Estimate the Impact of Opioid Control Policies

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Executive summary

The opioid crisis poses a multifaceted challenge, intertwining prescription rates and tragic overdose fatalities. This project endeavors to understand this crisis by examining opioid shipment data and drug overdose death records across counties. Through pre-post and difference-in-differences analyses, we evaluate the outcomes of policy interventions in Florida, Texas, and Washington. Our focus is to determine whether the policy interventions translate to reductions in opioid shipment and overdose deaths.

The analysis reveals the following insights. For opioid prescriptions, Florida's policy appears effective, showcasing a significant reduction post-intervention. However, Washington's policy impact is less pronounced, suggesting a need for ongoing adjustments. In terms of overdose deaths, Florida’s and Washington’s policy policy changes show effectiveness through difference-in-differences analysis, meaning that the policy changes likely caused a reduction in overdose death rates compared to similar peers. Florida experienced a notable decline in deaths post-policy, while Washington avoided a spike seen in control states. Texas’ opioid control policy, however, failed to show effectiveness in either pre-post comparison or diff-in-diff comparison against its control states, suggesting a lack of effectiveness in controlling opioid abuse.

In interpretation, we cautiously attribute observed changes to policy interventions, acknowledging potential external influences. Policymakers could draw lessons from Florida's success, but context-specific factors must be considered. The report underscores the human impact of the opioid crisis, emphasizing the need for nuanced, life-saving policies. As a contribution to a comprehensive understanding, our research aims to inform actionable insights for policymakers combating this critical public health issue.

Motivation

The opioid crisis has manifested not only in soaring prescription rates but also in a tragic uptick in drug-related fatalities. This dual facet of the epidemic forms the crux of research motivation. Alongside scrutinizing opioid prescription data, this project also delves into records that capture the number of drug-related deaths across various counties. This comprehensive approach allows us to paint a more complete picture of the crisis that spans the spectrum from prescription to mortality.

The imperative drives this research to understand the full impact of opioid misuse on public health. By examining drug-related death records, we aim to measure the ultimate human cost of the crisis. The analysis of mortality data serves as a stark indicator of the epidemic's severity and the urgent need for effective intervention strategies. By incorporating this dataset, we can better assess the correlation between opioid prescriptions and overdose deaths.

Employing pre-post and difference-in-differences (DiD) analytical frameworks, we evaluate the outcomes of policy interventions. The pre-post analysis provides an initial glance at the trends surrounding the implementation of regulatory policies, allowing us to observe whether there is an immediate impact on prescription/overdose rates. However, it is the DiD approach that offers a more robust insight. By comparing against counties that are not affected by policy change of interest but should otherwise be similar, we hope to gain causal insights that are not revealed by pre-post comparisons. For example, If reductions occurred post intervention, did the policy cause the reductions? Or could there be other factors occurring across states that drove the reductions? The DiD approach shows how differently counties change with and without the policy, thereby offering a causal perspective on whether the policy caused the changes. Of course, this approach is not perfect since no two counties are 100% representative of each other. Thus, we use heuristics like prior trends and similarity index to select counties or states that are similar.

This bifocal analysis—encompassing both opioid distribution and mortality rates—is pivotal. It acknowledges that the volume of prescriptions is only one side of the coin; the other is the genuine, often irreversible consequence of these drugs. By correlating the two datasets, we strive to determine whether policies aimed at controlling prescriptions effectively translate to a reduction in drug-related deaths.

The motivation extends beyond academic inquiry and is rooted in a humanitarian concern. With each number in the datasets representing a life affected by the opioid crisis, we are reminded of the stakes involved in the analysis. The knowledge gained through this research has the potential to inform policies that not only prevent misuse of prescriptions but also save lives.

Ultimately, the project seeks to contribute to a multi-dimensional understanding of the opioid epidemic. Through rigorous data analysis, we endeavor to provide actionable insights to support the development of nuanced, life-saving policies. The commitment lies in sponsoring a future where drug-related tragedies are not an epidemic but an aberration.

Data Overview

For the analysis of opioid prescriptions, we depend on the Drug Enforcement Administration's (DEA) [pain pill data obtained and released by the Washington Post]. This dataset covers all shipments of prescription opioids in the United States from 2006 to 2019. To investigate opioid overdose fatalities, we utilize information from the [US Vital Statistics records], which offer a comprehensive overview of mortality, encompassing both drug and non-drug-related causes, across all US counties from 2003 to 2015. Additionally, we gather county-level population data from the US Census Bureau, [2000-2010 intercensal estimates] and [2010-2020 intercensal estimates]. The population totals allow us to compute two crucial metrics: the per capita prescription rate and the mortality rates of deaths attributed to drug-overdose causes within the population. This approach addresses the substantial variations in population sizes observed among different counties.

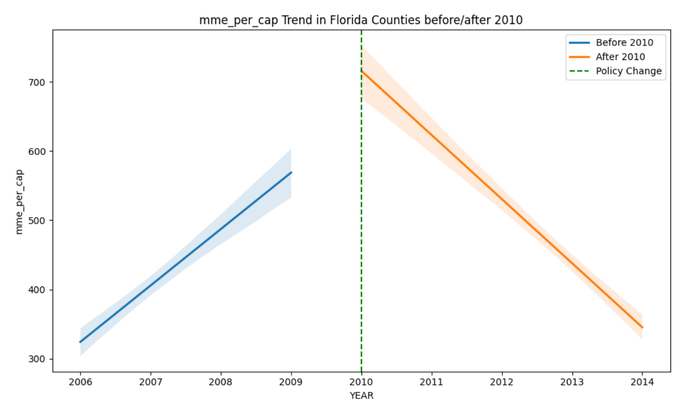
Analysis

Opioid Data: how is the volume of opioid shipments affected by opioid drug prescription regulations?

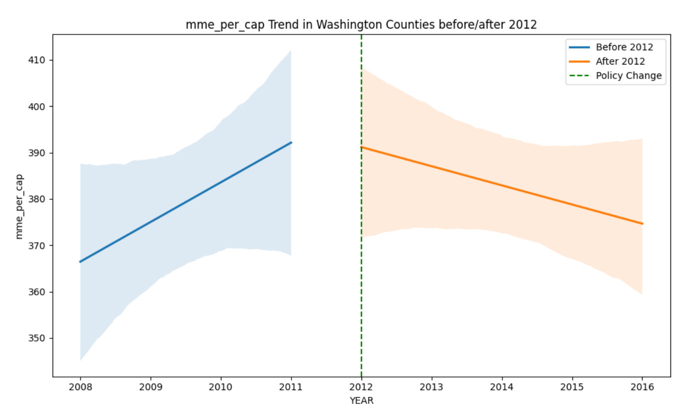
Pre-Post Analysis

The Pre-Post analysis focused on comparing trends in opioid use before and after the policy intervention. For both states, the pre-policy period consists of the years prior to the policy change, and the post-policy period is the years after the policy change is implemented. Since each county in each state varies in geographic location, population size, and type of medication used, we used the morphine milligram equivalent as a standard of comparison. During this period, the analysis includes looking at trends in per capita morphine milligram equivalent (MME) in each county, noting whether the change is increasing, stabilizing, or decreasing.

The two figures show the MME per capita use of opioids in various counties in the state of Florida and Washington. From Figure 1, there is a noticeable peak around the year 2010 in Florida, after this, however, the lines show a clear downward trend. For Figure 2, it can be seen that the line for Washington State shows a downward trend after 2012 as well.



(Figure 1: Pre-Post for Florida)



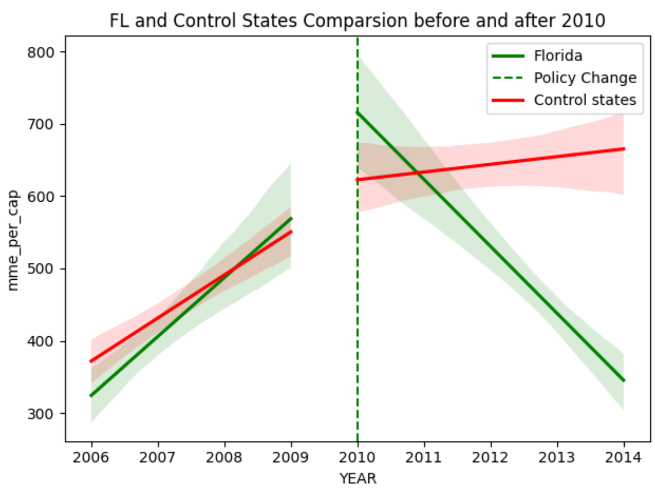
(Figure 2: Pre-Post for Washington)

However, the prepost analysis alone does not allow us to infer that the policy must have worked, so in the analysis that follows, control states will be selected for comparison.

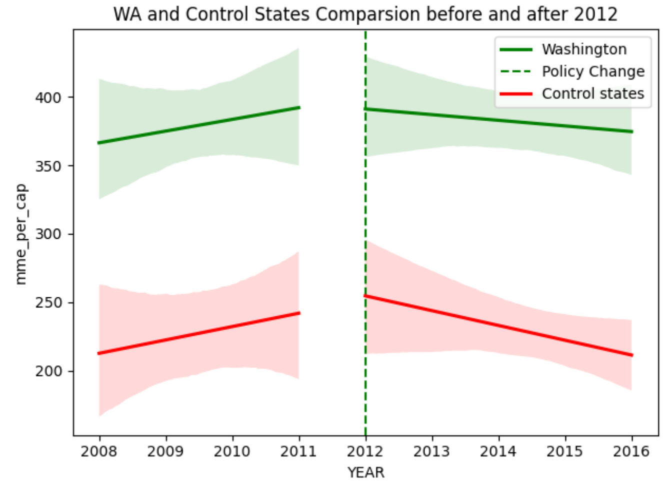
Comparison states selection is based on calculating the linear regression of the trend in opioid shipment for each state before the policy occurred, and finding the comparison state that is most similar to the target state by the slope of the straight line. By using this strategy, three control states were chosen for Florida and Washington. Then, the dataset of control states were combined as a compare indicator.

In Figure 3, prior to 2010, the rise in opioid shipment in Florida was more than in the comparison states, but after 2010, there was a significant drop due to policy controls, which leads the line of Florida lower than control states. Therefore, it is likely that the 2010 policy change was an important factor in the decrease in Florida's opioid shipment.

Figure 4 indicates a clear downward trend in shipment of opioids in all states after 2012, so this does not suggest that the 2012 policy necessarily played a controlling role for Washington. The situation in Washington state needs to be analyzed deeply in future.



(Figure 3: FL and Control States Comparison)

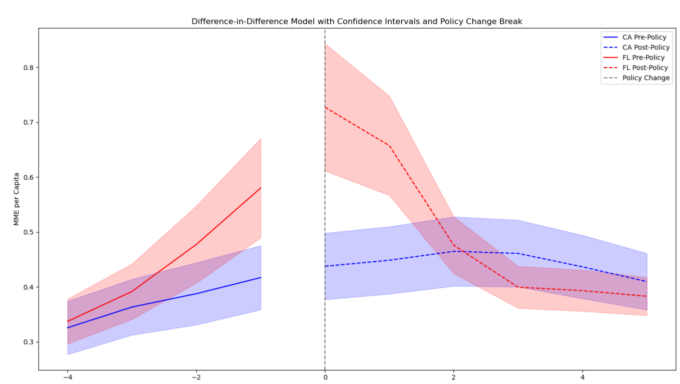


(Figure 4: WA and Control States Comparison)

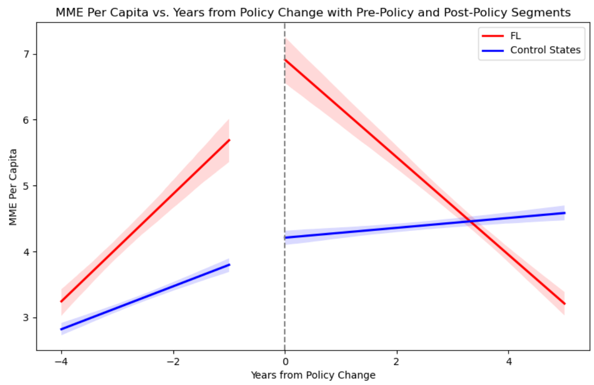
Diff-in-Diff Analysis

The pre-post approach looked only at changes in individual states. This may result in other factors needing to be noticed, such as the fact that all states had significant shifts in their data in that year due to natural circumstances or international policy. To make a good comparison, people must do more state-to-state comparisons to ensure that policy factors drive these changes. For better comparison, California (CA), North Carolina (NC) and New York (NY) are selected as control states. Because their data situation is similar to the target state.

In addition, to view the data transformation in more detail, in this analysis stage, we used manual calculation of confidence intervals and drawing of color blocks to assist the analysis instead of only using the built-in confidence interval method in drawing tools. The biggest reason is that the volatility of the data represents whether there is a factor that strongly affects the original trend of the data, so the analysis plan in this step needs to be as detailed as possible.



(Figure 5 Difference-in-Difference Florida vs California)



(Figure 6 Difference-in-Difference Florida vs Control States)

The graph 5 and 6 depict a Difference-in-Differences (DiD) analysis comparing opioid prescriptions per 100 people in Florida (FL), where a policy change was implemented, against California (CA) and other control state.

All the states show an increasing trend in opioid prescriptions per 100 people in the years leading up to the policy change. This suggests that absent any intervention, opioid use was on the rise in all the states.

At the point marked "Policy Change," there is a noticeable inflection in the trend for Florida, with the rate of opioid prescriptions per 100 people declining sharply post-intervention. California's rates, however, continue on the previous trajectory without any significant change in slope. Not only that, the size of the coloring section represents the oscillation of the data. In the years after the policy change, the area in Florida became significantly more significant. This indicates that there are factors that affect the stability of the data.

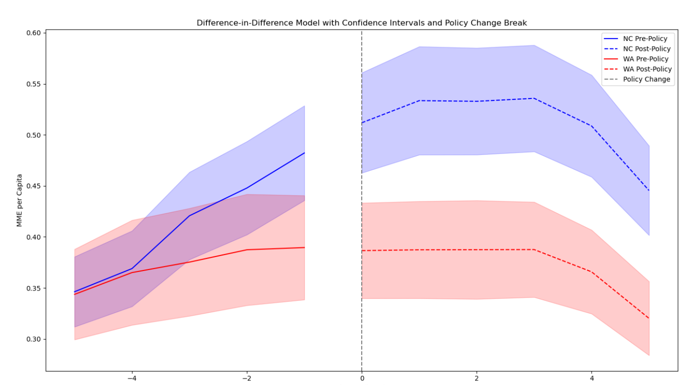
Therefore, DiD analysis assumes that, in the absence of the policy, the post-policy trend in Florida would have followed a similar trajectory to that of California. The difference in the actual post-policy direction in Florida from this counterfactual scenario (represented by California's trend) suggests the estimated effect of the policy.
The report proposes several potential factors based on this scenario.

First, the visual representation suggests that Florida's policy may have effectively reduced opioid prescriptions, assuming all other factors remain constant. The sharp decline contrasts with the control state, implying a positive outcome from the policy change.

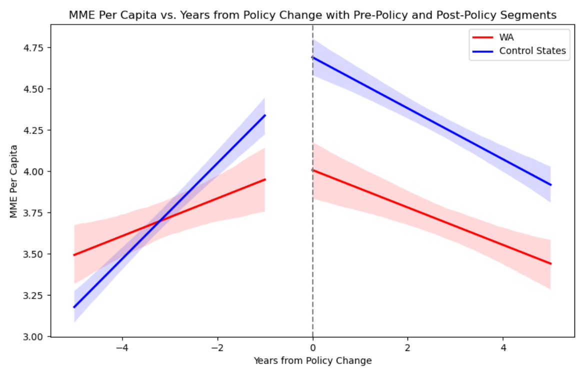
While the graph suggests a successful policy intervention, it is essential to acknowledge that other external factors not accounted for in the chart might have influenced the results. Such factors include economic changes, shifts in public awareness, or other concurrent public health initiatives. However, considering the significant changes in the average opioid usage in Florida before and after the policy, we can still safely admit that the policy has a direct impact on opioid usage.

Finally, assuming the policy was the primary driver of the observed changes in Florida, policymakers in other states might consider similar interventions. For California and other control states, however, no obvious turning point has been observed. It is probably partly because, in Florida, the government's pessimistic view of the rise in per capita opioid use has led to the emergence of a more stringent policy, which has significantly dampened growth. California and other states do not have a clear upward trend in the observation range, so there is no need for a draconian policy to force things to change. This may be due to the habits of the people of California, or there may already be a similar restriction treaty in California.

In conclusion, the graph suggests that Florida's policy change was associated with a significant reduction in opioid prescriptions, in contrast to the trend observed in California and other states.



(Figure 7 Difference-in-Difference Washington vs North Carolina)



(Figure 8 Difference-in-Difference Washington vs Control States)

The graph 7 and 8 presented another Difference-in-Differences (DiD) analysis, comparing opioid prescriptions per 100 people in Washington (WA) over several years surrounding the policy change.

Before the policy change (to the left of the dashed vertical line), NC, WA and other states showed an upward trend in the metric, with NC's growth slightly outpacing WA's. After the policy change point (the vertical dashed line), the growing trends in WA have disappeared. This may prove that policy is effectively restraining growth because the relative state data increased in the same year. However, this view seems to be overturned when we consider the data from other states, as shown in figure 8. Since the data of other states are also falling, the trend of decline seems to be little different from that of WA.

Judging by the size of the colored areas in figure 7, it seems that the data remains very documented even after the policy change. Therefore, for WA, people can not directly affect the level of opioid consumption per capita. However, such judgments are not absolute. If policy is carried out softly, it is reasonable that there will not be too much volatility in the data.

In conclusion, Compared with the curve of NC, WA does not have a further upward trend after the policy change. However, the relatively stable per capita purchase volume of opioids does not prove whether the policy causes it. For example, looking at all the data from other states, the trend in WA after the policy change does not seem to be significantly different. Moreover, the stability of the color blocks may be evidence that the policy does not change the data that much. However, given that the trend of WA changes before the policy change year was not very rapid, the policy may have been implemented peacefully.

Some other methods may be needed to carry out further analysis.

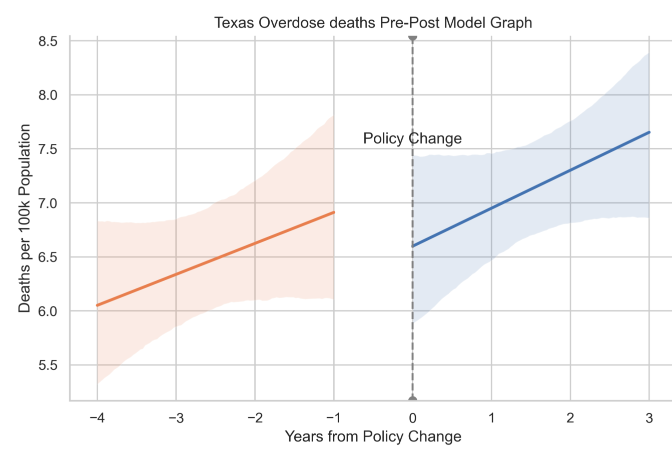
Overdose Data: how are drug overdose deaths affected by opioid drug prescription regulations?

Scoping by Population

For privacy, the US Vital Statistics Agency censors some data. If the number of people in a given category (i.e. one county / year / cause of death category) is less than 10, that data does not appear in the data. Because of this, most counties with a lower population have missing overdose deaths entries.

In order to select counties that have complete data for our analysis, we opt to scope by population. In essence, we limit this analysis to the study of large counties so that this “less than 10” issue never occurs over the timespan of interest. For each state’s analysis, we find that a population threshold of around 400,000 suffices. With these thresholds, roughly 100 of the nation’s largest counties remain.

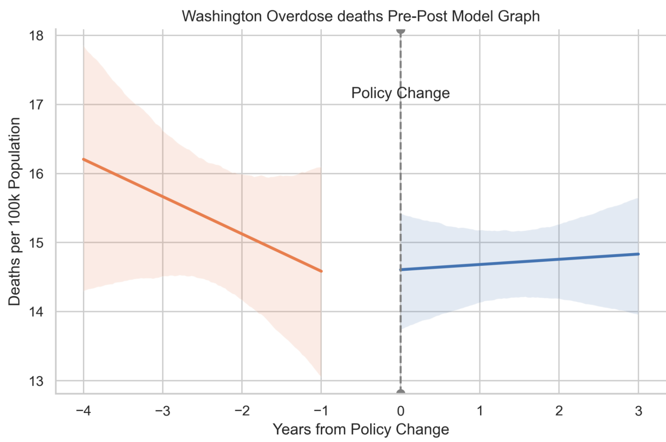
Pre-Post Analysis



(Figure 9 Overdose Pre-Post, Texas)

Figure 9 shows the overdose pre-post analysis for Texas. The left half of the plot shows the trend of overdose deaths in Texas in the 4 years prior to its opioid control policy implementation in 2007, which we can see increased roughly from 6 per 100K to 7 per 100K. The right half shows the trend of overdose deaths in Texas in the 4 years since its opioid control policy implementation. If a noticeable decline in the trend occurred post intervention, it would suggest that the policy change was effective in curbing drug overdose deaths.

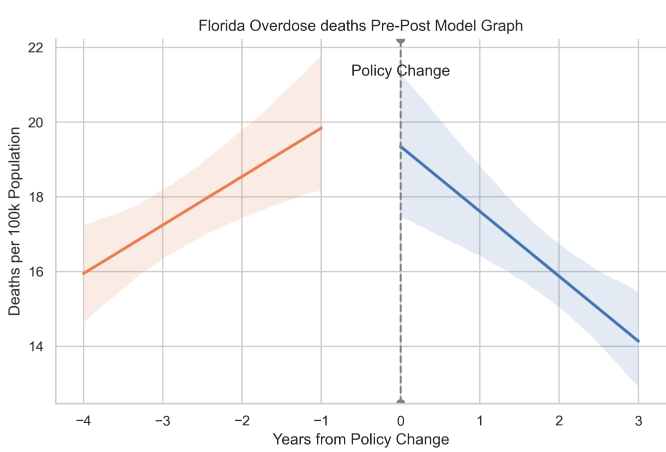
However, as we can see, this pre-post comparison seems to indicate that Texas' opioid policy change had little to no effect on the trend of drug overdose deaths. The regression lines before and after the policy change are almost parallel, meaning that overdose deaths continued increasing at a similar pace despite the policy interventions.



(Figure 10 Overdose Pre-Post, Washington)

The Pre-post comparison shown in figure 10 doesn't paint a promising picture for Washington's policy change either. The left half of the plot showed that Washington's overdose death rate decreased roughly from 16.2 per 100K to 14.6 per 100K. However, the trend reversed after its opioid control policy was introduced in 2012, increasing slightly from 14.6 per 100K to 14.8 per 100K.

Based on these results, it would seem that Washington's opioid control policy failed to help reduce the number of overdose deaths.



(Figure 11, Overdose Pre-Post, Florida)

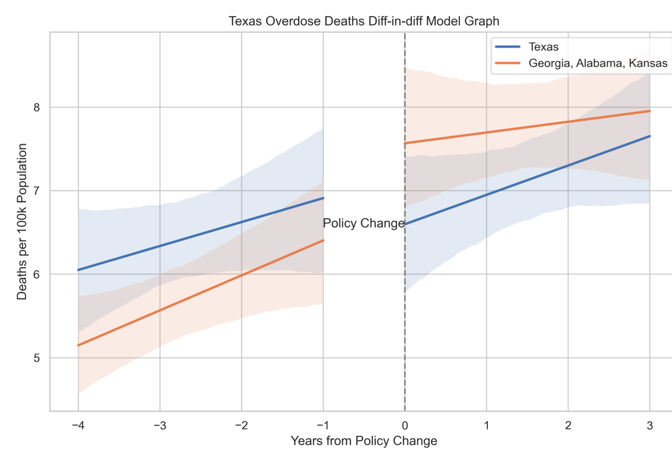
Florida is the only state out of the three where pre-post comparison shows a noticeable reduction in drug overdose death rate after its policy change. As we can see, the slope changes from rapidly increasing to decreasing after the policy change.

In summary, we only see definite decline in overdose deaths post policy interventions in Florida. Texas's overdose deaths increase at a similar rate before and after its policy change. Washington's pre-post results were the most surprising, with its overdose deaths on the decline before its policy change but changing to increase slightly afterwards.

Control states selection

For the following DiD analysis, we find 3 control states for each of the 3 states of interests. We select based on a combination of [State Similarity Index] and overdose death trends exhibited prior to the 3 policy changes. In short, the control states for a state that we are examining are states that are similar (in terms of geography, culture, politics, etc.), and exhibit similar overdose death trends.

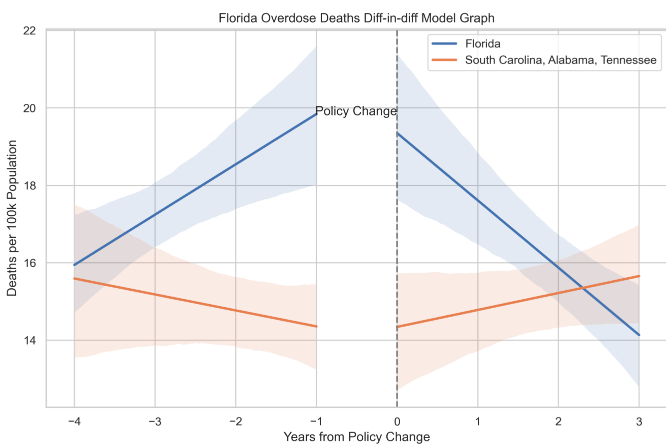
Diff-in-Diff Analysis



(Figure 12 Texas vs Georgia, Alabama, Kansas)

In this diff-in-diff analysis, Texas is compared against Georgia, Alabama, Kansas, which showed similar trends before its policy change in 2007. On the left half of figure 12, we can see that the control states' counties and Texas' counties show similar increasing trends in the 4 years prior to 2007, with the control states increasing slightly faster. After Texas' policy change in 2007, however, the control states showed a significant slowdown in overdose deaths, while Texas showed no sign of such slowdown.

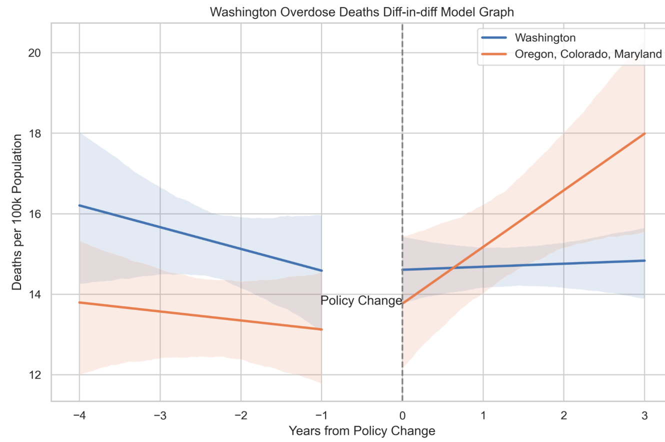
If the control states after 2007 are representative of a Texas that did not have its opioid policy, which is likely due to their similarities, then it is reasonable to suspect that Texas' interventions failed to curb overdose deaths. The control states, without being affected by this policy shift, showed slowed overdose increase while Texas did not. This could even imply that Texas' opioid interventions stifled factors that would have helped reduce overdose deaths, leading to worse outcomes than its peers.



(Figure 13 Florida vs. South Carolina, Alabama, Tennessee)

In this diff-in-diff analysis, Florida is compared against South Carolina, Alabama, Tennessee. On the left half of figure 13, we can see overdose deaths increasing rapidly in Florida but decreasing in the control states prior to 2010. On the right half of the plot, the trends saw a complete reversal: overdose deaths rapidly decreasing in Florida but increasing in the control states.

This DiD picture for Florida shows its policy's effectiveness quite clearly. The outcome for Florida's peers indicated that the overall environment is in favor of an increase in overdose deaths. This would imply that the policy change in Florida had such a strong effect on overdose deaths, that it was able to reverse the rapidly increasing trend in the midst of an adverse environment for overdose.



(Figure 14 Washington vs Oregon, Colorado, Maryland)

In figure 14, we see the diff-in-diff comparison between Washington and Oregon, Colorado, Maryland. On the left half of the graph, we see overdose deaths decreasing at similar rates for both Washington and the control states prior to Washington's policy change in 2012. On the right half of the graph, we see a significant increase in overdose death rate for the control states, while little change for Washington.

Considering that Washington and the control states had similar overdose trends before 2012, the control states are likely representative of Washington post 2012 in terms of overdose deaths in a world where it did not undergo the policy change. This would imply that the policy change did steer Washington away from seeing a spike in overdose rates compared to its peers, meaning that the policy was effective in curbing drug overdose.

In summary, the diff-in-diff analysis on overdose deaths indicate that Florida's and Washington's policy changes were effective in curbing drug overdose deaths, while Texas' were not.

Interpretation

Strengths

overdose

We used population-based scoping in overdose deaths analysis, eliminating all counties below population thresholds instead of just dropping all counties with missing overdose records. This reduces the bias in selecting counties that are likely to have more issues with drug overdose.

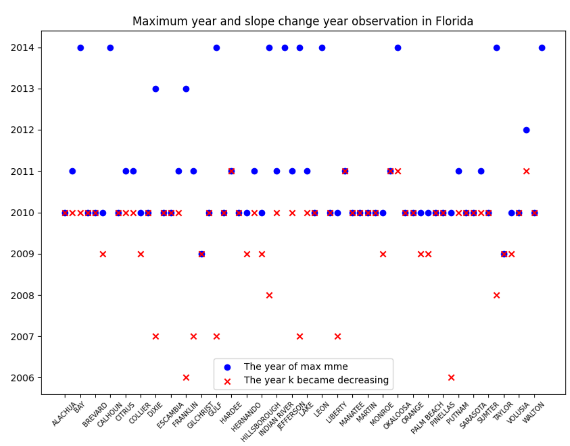
Weaknesses

overdose

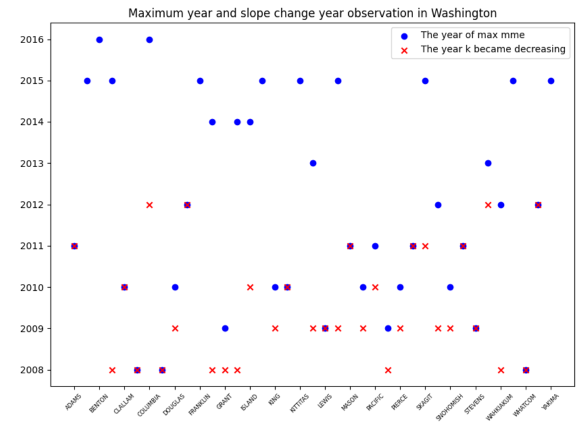
For each state, we are using the maximum population of counties with missing overdose records as population thresholds, which may still introduce bias against counties with less overdose issues, as we are eliminating all counties with missing records very precisely.

Opioid shipment

The post-post analysis reviewed changes in the data, but did not indicate whether the changes were caused by time or policy changes and very general. To improve clarity, we therefore attempted to analyze each county in the state. We used a different approach to examine trends: we tracked state data every three years to detect a decline in the slope of opioid shipment, which indicates a downward trend. We matched the year to a peak period of use. For example, in Figure 13 for Florida, most counties peaked in 2010, matching the decline in the slope, which suggests policy is having an impact. In contrast, in Washington State (Figure 14) the impact in 2012 was not significant. This is consistent with the previous analysis, but allows for more precise identification of policy impacts.



(Figure 15 Trend of Florida Counties)



(Figure 16 Trend of Florida Counties)

Appendix

Data Preprocessing

This analysis elucidates the methodological rigor applied to merge disparate datasets and to conduct a comprehensive analysis that informs the understanding of the opioid crisis and the impact of policy interventions.

After downloading the opioid data from the Washington post, read it into memory for every 10,000 rows, process each piece of data to get the month and year, and then merge the data based on the state and county for the same year and month to get the final parquet file for analysis.

The second phase of the data consolidation involved integrating opioid prescription data across different states. Given the heterogeneity of data sources and formats, we developed a systematic approach to standardize the datasets, ensuring consistency in critical variables such as state identifiers, county names, and time frames. This meticulous harmonization process was crucial for creating a cohesive dataset that accurately reflected prescription patterns across state lines.

Subsequently, we faced the challenge of incorporating population data into researchers' analysis to enable a per capita examination of opioid prescriptions. This step was vital for normalizing the data, allowing equitable comparisons across counties with varying population sizes. To achieve this, we leveraged the intercensal population estimates provided for each county, ensuring that per capita calculations were grounded in the most accurate and up-to-date demographic information available.

The integration of population data into the state-specific opioid datasets was accomplished through a series of data transformations and merges. By aligning county and state identifiers across the two datasets, we could append population figures to the corresponding entries in the opioid dataset. This merge was performed carefully to preserve data integrity, mainly where discrepancies in county nomenclature existed.

With the comprehensive dataset in place, we focused on classifying the data based on the policy change year. The states of Florida, Washington, and Texas, which had implemented specific opioid prescription policies, were marked as treatment groups, while the remaining states were designated as control groups. We then created a relative time scale that pivoted around the policy implementation year. This enabled us to categorize the data into pre-policy and post-policy periods, setting the stage for the pre-post and difference-in-differences analyses.

In summary, the data integration process was meticulous and methodical, ensuring that the analyses rested on a robust and comprehensive dataset. The classification based on policy year was instrumental in shedding light on the temporal effects of policy interventions. By considering both opioid prescriptions and mortality data, we aimed to provide a holistic assessment of the policies' efficacy in addressing the opioid crisis.

Details of the data used and how different datasets have been related to one another

For the opioid data:

In the deeper layers of our report, we elucidate the methodological rigor applied to merge disparate datasets and to conduct a comprehensive analysis that informs our understanding of the opioid crisis and the impact of policy interventions.

How was the data processed and cleaned to get information about different states

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Explain the rationale behind the research design

This analysis aimed to assess the impact of opioid prescription regulations on opioid prescribing volumes and drug overdose mortality rates in multiple U.S. states.

We focus on measurable outcomes (prescribing volumes and mortality rates) that directly relate to policy interventions to answer the question for the research.

The research used a data-driven approach, utilizing data from reliable sources, the Washington Post's opioid dataset, the Vital Statistics mortality dataset, and U.S. County population totals. This approach ensured that the analysis was based on experiential evidence.

The use of both pre-post and difference-in-difference analysis methods allows for a comprehensive evaluation of the policy impacts. Pre-post analysis examines changes within states before and after policy implementation, while difference-in-difference analysis compares these changes with control states that did not implement similar policies, providing a more robust understanding of the policy's effectiveness.

Through a review of the data, it was decided to use per capita MME as a measure. Recognizing that different types of opioids have different effects, MME provides a method of standardization. Considering differences in geographic area and population size across counties, we calculated per capita MME to analyze the actual intensity of opioid prescribing relative to the size of the population that reflects it.

Finally, we created visualizations to make the data more accessible and understandable.