Estimating the Efficacy of Opioid Control Policies

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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 beginning an analysis of these policies, there are two noteworthy observations to identify. First, Washington state was the only state to specifically place a threshold of sorts on the quantity of opioids that could be prescribed to a patient at a time. While this regulation had workarounds built-in for extreme cases, it did pose a unique challenge for patients and providers. This policy may have created a dilemma for patients who wanted more painkillers but could not acquire them legally. Second, 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 policy 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 it is impossible for drug users to 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. We will only analyze 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.

Pre-Post Analysis

In this analysis, we will look at the trend of 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. Here we include an added dimension of comparing the current state with similar states based on geographic proximity and cultural demographic similarity. We compare the groups before and after the implementation of the specific policy. If the policy was 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, according to 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 HIPPA 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, quantity, and unit. While reading the chunk, we filtered for only states in the desired analytical group and generated month and year columns from the transaction date. Before completing

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[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

work on each chunk, we grouped by county, state, year, and month while summing the 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, which arrived in the form of several .txt files, one per year from 2003 to 2015. We used a loop to read these files and concatenate them to each other, skipping over the bottom 15 rows of each file, which we learned were descriptive information in a different text format.

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.

From there, we created a column as a Boolean flag for whether or not each record was of interest to our analysis: namely, if the fatalities were drug-overdose related. This reduced the fatality causes to four candidates. We then dropped one more category, "all other non-drug and non-alcohol causes." After this step, we grouped by the county, state, FIPS, year, and drug death Boolean flags, summing the death counts.

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 before we saved the output to a .csv for later use.

FIPS Codes

The third dataset ingested was the FIPS data. Due to the messy nature of the .txt file the FCC stores this information in, we had to do quite a bit of transformation to make it usable. First, we used a targeted read table command to extract the rows of text specific to counties, temporarily skipping over the state rows at the head of the file. We slightly transformed the county rows before doubling back to the states.

Having a county name with a state abbreviation would be critical for later possible merging permutations. As such, we also ingested the top of the .txt file that included state-level FIPS codes. In this second data frame, we used the 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 a messy excel file that required some cleaning at ingest. 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. We also made a patch to the code to correct the spellings of two counties, which was one of several issues that would arise in the next step. We changed "DOÑA ANA COUNTY, NM" to "DONA ANA COUNTY, NM" and "DE BACA COUNTY, NM" to "DEBACA COUNTY, NM" to match county names with other files.

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

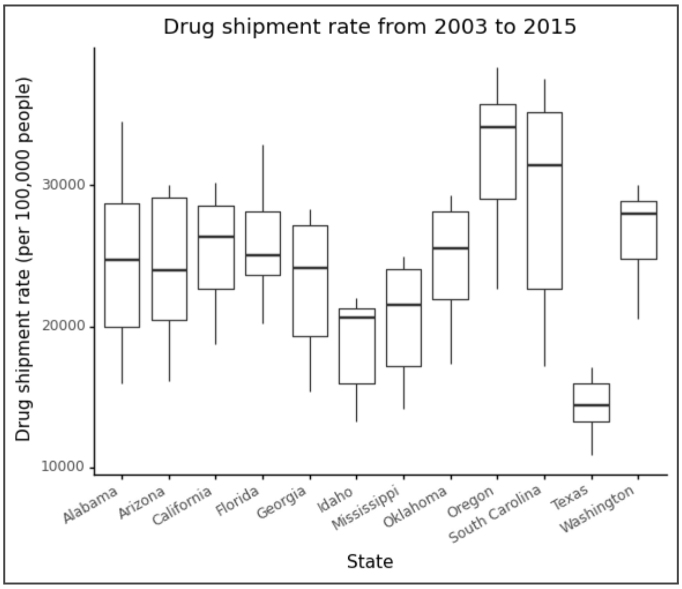
Following the preparation and merging of data, the team confronted missing data in our dataset before beginning the analysis. There are two categories of data for which we may be missing data: opioid shipments and drug overdose-related fatalities. In the case of the former, we expect that the WaPo dataset 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 the years earlier than 2006 or later than 2014 which meant that we had 404 observations within the interested year range without information.

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 selected an imputation of zero for those observations. We believe this approach is warranted, as it proposes the slightest potential change in our dataset. Our theory is that among small counties, the rate of drug overdose fatalities could be very high per capita, even if only a small number of people died. Imputing a zero in these cases prevents the possibility of overestimating the impacts of those potentially small communities. We noticed that only 3064 counties have records from 13,507 rows, approximately one-quarter of the dataset.

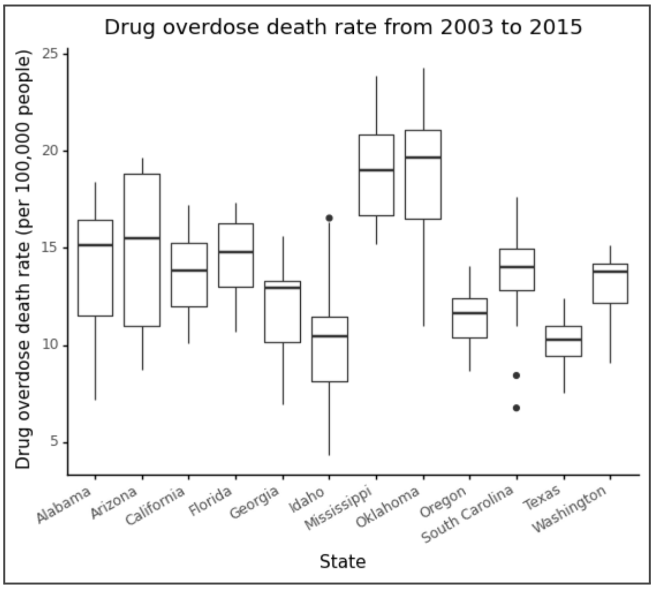
Summary Statistics

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 distribution of opioid shipments and overdose deaths between the states of interest and how they changed over time. There are 13507 observations, where each observation is the county with its corresponding state for the years ranging from 2003 to 2015. Thus, our data consists of 1039 counties among 14 states over 13 years. For each observation, we record drug related deaths, drug shipment quantity and population. We then calculate the overdose death rate per capita and drug shipment rate per capita as an incidence rate per 100,000 residents.

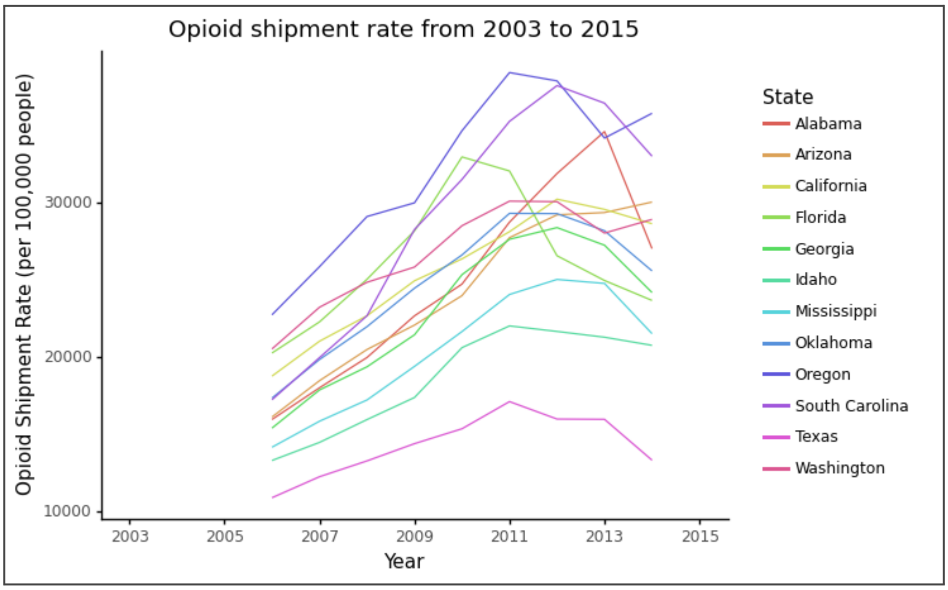
To have a glance of drug shipment rate and overdose death rate for each state within the respective year range, we draw box plots to help us get a preliminary idea of what the data looks like.



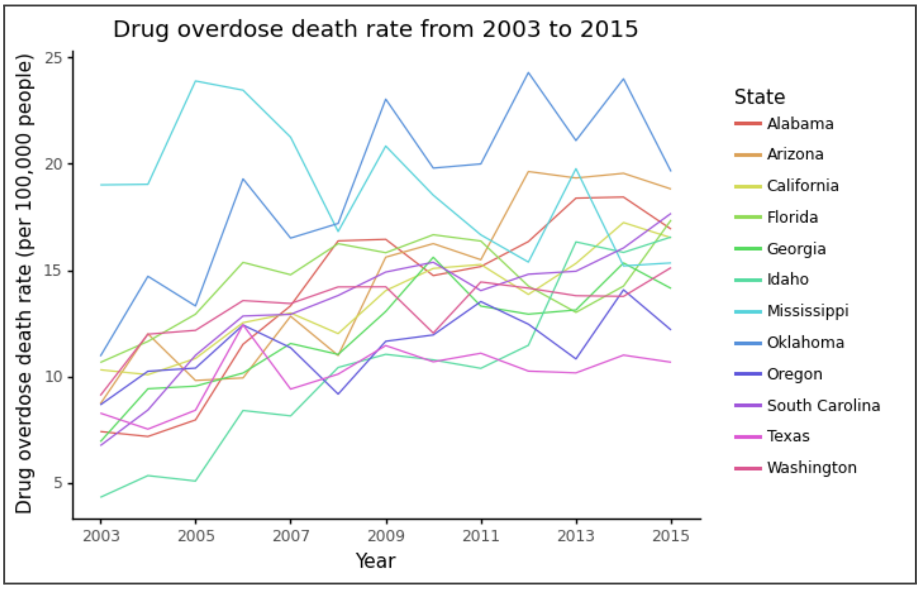
According to the drug shipment rate box plots from 2003 to 2015 shown above, , we see that Oregon has the highest drug shipment rate median while Texas has the lowest one. South Carolina, on the other hand, has the widest range of drug shipment rate over the years.



The above plot shows that Oklahoma and Mississippi have the highest drug overdose death rates both in median and mean, while Texas and Idaho have the lowest ones. 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. That is, 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 similar rate of increase (slope) for all the states of interest until around 2011, after which they dropped steadily, with the most dramatic differences seen in Florida and Alabama.



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 South Carolina is higher than in most states, its drug overdose deaths are relatively lower instead.

Analysis and Interpretation

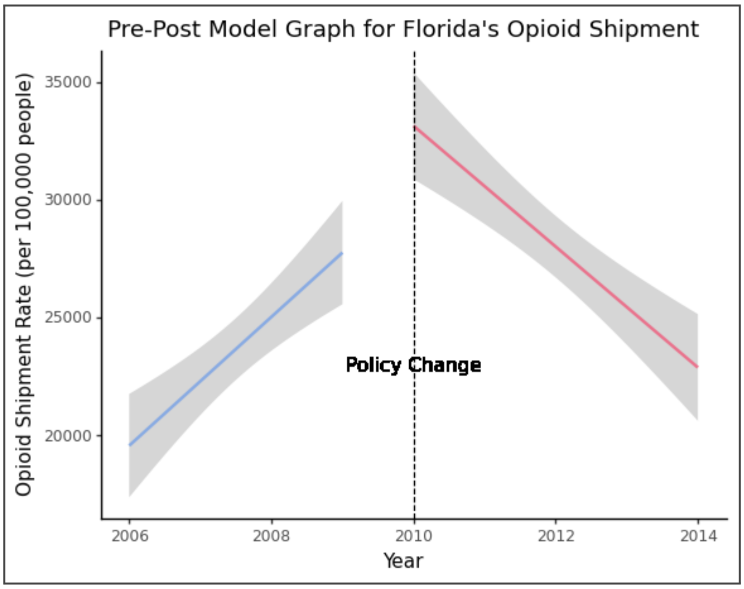
To better estimate the effectiveness of policy changes, we need to do both pre-post comparison and difference-in-difference analysis of the opioid shipments rate and overdose deaths rate. In all cases, we describe per capita rates of drug shipments and overdose deaths as an incidence rate per 100,000 residents. Because of limitations on data availability due to HIPPA, 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. To avoid errors, we replace all missing and null values with 0. The result of whether a policy is successful can be concluded 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.

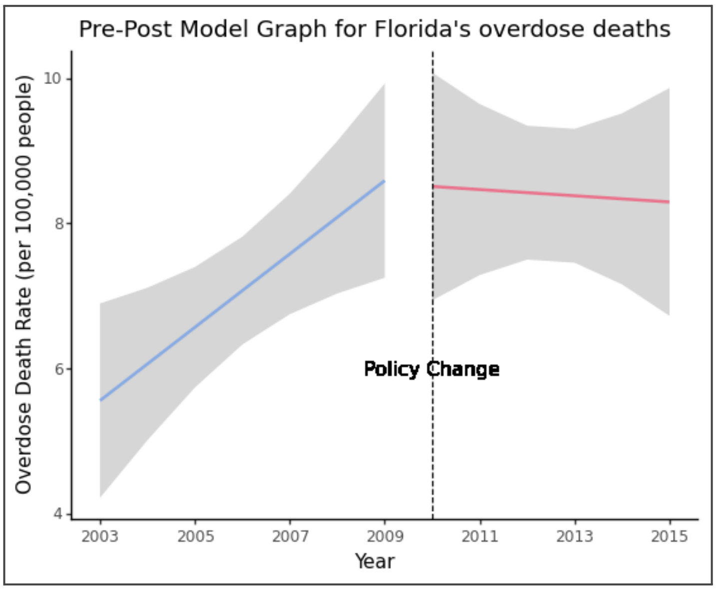
Florida

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 change 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.

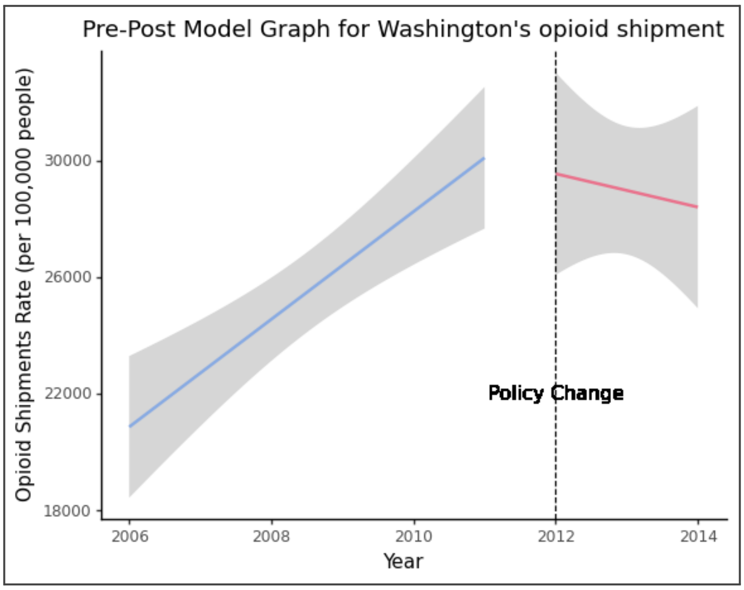
Pre-Post analysis for Florida's drug overdose deaths



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 change in direction. The trend becomes negative, and the overdose death rate decreases with time. We can conclude that the implementation of the policy was successful in reducing drug overdose death rates.

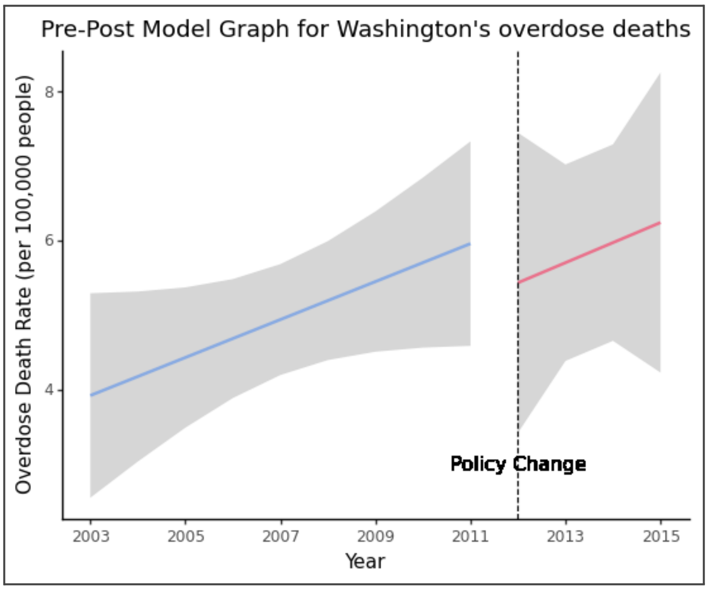
Washington

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 change 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.

Pre-Post analysis for Washington's drug overdose deaths

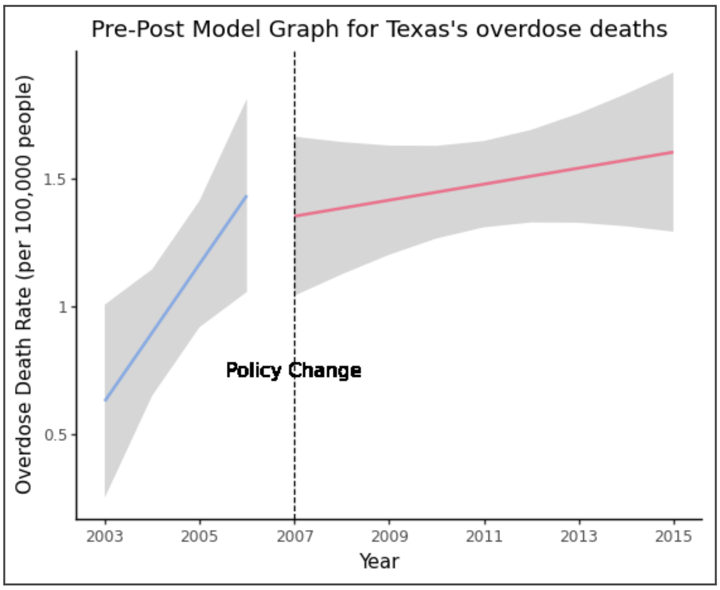


Interpretation: From the plot for Washington's drug overdose death rate, we see that the trend for overdose death rate was positive before the implementation of the opioid policy, increasing with time.

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 policy was implemented, the trend is still increasing at the same rate. We can conclude that the policy implementation did not decrease drug overdose death rates.

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 change 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.

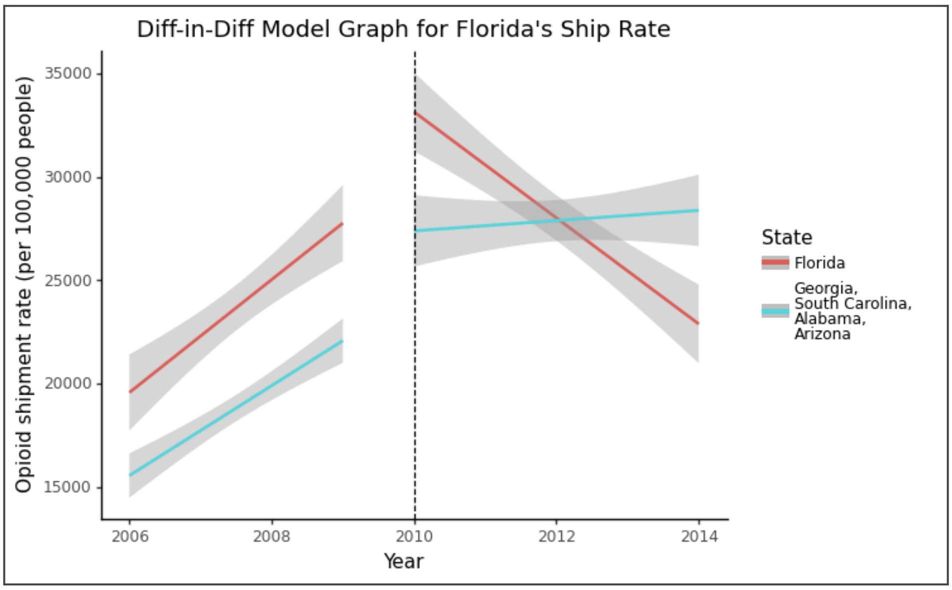
Difference-in-Difference Analysis

To conduct a difference-in-difference analysis, we first select states similar to each state of interest. 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 states similar to it. We plot two trend lines for each subset. We do this for both drug overdose deaths and opioid prescriptions.

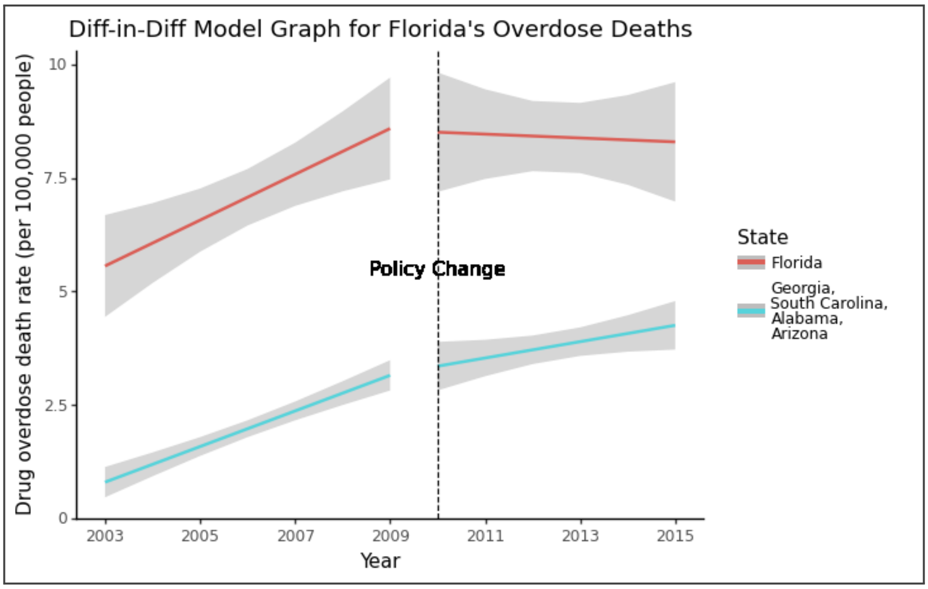
Florida

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 had the policy not gone into effect, this trend would continue. After the policy change, the rate of increase in drug shipment rate decreases for the states similar to Florida while for Florida, the trend changes direction with 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.

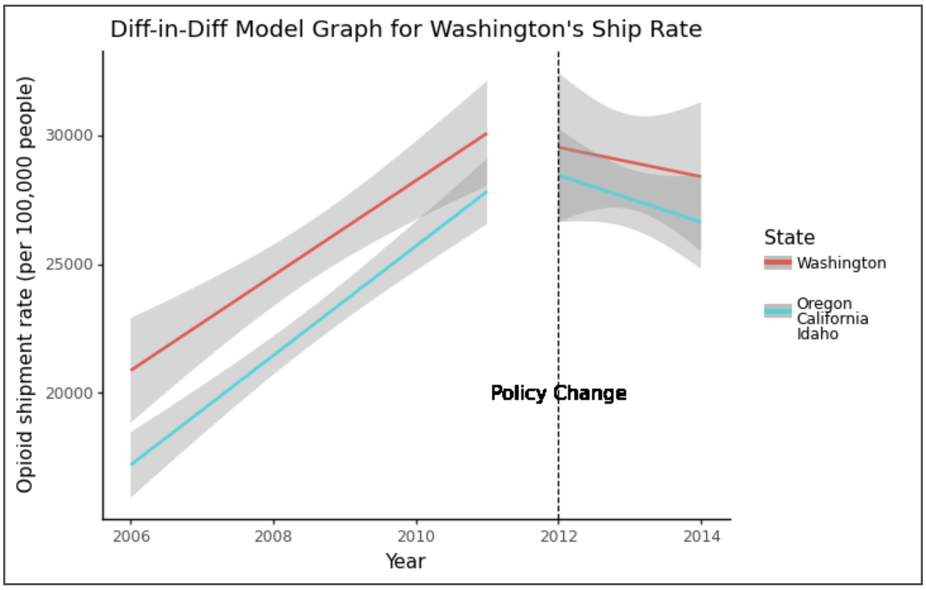
Difference-in-difference analysis for Florida's drug overdose deaths



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 had the policy not gone into effect, this trend would continue. After the policy change, the trend continues to stay the same for states similar to Florida while for Florida, the trend changes direction with the overdose death rate decreasing slowly over time. There were more noticeable changes in overdose deaths 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 decreased drug overdose death rates.

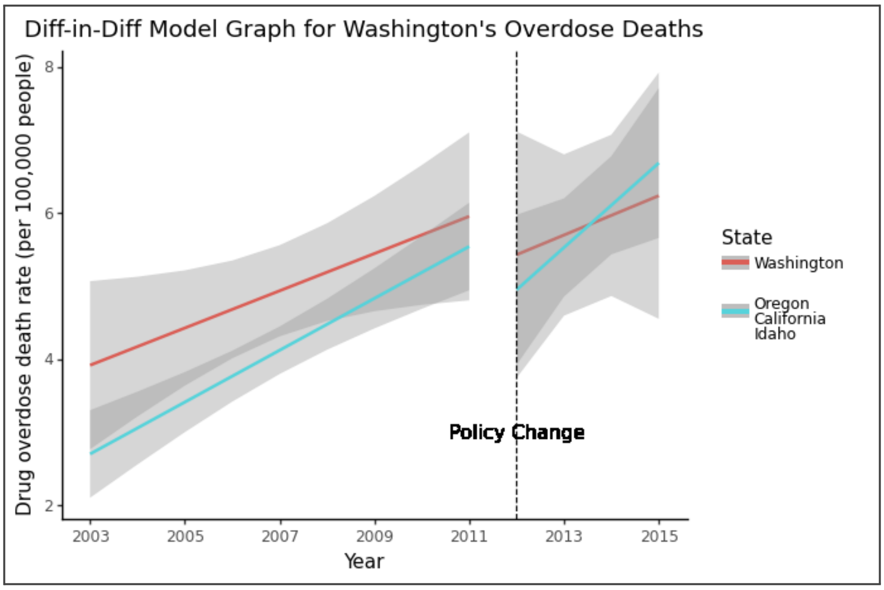
Washington

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 had the policy not gone into effect, this trend would continue. After the policy change, the trends for both groups change to a decreasing trend. There is no change between shipment rates in Washington before and after the policy and in 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.

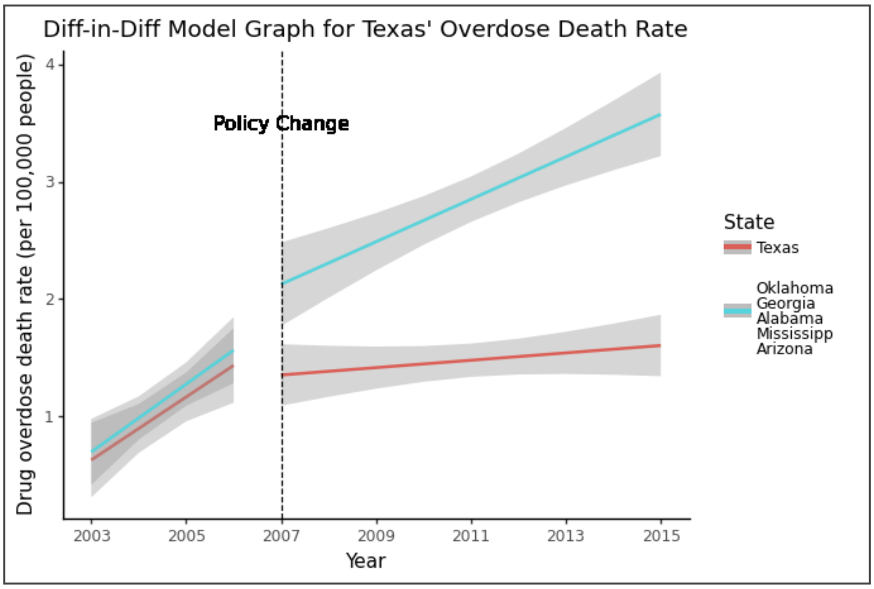
Result for diff-in-diff analysis for Washington's drug overdose deaths



Interpretation: From the diff-in-diff 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 had the policy not gone into effect, this trend would continue. 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 no change 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.

Texas

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



Interpretation: From the diff-in-diff 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 rate of 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.

Conclusion

After doing the pre-post comparison and difference-in-difference analysis for the effect of policy changes, it can be concluded that Florida's policy change was successful in both significantly decreasing the opioid shipments rate and overdose deaths rate. Washington's policy change was unsuccessful since neither the opioid shipments rate nor the overdose deaths rate fell, although the overdose death rate increase is slower than in the nearby 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 is only a regulating rule for 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. Thus, to make a successful policy, these aspects need to be considered.

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 need to be continuously updated and optimized based on social changes, and policymakers should carefully evaluate the policies' effectiveness and pay sustained attention.

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