaborate on our practices in the sections below.

Pre-Post Analysis

In this analysis, we will look at the trend of unintentional drug overdose deaths and opioid prescriptions before and after the year the policies were enacted in each state. Here we assume that if the policy had not been implemented, the trend would continue in the same direction. If the policy was effective, we should see a change in the trend for the years after the policy. If the policy is ineffective, the trend should continue in the same direction. For opioid prescriptions, we expect to see decreases in the slope of the trend lines, whereas we may observe an increase in overdose deaths.

Difference-in-Difference Analysis

Since other unknown factors may have resulted in the change in trend in pre-post analysis, we will also carry out a difference-in-difference analysis. Examples of such factors include prescription drug shortages that limit distribution, new dosage guidelines that lower prescription amounts, or the advent of an emergency treatment to counteract an overdose in progress. Any of those elements could affect the pre-post analysis for a given state. To compensate, we include an added dimension of comparing the current state with similar states based on geographic proximity and cultural and demographic similarity. We compare the groups before and after the implementation of the specific policy. If the policy were effective, there would be a more considerable change in opioid prescriptions and overdose deaths than in other states that didn't change their policies. If the policy was ineffective, the difference-in-difference should be low. Here we assume parallel trends between the states before the policy went into effect.

Data

The data in this analysis come from five primary sources before transforming and merging into a final, compiled dataset for analysis.

- FIPS Codes (Derived from the Federal Communications Commission) – Federal Information Processing System (FIPS) codes are unique, five-digit numeric identifiers for each legal county in the U.S. These codes, when partnered with a year, form a unique record for a row of the final dataset before analysis.[1]
- U.S. Census Data, 2010[2] - County-level population data for each county in the U.S. as captured by the 2010 Census survey and report.
- Opioid Shipment Information[3] - Data regarding the shipment of opioids to counties in the U.S., as tracked by the Drug Enforcement Agency (DEA).
- Drug Overdose Mortality[4] – Derived from a dataset that captures mortality information at the county level.
- A self-generated list of U.S. state names and their standard abbreviations derived from the U.S. Postal Service.

Data Preparation

Data preparation began after the team identified the appropriate construct for analysis and where each requisite data point would be derived from. Each source dataset provided unique information. The key to the research would be a high-integrity merging of that data to permit the analytical steps. Thus, the source data was approached through the lens of preserving information for the states required in the analysis while generating options for merging keys.

"WaPo" Data

The first source dataset we used was the Opioid Shipment Information dataset, which we refer to as the "WaPo" dataset. We began with this dataset because it was the largest and would take the most time to ensure that we had captured its information correctly and in the format we desired. This dataset contains information about drug shipments to geographical locations in the United States, which will be used as a stand-in measurement for prescriptions, which we cannot access due to Health Insurance Portability and Accountability Act limitations.

We read this file in chunks, keeping only the columns that we felt would be useful for future merging or containing information needed for the analysis: buyer county, buyer state, drug name, transaction date, base weight, and a conversion factor. While reading the chunk, we filtered for only

[1] https://transition.fcc.gov/oet/info/maps/census/fips/fips.txt
[2] https://www.census.gov/data.html
[3] Drug Enforcement Agency, from a FOIA request through the Washington Post
[4] Presumably derived from the National Vital Statistics Website at https://www.cdc.gov/nchs/nvss/index.htm

states in the desired analytical group and generated month and year columns from the transaction date. We also converted each shipment to a standardized, morphine equivalent amount. Before completing each chunk, we grouped by county, state, year, and month while summing the shipment quantity. This temporarily left us with an odd-looking data frame at the end of this step. Still, the strangeness was justified by the significant reduction in memory required to complete the whole chunking process at only a minimal speed trade-off in our trials.

Once the data read-in was complete, we completed the preparation actions on this dataset by generating a county name column that combined the state and county names into one string. This ensured that duplicate county names in different states would not be represented as such in our dataset. We also convert the month and year to strings. Both actions were necessary for generating options for future merging keys, as seen in the merging section. Finally, we re-grouped this data by creating rows unique to each county, state, year, and month with the shipment quantity as a sum value. We tested this dataset to ensure we had no null values for the key columns and that the states we captured were indeed the ones we identified for analysis.

Vitality Statistics Data

The second source dataset we actioned was the Vitality Statistics data. To clean this data after ingesting, we performed several actions similar to those required in the WaPo dataset. We transformed the year into a string and captured the FIPS county code as a string as well. The FIPS string designation was critical to ensure we did not drop leading zeroes (zero-padded format) at this data transformation stage. We added a county name column to be consistent with prior datasets and then subset the data to include only the states of interest. After grouping the data appropriately and filtering for only accidental ovedose fatalities, we verified that the states were correct from our analysis group and tested to ensure that the total number of deaths captured in our final dataset equaled those in an earlier subset.

FIPS Codes

The third dataset ingested was the FIPS data. Having a county name with a state abbreviation would be critical for later possible merging permutations. As such, we ingested the the parts of the file that included state-level FIPS codes in addition to the county-level codes. In this data frame, we used generated abbreviations to merge and add state abbreviations for all 50 states. Using a left merge, we arrived at a data frame with several redundant columns, but we notably had all our FIPS codes, the county name, and the state in which the county was. Using a forward fill command, we could add state abbreviations to all states before down filtering to only the states and columns of interest and saving the resulting data frame.

Census Data

The last dataset to prepare was the census data. This data was downloaded from the Census Bureau website in an excel file. We do work to capture the population total as an integer and then construct the same county name and state identifier column in some of our other datasets. We again filtered this dataset for the states of interest before undertaking rigorous testing. We verified that each state had recorded the correct number of counties as found by internet research, assured that we had no null values for our counties and that we had the right states.

Data Merging

At the end of data merging, we desired a data structure with one row for each unique county and year and the observed data for population, drug shipments, and overdose deaths to engineer both rates per 100,000 residents for better interpretations. To do this, we recognized that the FIPS codes would be the logical place to start. Because the FIPS codes are unique, we needed to make a row for each FIPS code for each year and combine the FIPS code and year to create a unique merge key that we could use in later datasets. Hence, we began data merging with this end state in mind as we made minor adjustments to the process through trial and error.

First, we ingest all four output files from the preparation step: vital stats, WaPo, census, and FIPS codes, ensuring that our specified date and FIPS columns ingest as strings. Through several trials, we identified issues addressed early in the eventual script to conduct the merging actions. They are:

- Dade County, FL, changed its name to Miami-Dade County, FL, in 1997, but not all datasets reflect this change. Because the FIPS codes still had Dade County, we coerced all other datasets to that record.
- Counties in several states had spelling inconsistencies: "Saint" vs. "St." was a typical example that required pre-processing.
- In some cases, FIPS codes had leading zeros, which we needed to preserve to generate the unique year and FIPS key for merging.

After primary verification of the census data to use as a testing baseline for later steps, we began preparing for merges. We removed state-level FIPS codes to reduce that data to only the counties in our states of interest. We then verified the resulting dataset for content against the census data and saw that the unique county count aligned. We then replaced the Miami-Dade designations in the Vital Statistics data frame with those from Dade County in the FIPS dataset. We verified the number of rows of this dataset before continuing.

To enable a cleaner, final merge, we learned that we would have to do additional work to our WaPo dataset to prepare it. Because this dataset did not have FIPS codes that we could verify, we constructed our unique string identifier from the county name, state, and year of each row. After several tests, we correctly aligned the FIPS county names with the WaPo spellings and prepared the merge on this unique column. This allowed us to use the FIPS code to construct a merge key consistent with the one we would use in the final dataset.

To begin the merge, we set up a base data frame using a loop with a row for each county in our FIPS dataset per year of interest from 2003-2015. We also preserved the state name and generated the unique merge key when each row was created. At the end of the loop, we verified that our data frame dimensions match the expected outcome of FIPS counties multiplied by the number of years in our analysis.

The next step was to add the vital statistics data using a left merge on this unique key we created for merging. Initially, we lost thirteen records, which became exposed during outer merges as belonging to Miami-Dade County. This revelation prompted us to use Dade County as the identified name for this county before re-attempting the merge. We then verified this merge by asserting that the number of rows now containing drug data matched the number of rows in the vital statistics dataset before dropping the duplicate columns.

The next dataset merged in was the WaPo data, which was uneventful after previous lessons learned. We used an outer merge to test this alignment and found a 1:1 match with our expectations. Inspecting the data frame yielded no "homeless rows" at the tail, and assert tests verified that we had successfully matched all rows. We dropped duplicate columns before preparing to add population data.

The population data merge was conducted using a left merge on the column we previously created to contain the county name and state. Because we used only one census year, 2010, for this analysis, we are not concerned with creating additional keys for this merge. This merge was successful, and we found no rows with missing population data throughout the resulting dataset after assert tests.

The final step was to create two columns: one for shipment rate and one for drug overdose death rate. We used the drug shipment quantity, divided by population, and multiplied by 100,000 to get a per 100,000 residents rate for opioid shipments to a county. We used a similar technique with overdose deaths to obtain an incidence rate. At the conclusion, we tested one more time to verify that we had the correct number of counties and that the counties were consistent with the one we expected to find before saving the output dataset as a .csv for analysis.

Data Missingness

Following the preparation and merging of data, the team confronted missing data in our dataset before beginning the analysis. There are two categories of data for which we may be missing data: opioid shipments and drug overdose-related fatalities. In the case of the former, we expect that the WaPo dataset and its underlying DEA tracking mechanism capture data correctly. We should have no reason to suspect anything meaningful is represented by missing data other than no shipments going to those counties during the years specified. We identified that 4560 counties are missing data from 13,507 records, but 4156 missing values out of 4560 belong to years earlier than 2006 or later than 2014, which meant that we had 404 observations within the interested year range without information. We impute a zero to fill the missing shipment values in our 2006-2014 window and proceed with the analysis.

The second and more problematic set of missing data is among the overdose fatality measurements. Since the data collection mechanism, presumably the CDC, set a data floor at an annual count of ten, we have reason to suspect that there could be potentially significant amounts of data missing from that dataset. To compensate, the team explored several options. Ultimately, we settle on filtering the dataset for county populations over 250,000 according to the 2010 Census.

Method	Begin Rows	End Rows	Drop %	Drug Deaths NA	Missing %	Unique Counties
Baseline	13507	13507	0	10490	77.66	1039
'Zero' Impute	13507	13507	0	0	0	1039
Drop NA	13507	3017	77.66	0	0	370
Pop Over 250,000	13507	1534	88.64	52	0.38	118
Complete Cases	13507	1703	87.39	0	0	131

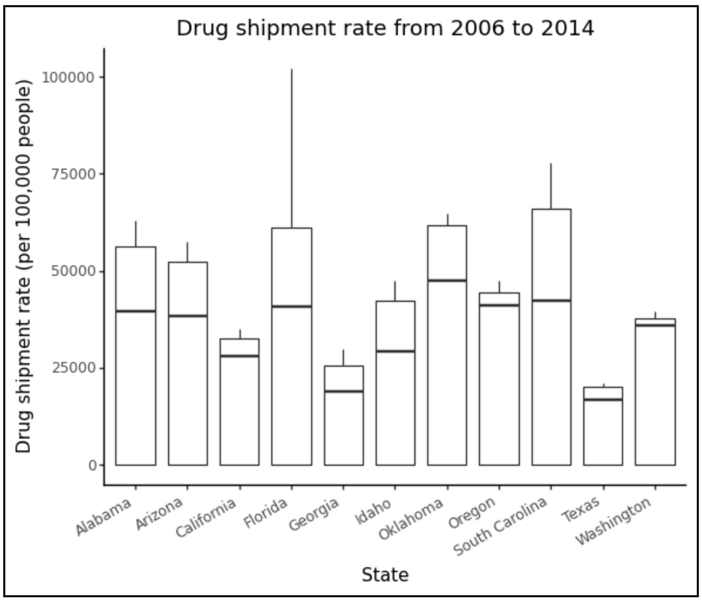
The above table lays out the data and methods faced in compensating for the missingness in unintentional drug overdose fatalities. The key takeaways are:

- At baseline, we see that over 77% of the unique county-year combinations are missing a value.
- Imputing a "0" for all missing values solves the problem up front but causes a waterfall effect wherein over three-quarters of the data is now manufactured.
- Dropping missing values removes the missing 77% but causes a secondary problem: we did not verify that the remaining rows were all complete cases and therefore have the potential for varying sample sizes pre and post-policy change.
- Using a population cut-off of 250,000 seems reasonable and is what the team selected. We are left with the fewest counties, but they are all generally homogenous as "large" counties, and the data is missing less than 0.5% of rows, a number we believe is acceptable in this analysis.
- Subsetting to only complete cases removes all missingness and results in slightly more counties using a population floor. However, there are few generalizations we can make about this non-homogenous population.

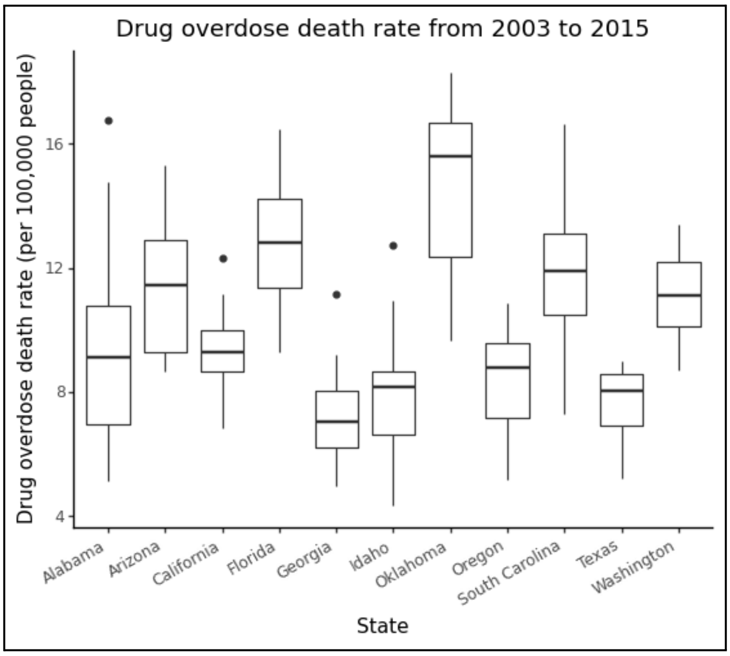
Summary Statistics

Once we finished pre-processing the data and merging to obtain the desired data points, we carried out exploratory data analysis to understand more about the differences in the distribution of opioid shipments and overdose deaths between the states of interest and how they changed over time. Our data initially consists of 1039 counties from 14 states over 13 years. After filtering for the population, we are left with 1,534 observations for 118 unique counties across the study timeline. We record drug-related deaths, shipment quantity, and population for each observation. We then calculate the overdose death rate per capita and drug shipment rate per capita as an incidence rate per 100,000 residents.

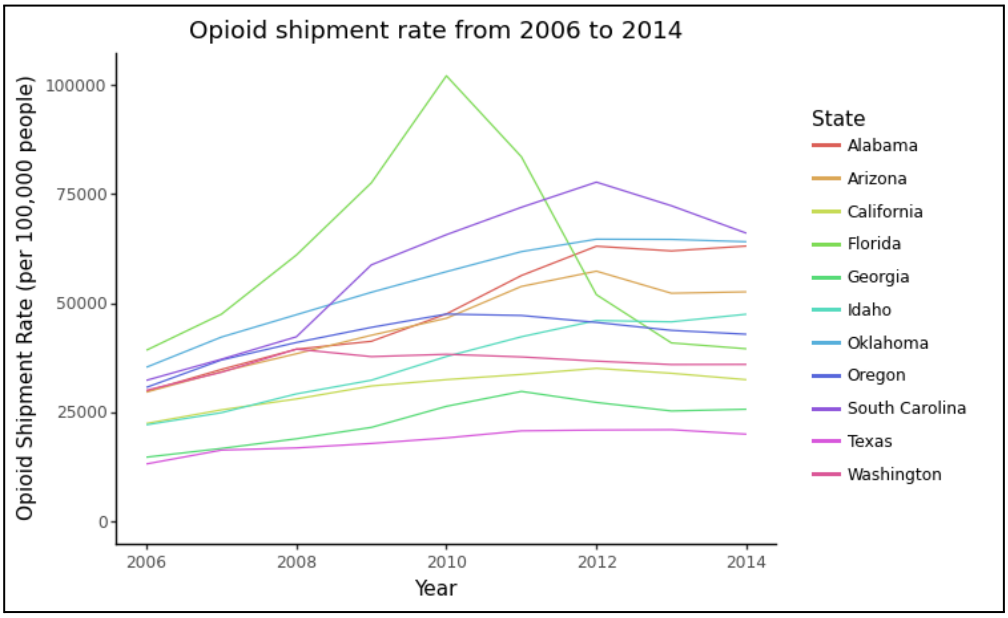
To visualize the drug shipment rate and the overdose death rate for each state within the respective year range, we draw box plots to help us get a preliminary idea of what the data looks like.



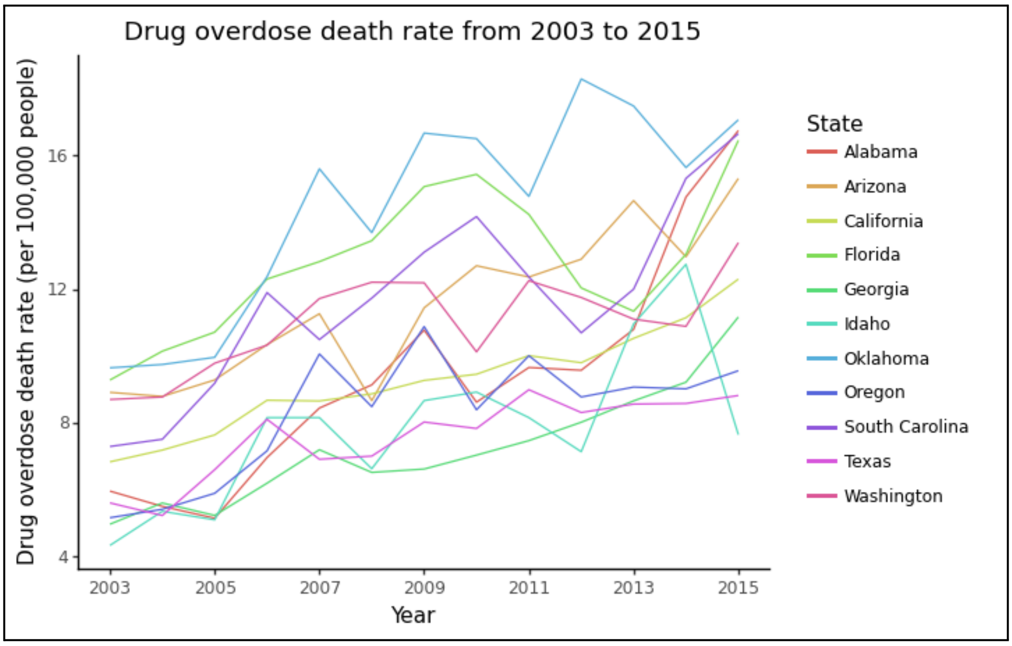
According to the drug shipment rate box plots from 2006 to 2014, Florida has the highest maximum drug shipment rate, while Texas has the lowest maximum with the narrowest range over the years.



The above plot shows that Oklahoma has the highest median and mean drug overdose death rates, while Georgia, Idaho, and Texas have the lowest. Comparing the above two plots, we see that the states with high opioid shipment rates do not necessarily have the highest drug overdose death rates and vice versa. The states with the highest average drug overdose death rates do not necessarily have the highest average opioid shipment rates.



We see from the above plot that the opioid shipment rates followed a general increasing trend with a similar rate of increase (slope) for all the states of interest until around 2011 (2010 for Florida), after which they dropped steadily, with the most dramatic difference seen in Florida.



We see from the above plot that the drug overdose death rates followed a choppy trend, with an overall increase over time for all the states of interest. Comparing the two plots, we see that while the drug shipment rate in Oklahoma is not the highest among all the states, its drug overdose deaths are the highest.

Analysis and Interpretation

To better estimate the effectiveness of policy changes, we need to do both pre-post comparison and difference-in-difference analysis of the opioid shipments rate and overdose deaths rate. In all cases, we describe per capita rates of drug shipments and overdose deaths as an incidence rate per 100,000 residents. Because of limitations on data availability due to HIPAA, we are using opioid shipments as a stand-in measurement with the assumption that there is a near 1:1 relationship between opioids sent to a geographic area and the amount prescribed in the same area. We can conclude whether a policy is successful from the plots.

Pre-Post Analysis

To conduct pre-post analysis for each state, we pre-process the data so that the resulting dataset has a unique row for every county-year combination. We then subset the data for the years before and after the policy was implemented. We plot two trend lines for each subset. We do this for both drug overdose deaths and opioid prescriptions. After comparing the effects post-policy change, we proceed to the difference-in-difference analysis.

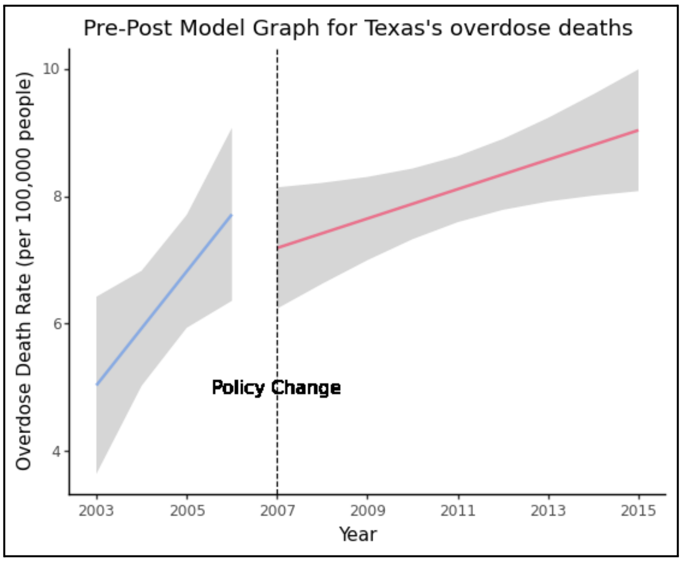
Difference-in-Difference Analysis

We first select states similar to each state of interest to conduct a difference-in-difference analysis. We construct a comparison group for Texas from Oklahoma, Georgia, Alabama, Mississippi, and Arizona. The consideration for these states is balancing geographic proximity, cultural similarity as southern states, and population, although Texas is easily the largest state in the group. In the case of Florida, we will construct the comparison group of Georgia, South Carolina, and Alabama for geographic proximity and cultural similarity and Arizona for demographic similarity. For Washington, we elected to construct the comparison group from Oregon, Idaho, and California, all states geographically close and somewhat similar to Oregon's demographic and cultural balance.

Next, we pre-process the data so that the resulting dataset has a unique row for every county, state, and year. We then subset the data for the years before and after the policy was implemented. We also subset based on the state of interest and similar states. We plot two trend lines for each subset. We do this for both drug overdose deaths and opioid prescriptions.

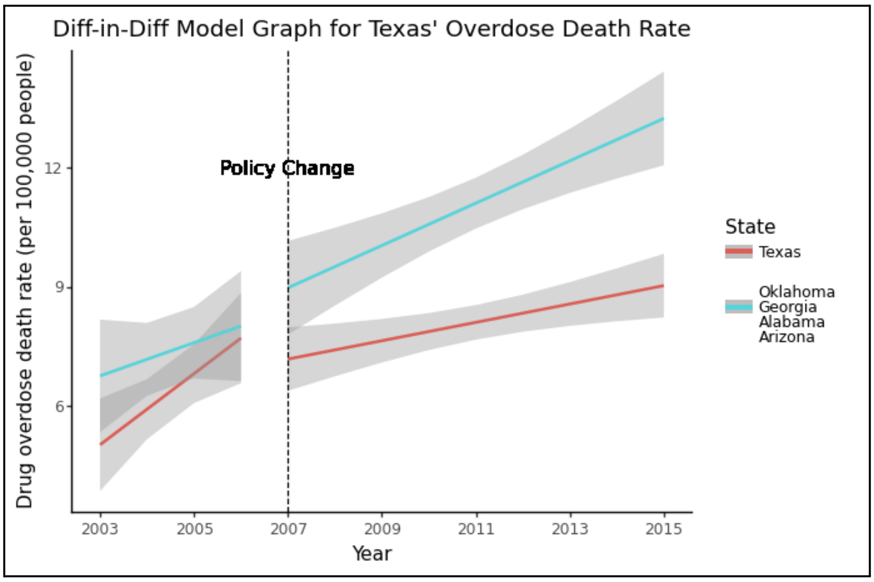
Texas

Result for pre-post analysis for Texas' drug overdose deaths



Interpretation: From the plot for Texas' drug overdose death rate, we see that the trend for overdose death rate was steeply positive before the implementation of the opioid policy, increasing quickly with time. We assume this trend would continue if the policy did not go into effect. After the policy change, we see a difference in the rate of increase. That is, overdose death rates still increase but more slowly over time. We can conclude that the implementation of the policy was successful.

Difference-in-difference analysis for Texas' drug overdose deaths



Interpretation: From the difference-in-difference plot for Texas' drug overdose death rate, we see that the trend for overdose deaths was positive before the implementation of the opioid policy, increasing with time. The same is true for states similar to Texas. The parallel trends assumption holds here since the two groups exhibited similar trends before implementing the policy. We assume this trend would continue if the policy did not go into effect. After the policy change, the trend for the states similar to

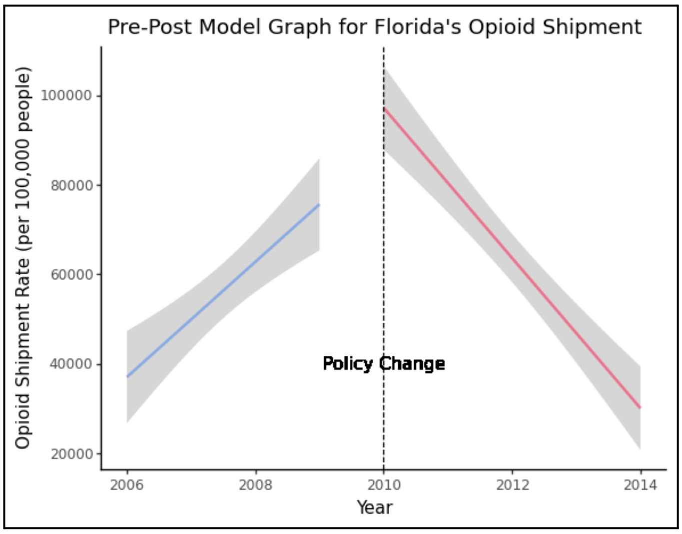
Texas continues to remain the same, while for Texas, the increase in overdose deaths over time decreases. That is, there is still an increase in overdose deaths over time, but more slowly now than before the policy. There were more significant changes in overdose deaths in Texas before and after the policy than in other states that didn't change their opioid policy. We can conclude that the implementation of the policy was successful.

Overall Interpretation

The analysis shows that the policy changes in Texas did have an effect on the unintentional overdose fatality rate in the state. We can conclude that this is a favorable outcome from the policy, especially given that we did not expect a decrease in fatalities where policies successfully limit legal opioid access. Since we cannot measure opioid shipments for Texas in this analysis, we cannot call this policy a universal success, but we have a favorable opinion.

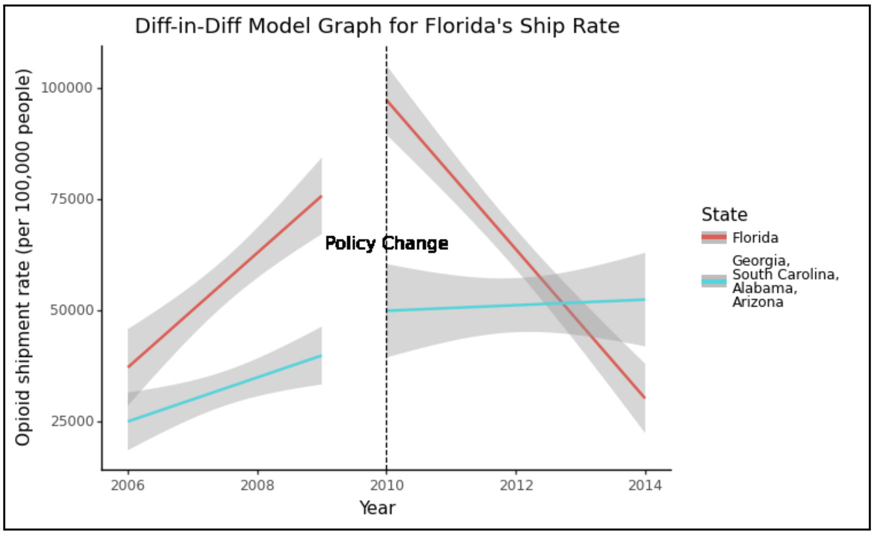
Florida

Pre-Post analysis for Florida's opioid shipments



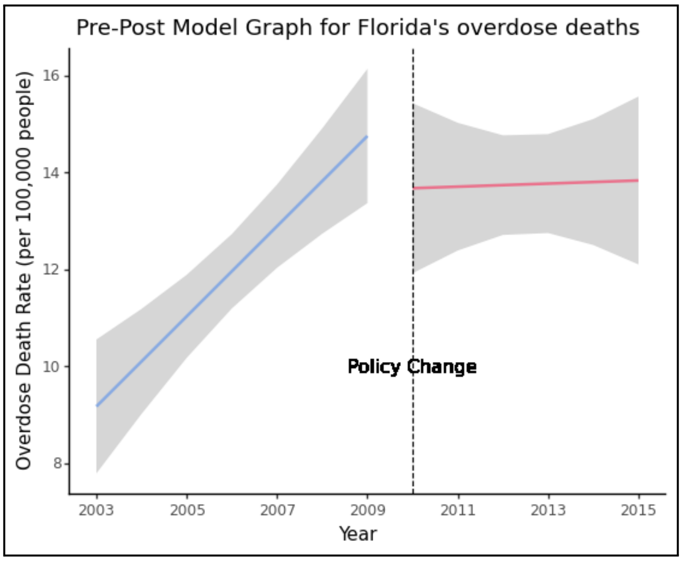
Interpretation: From the plot of Florida's drug shipment rate, we see that the trend for shipment rate was positive before the implementation of the opioid policy, increasing with time. We assume this trend would continue if the policy did not go into effect. After the policy change, we see a shift in direction. The trend becomes negative, and the shipment rate decreases with time. Since, for this analysis, the drug shipment rate is analogous to the prescription rate, the policy's implementation succeeded in reducing drug prescription rates.

Difference-in-difference analysis for Florida's opioid shipments



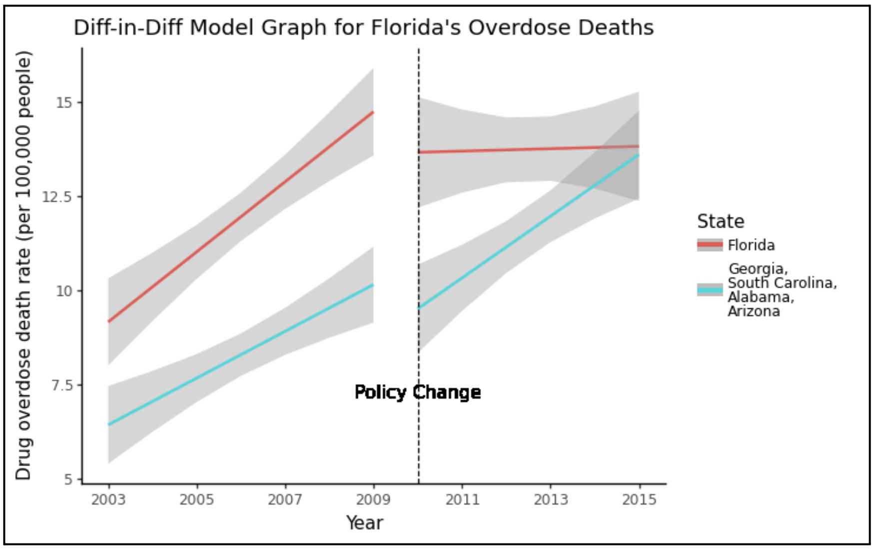
Interpretation: From the difference-in-difference plot for Florida's drug shipment rate, we see that the trend for drug shipment rate was positive before the implementation of the opioid policy, increasing with time. The same is true for states similar to Florida. The parallel trends assumption holds here since the two groups exhibited similar trends before implementing the policy. We assume that this trend would continue if the policy did not go into effect. After the policy change, the rate of increase in drug shipment rate decreases for states similar to Florida. In contrast, the trend changes direction for Florida, with the drug shipment rate decreasing over time. There were more noticeable changes in shipment rates in Florida before and after the policy than in other states that didn't change their opioid policy. We can conclude that the implementation of the policy was successful in decreasing drug shipment rates.

Pre-Post analysis for Florida's drug overdose deaths



Interpretation: From the plot of Florida's drug overdose death rate, we see that the trend for overdose death rate was positive before the implementation of the opioid policy, increasing with time. We assume this trend would continue if the policy did not go into effect. After the policy change, we see a decrease in the trend for the overdose death rate. Although the overdose death rate still increases with time, the growth becomes almost zero. We can conclude that the policy's implementation successfully reduced the increase of drug overdose death rates.

Difference-in-difference analysis for Florida's drug overdose deaths



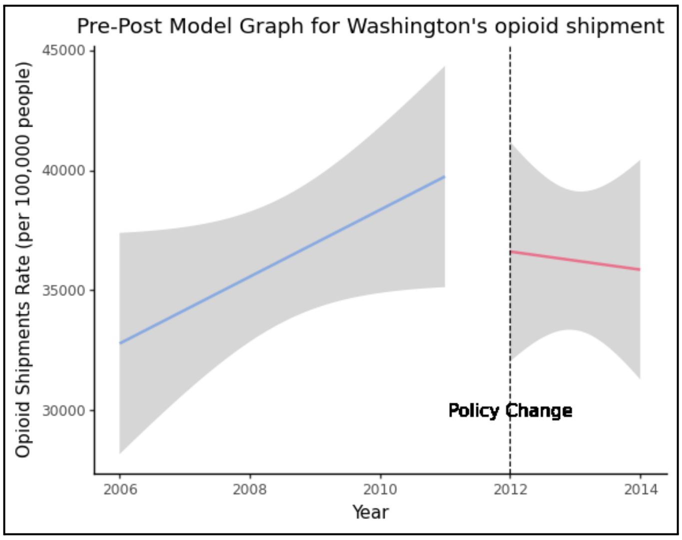
Interpretation: From the difference-in-difference plot for Florida's drug overdose death rate, we see that the trend for overdose deaths was positive before the implementation of the opioid policy, increasing with time. The same is true for states similar to Florida. The parallel trends assumption holds here since the two groups exhibited similar trends before implementing the policy. We assume that this trend would continue if the policy did not go into effect. After the policy change, the trend continues to stay the same for states similar to Florida. In contrast, the trend decreased for Florida, with the overdose death rate growth becoming almost zero. There were more noticeable changes in overdose deaths' trend in Florida before and after the policy than in other states that didn't change their opioid policy. We can conclude that the policy's implementation successfully reduced the increase of drug overdose death rates.

Overall Interpretation

Policy actions in Florida appear to be universally successful in both limiting the flow of prescription opioids and preventing unintentional overdose fatalities when compared to similar states. There are plenty of reasons why this may be the case, but that discussion is outside the scope of this research. Instead, we note that Florida was successful in limiting opioid use and also managed to avoid the expected result of increased overdose fatalities as a second-order effect.

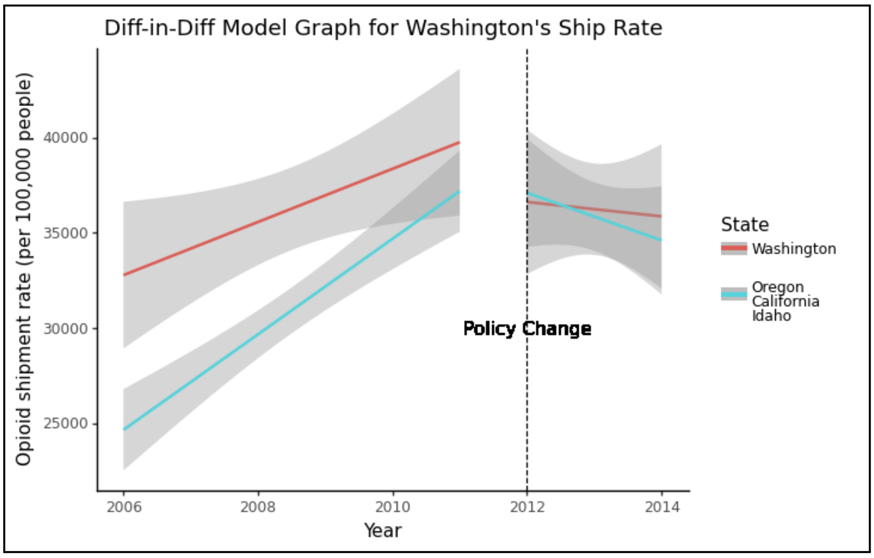
Washington

Pre-post analysis for Washington's opioid shipments



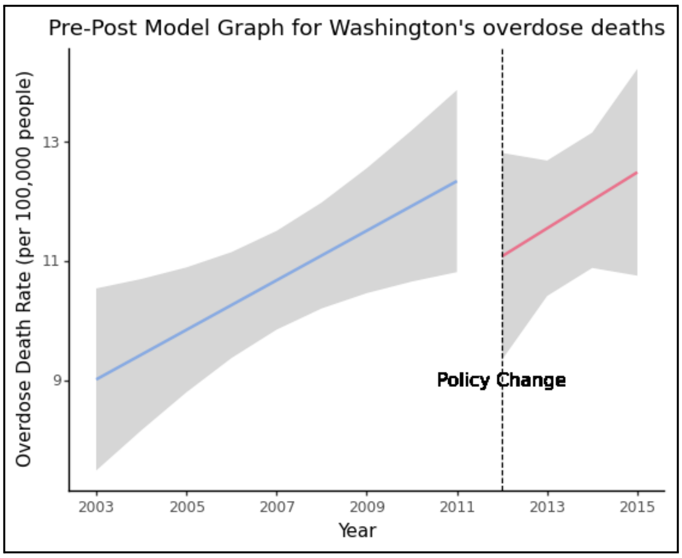
Interpretation: From the plot for Washington's drug shipment rate, we see that the trend for shipment rate was positive before the implementation of the opioid policy, increasing with time. We assume this trend would continue if the policy did not go into effect. After the policy change, we see a shift in direction. The trend becomes negative, and the shipment rate decreases with time. Since, for this analysis, the drug shipment rate is analogous to the prescription rate, we can conclude that the policy's implementation succeeded in decreasing drug prescription rates.

Difference-in-difference analysis for Washington's opioid shipments



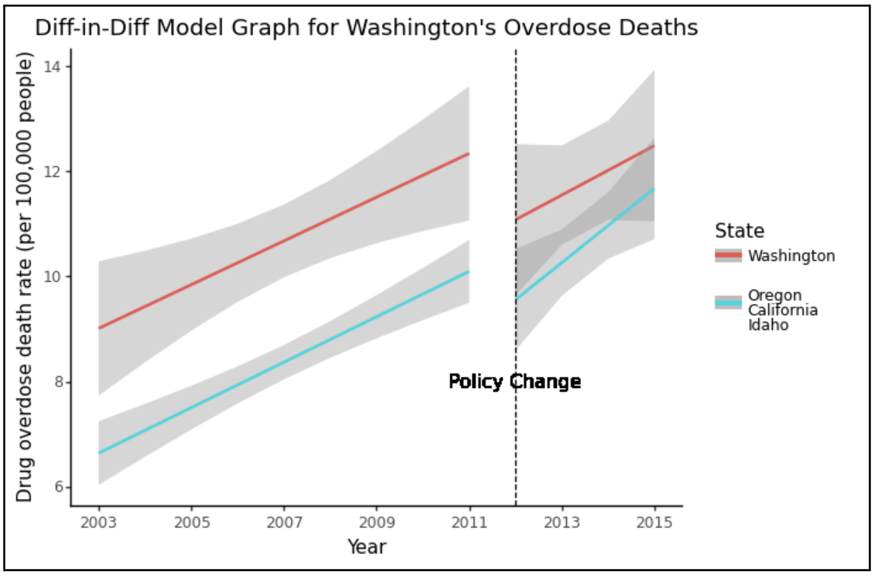
Interpretation: From the difference-in-difference plot for Washington's drug shipment rate, we see that the trend for drug shipment rate was positive before the implementation of the opioid policy, increasing with time. The same is true for states similar to Washington. The parallel trends assumption holds here since the two groups exhibited similar trends before implementing the policy. We assume that this trend would continue if the policy did not go into effect. After the policy change, the trends for both groups change to a decreasing trend. There is a smaller decrease between shipment rates in Washington before and after the policy compared to other states that didn't change their opioid policy. The decreasing trend in both groups may be due to a reason other than the implemented policy. We can conclude that the policy implementation was unsuccessful in decreasing drug shipment rates in Washington.

Pre-Post analysis for Washington's drug overdose deaths



Interpretation: From the plot for Washington's drug overdose death rate, we see that the trend for overdose death rate was positive before the implementation of the opioid policy, increasing with time. We assume this trend would continue if the policy did not go into effect. After the policy change, while there was an initial decrease during the year the state implemented the policy, the trend is still increasing at the same rate. We can conclude that the policy implementation did not decrease drug overdose death rates.

Result for difference-in-difference analysis for Washington's drug overdose deaths



Interpretation: From the difference-in-difference plot for Washington's drug overdose death rate, we see that the trend for overdose deaths was positive before the implementation of the opioid policy, increasing with time. The same is true for states similar to Washington. The parallel trends assumption holds here since the two groups exhibited similar trends before implementing the policy. We assume that this trend would continue if the policy did not go into effect. After the policy change, the rate of change in the drug shipment rate increased for the states similar to Washington, while for Washington, the trend remained the same, with an initial decrease in drug overdose rate in 2012. Since there was less increase but almost the same in the trend in Washington before and after the policy, we can conclude that the implementation of the policy was unsuccessful in decreasing drug overdose deaths.

Overall Interpretation

Washington's policy actions are the least effective of those analyzed in this research. There is little discernible effect among both opioid shipment rates and overdose fatalities when compared to the control groups. In both cases, Washington closely mimics the trends of the comparison states, with opioid shipments showing a slight but insignificant deviation. Several factors outside this analysis's scope could cause this policy's ineffectiveness.

Conclusion

After doing the pre-post comparison and difference-in-difference analysis for the effect of policy changes, we can conclude that Florida's policy change significantly decreased the state's opioid shipment rate and overdose death rate. Washington's policy change was unsuccessful since neither the opioid shipments rate nor the overdose deaths rate fell compared to similar states. Texas's policy change was somewhat successful, as it slowed the trend of overdose deaths' increase.

The potential reasons for a successful policy can be estimated by comparing the successful change in Florida and the unsuccessful change in Washington. In Florida, the policy combines several step-by-step measures and severe punishments for failure to cooperate with the legislature, the drug enforcement administration, and law enforcement agencies. However, in Washington, the policy only regulates pain treatment, requiring annual reviews, specialist consultations, and recommendations. It can be noticed that the policy in Florida has more mandatory requirements and regulations, as well as setting effective supervision measures and strict penalties. While a definitive explanation of the differences in outcomes is beyond this analysis, these points are worth considering in tandem with our results.

Although the combination of pre-post comparison and difference-in-difference analysis could reasonably evaluate the effects of policy changes, the conclusion is not perfect. The difference in opioid shipments rate and overdose deaths rate can result from various factors' effects. Even after these rates have been decreasing, the use and abuse of prescription opioids are still a severe problem. The policies must be continuously updated and optimized based on social changes, and policymakers should carefully evaluate the policies' effectiveness and pay sustained attention.

Works Cited

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