Estimating the Effectiveness of Opioid Control Policies

A Data Science Analysis Using Pre-Post and Difference-in-Differences Methods

PDS 720: Practical Data Science

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1. Executive Summary

The opioid crisis is one of the most significant public health challenges in the United States, resulting in devastating consequences for individuals and communities. Between 1999 and 2022, opioid-related overdose deaths escalated exponentially, rising from 21,000 in 2010 to over 80,000 in 2022 (Centers for Disease Control and Prevention [CDC], 2023). States responded to the crisis by implementing regulatory policies aimed at reducing prescription opioid misuse, overdose deaths, and the societal burden of addiction.

Using data from opioid shipments and drug-related mortality records, we employed two primary methods: pre-post analysis to evaluate immediate changes within each state and difference-in-difference analysis to compare treated states with control states lacking similar policy interventions. These methods allowed us to isolate the effects of the policies from broader trends and external factors.

1.1 Key Findings

Florida: The policy resulted in a significant and lasting reduction in both opioid shipments and overdose deaths, indicating its effectiveness as a targeted intervention.
Washington: While the policy initially reduced opioid shipments and fatalities, these effects were not sustained. A rebound in both metrics reflects the difficulty of achieving sustained impact and suggests the policy's limited effectiveness.

This study identifies Florida's approach in handling the opioid crisis to be the most effective, suggesting that policymakers could implement similar policies in other states against the opioid crisis, while the approach adopted in Washington necessitates further review and analysis.

2. The Opioid Crisis

The opioid epidemic in the United States emerged during the late 1990s, driven by increased focus on pain management and aggressive marketing of opioids as safe and non-addictive. By the early 2000s, the over-prescription of opioids became a significant driver of addiction and overdose deaths (CDC, 2023). Many individuals transitioned from prescription opioids to illegal drugs like heroin and fentanyl, which posed higher risks due to their potency and lack of regulation (Franklin et al., 2015).

The Centers for Disease Control and Prevention (2023) reports that over 500,000 people died from opioid overdoses between 1999 and 2019. Prescription drug monitoring programs helped reduce the availability of legal opioids; however, many individuals with opioid dependence turned to illicit substances, exacerbating the crisis (Kennedy-Hendricks et al., 2016).

2.1 Policy Implementation

In response to the crisis, many states implemented policies to tackle the issue. These policies differed in approach and scope but shared the common aim of reducing the deaths resulting from the opioids and amount of opioids available to the public. Therefore, this study aims to evaluate the effectiveness of these policy interventions designed to curb opioid abuse. In particular, this study will focus on the states of **Washington** and **Florida**. Metrics used to evaluate the effectiveness include changes in the morphine equivalent of opioid prescriptions per capita and overdose mortality per capita - both preceding and following the implementation of these policies.

2.1.1 Florida

Florida implemented a multi-faceted approach to address the opioid crisis, focusing on prescription regulations, monitoring programs, and public health initiatives. A key legislative action in 2018 restricted prescriptions for acute pain to a maximum of three days, with an extension to seven days under specific conditions (Florida Department of Health, 2018). The state also mandated the use of its Prescription Drug Monitoring Program (PDMP), E-FORCSE, to prevent over-prescription and "doctor shopping" (Florida Health, 2023). Regulations targeting "pill mills" required pain clinics to register with the Department of Health and comply with operational standards, effectively reducing the availability of prescription opioids (Centers for Disease Control and Prevention [CDC], 2020). Florida further enhanced overdose prevention efforts by distributing naloxone kits and initiating the Overdose Data to Action (OD2A) program to improve surveillance and data-driven interventions (Florida Department of Health, 2023). Legal actions also played a role in Florida's response, including a $683 million settlement with Walgreens in 2022 to address its role in opioid distribution (Moody, 2022).

2.1.2. Washington

Washington State has similarly taken a proactive approach to combat the opioid crisis by emphasizing safe prescribing practices, public education, and harm reduction strategies. In 2018, Washington implemented new prescribing guidelines that limited opioid prescriptions for acute pain to seven days and required providers to document their justification for prolonged use (Washington State Department of Health [WSDOH], 2018). Washington's Prescription Monitoring Program (PMP) mandates that healthcare providers review a patient's prescription history before issuing opioid prescriptions. (WSDOH, 2023). Harm reduction efforts in Washington include expanded access to naloxone and the establishment of syringe service programs, which aim to reduce the spread of infectious diseases among individuals using illicit opioids (CDC, 2020). Additionally, Washington's public health campaigns focus on educating communities about the dangers of opioids and promoting available treatment resources (WSDOH, 2023). Legal actions against pharmaceutical companies have also been pivotal in Washington's response. For instance, the state reached a $518 million settlement with three major drug distributors in 2022, which will be used to fund prevention and treatment initiatives (Inslee, 2022).

2.2 Research Design

The analysis will employ both **pre-post** and **difference-in-difference** methods to measure any differences that emerge post-policy implementation, providing insights into the impact of these interventions on prescription volumes and overdose rates. The specified states, **Florida** and **Washington**, will be compared with other states without Opioid interventions to ensure that trends in opioid-related metrics before the policy changes are similar across groups.

Research Question

What are the changes in opioid prescription rates (Y1) and overdose mortality (Y2) following the implementation of opioid policies?

Null Hypothesis (H0)

Pre-Post Analysis (PP) There are no significant changes in opioid prescription rates (Y1) and overdose mortality (Y2) following the implementation of these policies within the same state, comparing data from two years prior to the policy to three years after the policy implementation. **Difference-in-Differences**

(DiD) There are no significant differences in changes to opioid prescription rates (Y1) and overdose mortality (Y2) over the same time period when comparing states with implemented policies to states without such policies.

Alternative Hypothesis(H1)
Pre-Post Analysis (PP) There are significant changes in opioid prescription rates (Y1) and overdose mortality (Y2) following the implementation of these policies within the same state. Specifically, opioid prescription rates (Y1) and overdose mortality (Y2) are expected to be lower in the three years after the policy implementation compared to the two years preceding it.
Difference-in-Differences (DiD) There are significant differences in the changes to opioid prescription rates (Y1) and overdose mortality (Y2) over the same time period. Opioid prescription rates (Y1) and overdose mortality (Y2) should be lower in states with implemented policies compared to states without such policies.

Control States
In order to perform a difference-in-difference analysis we evaluate the control states. When analyzing trends for Florida, the control states selected were Georgia, Alabama and Oklahoma. This control selection was based on the tendency for these control states to adhere to similar regulations and policy views to Florida before and after policy implementation. In addition, these states did not develop a clear policy for opioids throughout the years of analysis nor did they have confounding factors that could lead to disproportionate cases of opioid shipments and mortality, ultimately making them appropriate as control states. For the same reasons as above, the control states selected when evaluating opioid-related trends in Washington were Oregon, Colorado and Maine.

3. Data
3.1 Defining the Scope
The temporal scope includes 3 years before and after the policy changes, allowing for pre-post and difference-in-difference analyses.
The following datasets were utilized in our study:

1. Opioid Shipments dataset from Washington Post (The Washington Post, 2024)
2. Vital Statistics Mortality Data (National Center for Health Statistics, 2024)
3. Population Data (U.S. Department of Commerce, Bureau of the Census, 2024)

3.2 Opioid Shipments Dataset
This dataset details the drug transactions of pharmaceutical companies/suppliers to pharmacies between the years 2006 to 2019 inclusive. These drug transactions were reported to the Drug Enforcement Administration and lists information on the pharmaceutical companies/suppliers, pharmacies, opioid drug type, opioid drug quantity, and transaction date of sales. Given the large size of the dataset, chunking techniques are employed for efficient processing. Data for each year are segmented into smaller, manageable chunks, ensuring that memory usage is optimized during analysis.
Since different opioids have different doses and potency, conversion to Morphine Milligram Equivalent (MME) will allow for an accurate comparison as a standard unit of measurement to quantify and standardize the volume of opioids shipped.

The dataset was largely complete. Florida and Georgia had about 8 counties which did not report any shipment data for opioids. Given 1. The small population of these countries (all below 10,000 residents) 2. The negligible effect these would have in our final results – these 8 counties were excluded from the analysis.

3.3 Mortality Data

The mortality data used in this analysis comprises annual drug-related mortality records across U.S. counties from 2003 to 2015. It includes critical variables such as county names, state codes, causes of death, and death counts. To prepare this dataset for analysis, yearly files were combined, irrelevant columns removed, and variables standardized with clear naming conventions. Filtering focused on drug-related causes like overdoses and suicides and restricted the dataset to states relevant to the study. County codes were standardized into a consistent five-digit format. Data was aggregated at the county-year level to compute annual death totals. These steps ensured the dataset's reliability and readiness for evaluating opioid control policies.

Missing values were identified during the data cleaning process. Given the substantial presence of counties with missing overdose mortality data, directly addressing them was not feasible. Instead, we evaluated a predicted overdose death value for the majority of these counties. The *missing values* portion of this analysis addresses how overdose mortality was predicted using a Random Forest Model.

3.3.1 Missing Values

Once reduced to drug related mortality, many counties in our analysis states did not present data that was clear and all encompassing of drug related deaths. The chart below(Figure 1) illustrates the percentage of counties without such a metric being reported. The range of counties containing missing mortality data ranged between 46%(in FL) of all counties in a given state to as much as 84% (in GA). Among the various causes for missing data are privacy restrictions on low population counties, reporting limitations, and potential systemic challenges. The Vital Statistics Mortality dataset censors data for categories where fewer than ten deaths occur in a given county, year, or cause of death, to preserve an individual's privacy in these small communities. Zero counts are also not reported, which means counties with no drug-related deaths are absent from the dataset. Privacy thresholds disproportionately affect smaller counties with low population sizes, where fewer drug-related deaths are likely to occur, resulting in significant gaps in the dataset for these regions.

The issue is further compounded by challenges in reporting infrastructure. Counties with smaller populations often face resource constraints that impact their ability to reliably track and report mortality data. This is especially true in rural areas where healthcare access and administrative capacity may be limited. These factors, combined with restrictions on data extraction processes (e.g., limiting record pulls to 75,000 at a time), contribute to the gaps in the dataset for certain counties and states.

State	Total # of Counties	Count of Counties Missing Mortality Data	% of Counties Missing Mortality Data
GA	1,518	1,256	83%
OK	770	643	84%
AL	670	520	78%
FL	667	310	46%
CO	580	473	82%
WA	390	233	60%
OR	346	264	76%
ME	160	113	71%

Figure 1: Missing Data by States used in the Analysis

The solution to address the missing data is to first evaluate a pattern for counties that exhibit mortality data. By observing such actual data, it was observed that there is an exponential relationship among mortality due to overdose in relation to the population of a given county. This indicates that in more populated counties(larger cities & suburbs) the amount of deaths increases exponentially when compared to smaller counties. The chart below clarifies this idea, which could be attributed to various causes such drug abuse & drug commercialization being more abundant in larger cities; larger cities have a tendency to have wider access to medications that lead to overdose - a phenomenon that could be explained by hospitals, clinics and pharmacies being much more profuse in these highly populated areas.

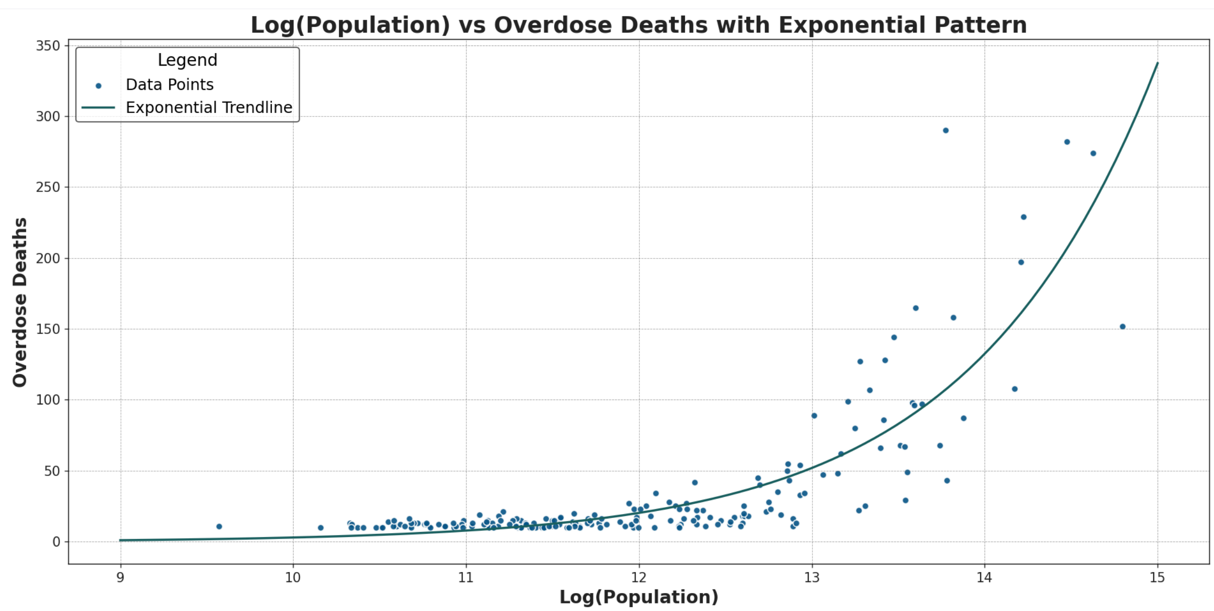

Figure 2: Relationship of Log Population and Overdose Deaths

Because the trend for overdose deaths in comparison to population followed a clear pattern, and given there was a substantial number of counties without mortality data for overdoses – our group decided to run a prediction model to fill missing overdose mortality metrics with an *estimate*. This *estimate* relies on the population size of a given county. The model is a Random forest model which was trained with the actual data that was successfully obtained from 1300 unique counties. The reason for choosing this model is because it can seamlessly identify an exponential relationship between population and overdose mortality. In addition it often functions well within datasets that have extreme outliers or missing values, as the model tends to weigh out any of the former non-conventional data points. Below there is an illustration of mortality predictions placed in parallel to actual mortality and it is clear the model successfully identified and followed exponential pattern initially observed.

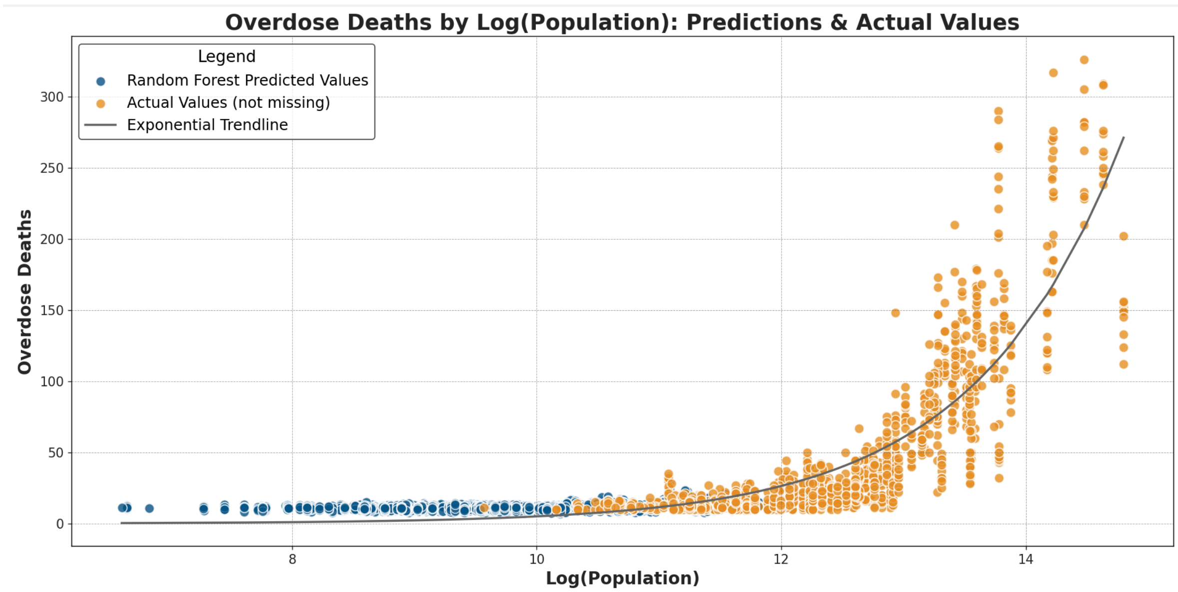

Figure 3: Actual & Predicted Overdose Deaths vs Log Population

One nuance that neither the model predicts well nor the actual values encompass them, are counties with an extremely small population. This can be seen in Figure 3 on the left side extremity of the data, where no actual values(Orange Dots) were reported. It is very plausible that due to a small population, these small counties would not have any overdose deaths even if an effort to report overdose deaths existed in the first place. It is also reasonable that the opioid crisis also reverberates into these smaller communities leading to potential cases of overdose. Yet the lack of reporting resources in these low population areas alongside restrictions on privacy for individuals makes overdose mortality in these areas very difficult to observe or predict. Because of the former reasons, to analyze mortality data that existed in the first place and mortality cases that were predicted in the Random forest model, any countries where the log-population is less than 8.5 will not be included in the subsequent steps of our analysis. The 8.5 threshold is a value obtained by the distribution of counties by log-population which you can see below. Note in the chart above how any values below 8.5 tend to deviate from the trendline and there are no actual predictors in those instances to rely upon.

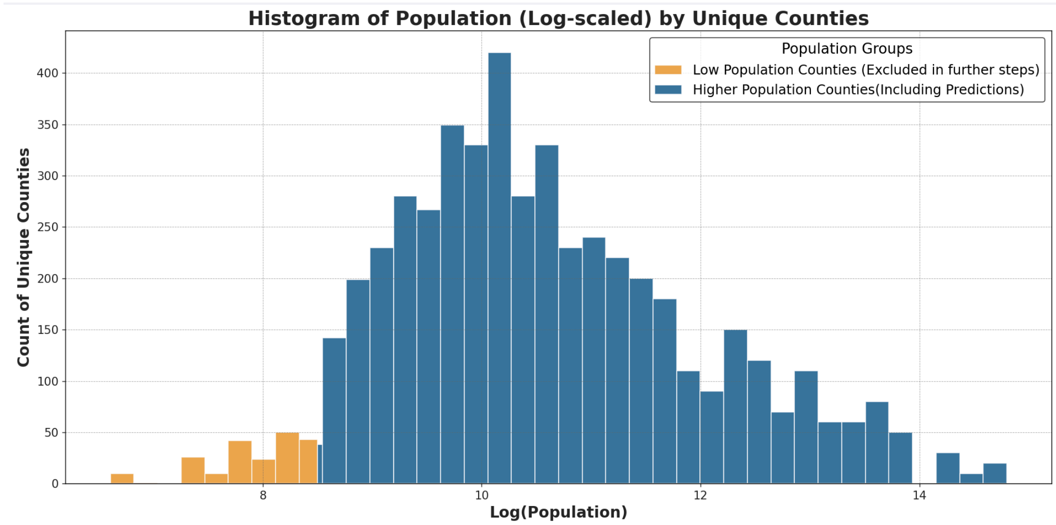

Figure 4: Histogram – Count of Unique Counties by Log Population

3.4 Population Data

The population dataset used in this analysis is derived from the table titled Population Estimates for the United States, States, and Counties, published by the U.S. Department of Commerce, Bureau of the Census, as part of the Population Estimates Program and the 2010 Decennial Census. This table was prepared by the USDA Economic Research Service, with data current as of June 20, 2024. Each row in the dataset represents county-level population estimates for a specific year.

For this analysis, the 2010 population data is used as a benchmark to control for population effects on our hypothesis. Using the 2010 data minimizes the impact of missing values compared to earlier years, such as 2000, ensuring a more robust and comprehensive foundation for the study.

4. Analysis

4.1 Pre-Post Analysis

To evaluate trends in opioid prescription rates (Y1) and overdose mortality rates (Y2) while accounting for population differences across states, we normalized these metrics by dividing them by the population of each state. This approach ensures that observed changes are not influenced by population size.
We conducted a pre-post analysis by computing the trends over a six-year period, encompassing three years before and three years after the policy change date. The image below aims to identify whether there are significant changes in the normalized metrics (Y1/population and Y2/population) following the policy implementation.

4.1.1 Washington

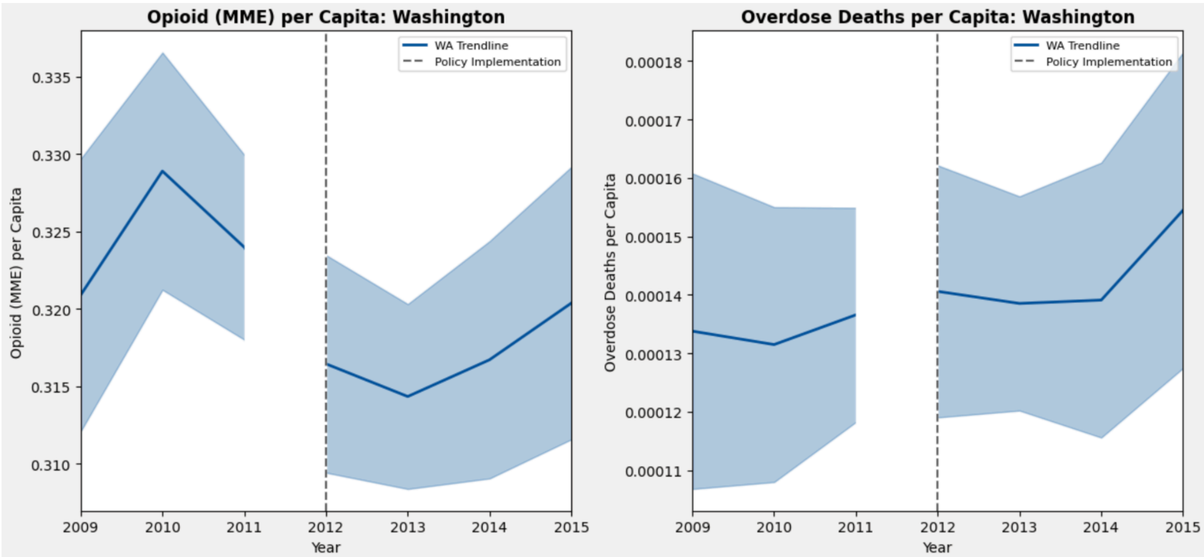

Figure 05: Pre-post Analysis for Washington

The year 2012 serves as the reference point to evaluate trends in opioid MME per capita and overdose deaths before and after Washington's policy implementation. In the three years leading up to 2012, MME per capita showed an initial increase from 2009 to 2010, followed by a gradual decline into 2012. Overdose deaths per capita, however, displayed no clear pattern, with a slight decrease from 2009 to 2010, a marginal rise from 2010 to 2011, and a subsequent decline leading into 2012. These mixed pre-policy trends suggest that external factors or random fluctuations may have influenced both opioid distribution and overdose fatalities during this period.

In the post-policy period, a more consistent trend is observed. MME per capita declined in the year immediately following 2012, potentially reflecting the initial effectiveness of the policy in reducing opioid shipments. However, this trend reversed in later years, with a gradual increase observed from 2013 to 2015. Similarly, overdose deaths per capita initially declined after 2012, mirroring the decrease in opioid distribution, but began rising sharply from 2014 onward. This post-policy rebound may point to the limitations of the policy in sustaining reductions over time or to other factors, such as increased access to illicit opioids or shifts in prescribing practices.

Overall, the analysis suggests that while the 2012 policy may have had an immediate impact on reducing opioid distribution and overdose deaths, its long-term efficacy appears limited. Additional external factors likely contributed to the observed post-policy trends. Complementary interventions and a more comprehensive approach may be needed to address the opioid crisis.

4.1.2 Florida

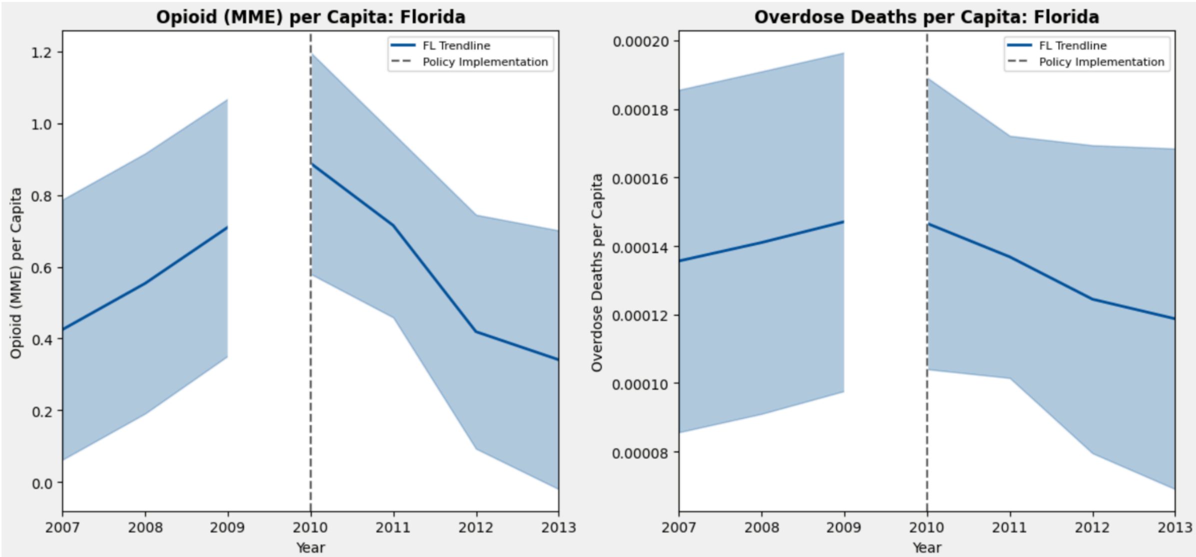

Figure 6: Pre-post Analysis for Florida

The year 2010 serves as the reference point to evaluate trends in opioid MME per capita and overdose deaths per capita before and after Florida's policy implementation. The pre-policy period (2007–2010) shows a steady increase in MME per capita, suggesting rising levels of opioid distribution leading up to the policy change. Overdose deaths per capita during this period exhibit a similar upward trajectory, which indicates a strong correlation between increasing opioid availability and overdose fatalities.

In the post-policy period (2010–2013), a significant decline in both MME per capita and overdose deaths per capita is observed. MME per capita shows a sharp and consistent downward trend immediately after 2010, suggesting that the policy effectively curtailed opioid shipments. Similarly, overdose deaths per capita also decreases steadily during this time, indicating that the reduction in opioid availability may have directly contributed to fewer overdose fatalities. Unlike Washington's trends, Florida's trends show a consistent decline with no signs of reversal. This suggests that the policy measures may have been more effective in sustaining reductions in opioid distribution and related harms.

Overall, the pre-post analysis for Florida reveals a clear reduction in both opioid shipments and overdose fatalities following the 2010 policy implementation. These findings suggest that Florida's policy measures were effective in addressing opioid-related harms during this timeframe.

4.2 Difference-in-Difference Analysis

Difference-in-Difference (DiD) is utilized as a robust method of analysis to account for external factors and isolate the causal impact of the policy change. This method estimates how much of the change in the outcome (e.g., overdoses per capita) in the treated group can be directly attributed to the policy change, while controlling for broader trends observed in the control group. By comparing the pre- and post-policy trends in both the treatment and control groups, DiD provides a clearer picture of the policy's effectiveness.

Selecting appropriate control states is essential for robust causal inference in evaluating the effects of opioid-related policies. Control states act as benchmarks, enabling accurate assessment of policy impact by comparing trends in opioid consumption and mortality. Florida's control states—Georgia, Oklahoma, and Alabama—and Washington's control states—Colorado, Maine, and Oregon—were chosen for their pre-intervention trends closely mirroring those of the treatment states. This ensures that observed post-intervention differences are attributable to the policy rather than pre-existing disparities as much as possible.

4.2.1 Washington

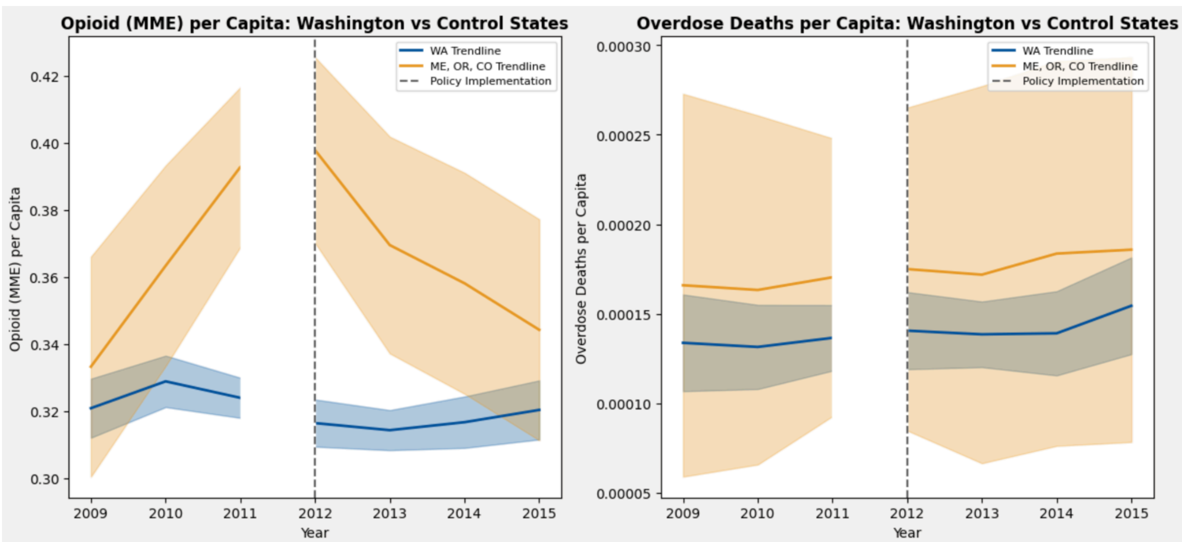

Figure 7: DiD Analysis for Opioid Consumption and Mortality Rate in Washington VS Control States Control States: Maine, Oregon, Colorado

This Difference-in-Differences (DiD) plot evaluates the impact of Washington's 2012 opioid policy by comparing trends in opioid MME per capita and overdose deaths per capita between Washington (treatment group) and the control states (Maine, Oregon, Colorado).

In the pre-policy period (2009–2011), both Washington and the control states show parallel trends in opioid MME per capita and overdose deaths, validating the comparability of the groups before the policy change. After 2012, opioid MME per capita in Washington declines slightly, but the decline is much steeper in the control states. This suggests that broader external factors may have driven reductions in opioid distribution nationwide, while Washington's policy contributed less prominently. Overdose deaths in Washington, however, exhibit a slight upward trend post-policy, contrasting with the stable trends observed in the control states. This divergence suggests that the policy may have been less effective in preventing opioid-related harm.

The DiD analysis shows limited evidence of Washington's policy significantly reducing opioid availability or overdose fatalities compared to trends in control states. Once again, complementary measures might be needed for addressing factors driving overdose deaths and to enhance the long-term effectiveness of the policy.

4.2.2 Florida

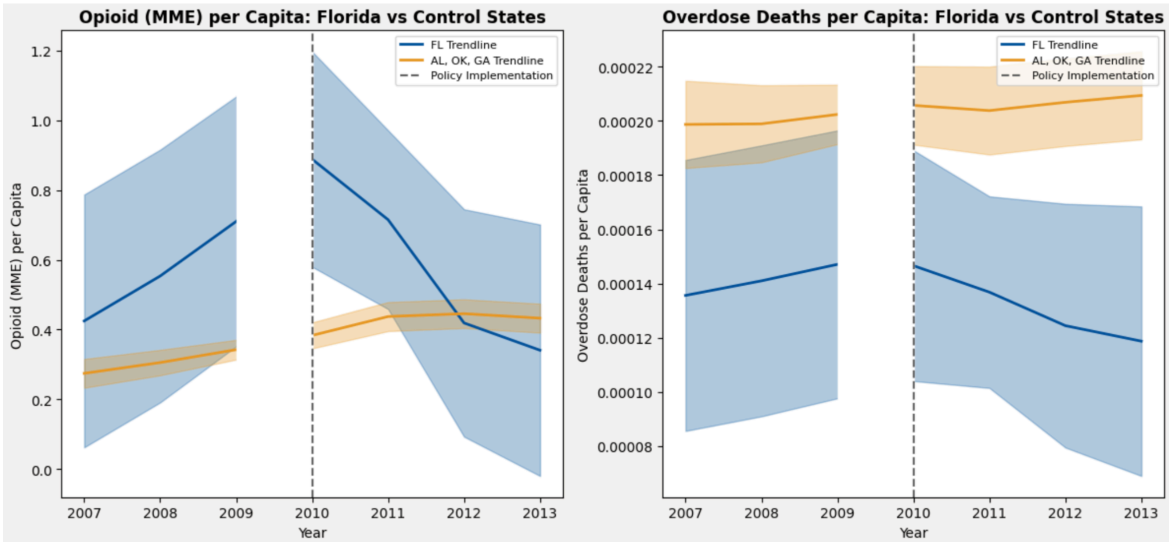

Figure 8: DiD Analysis for Opioid Consumption and Mortality Rate in Florida VS Control States
Control states: Alabama, Oklahoma, Georgia

Similarly, this Difference-in-Differences (DiD) plot compares trends in opioid MME per capita and overdose deaths per capita between Florida (treatment group) and selected control states (Alabama, Oklahoma, Georgia) to assess the impact of Florida's 2010 opioid policy.

In the pre-policy period (2007–2010), opioid MME per capita in Florida and the control states follows diverging trends. Florida exhibits a sharp upward trend, while the control states show a much smaller increase. This divergence indicates that Florida experienced significantly greater opioid distribution growth compared to the control states before the policy. Post-policy (2010–2013), opioid MME per capita in Florida shows a dramatic decline, while the control states maintain a steady but slight upward trend. This shows the significant impact of Florida's policy in reducing opioid distribution, where no comparable policy was implemented, particularly in contrast to the control states.

For overdose deaths per capita, Florida exhibits a notable decline post-policy, while the control states show a relatively stable or slightly increasing trend. The reduction in overdose fatalities in Florida aligns with the sharp decrease in opioid MME per capita, which further confirms the effectiveness of the policy implementation during this period.

5. Assumptions and Limitations

5.1 Parallel Trends

A critical assumption of DiD is the parallel trends assumption, which posits that while the policy-change state (e.g., Florida) does not need to have the same outcome levels as the non-policy-change states (e.g., control states), the two groups must exhibit similar trends prior to the policy intervention. This ensures that any divergence observed post-policy can be attributed to the policy change rather than pre-existing differences in trends. In practice, this assumption is tested by examining the pre-policy trends in the treatment and control groups. If the trends are parallel, the assumption is treated as fulfilled and the DiD analysis can reliably attribute changes in the outcome to the intervention.

5.2 Unobserved Confounders

Several factors beyond the analyzed policies may have influenced the observed trends in opioid shipments and overdose fatalities. Economic changes, national health campaigns, and public awareness efforts could have independently contributed to the declines. Variations in healthcare infrastructure, law enforcement practices, and the rise of illicit opioid markets also complicate the analysis. These unobserved confounders point to the challenges of isolating policy effects and the need to interpret results within a broader context.

6. Conclusion

This analysis examines the differing impacts of opioid policies implemented in Florida and Washington and provides a detailed understanding of their effectiveness. Florida's 2010 policy achieved significant and lasting reductions in both opioid MME per capita and overdose fatalities, which demonstrates its effectiveness in addressing opioid-related harms. In contrast, Washington's 2012 policy initially achieved reductions in opioid shipments and fatalities but struggled to sustain these improvements, with both metrics rising again in subsequent years. These outcomes show how differences in policy design and implementation can shape long-term success in addressing public health crises like the opioid epidemic.

Our findings suggest that Florida's approach, with its sustained impact, may serve as a blueprint for other states facing similar challenges. However, Washington's experience shows the importance of accounting for broader systemic factors, such as illicit opioid markets and regional differences, that may limit the efficacy of such policies. Policymakers must also prioritize ongoing monitoring and adaptive strategies to ensure sustained effectiveness over time. Overall, this study contributes to the growing evidence base on the role of well-crafted, evidence-driven policies in combating the opioid crisis.

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