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

Our analysis uses two statistical methods to measure the impact of opioid policies on prescription volumes and overdose rates: **pre-post analysis** and **difference-in-difference analysis**. Pre-post analysis compares changes within each state before and after the policy was implemented, allowing us to observe immediate effects. Difference-in-difference analysis compares changes in states with policies (Florida and Washington) to those in similar states without such policies, helping us isolate the policy's impact by accounting for broader trends. These methods provide valuable insights into how effective the policies were at reducing opioid use and overdose deaths.

Research Question

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

Approach and Expected Outcomes
To answer this question, we focus on two key outcomes: opioid prescription rates and overdose mortality rates. Building on the **pre-post analysis** and **difference-in-difference analysis** methods*,* our analysis links these methods to specific expected outcomes:

- **Within-State Trends:** By assessing changes in prescription and mortality rates before and after policy implementation in Florida and Washington, we evaluate the immediate effects of the interventions. If the policies are effective, we anticipate reductions in both opioid prescription rates and overdose mortality in these states following the intervention.
- **State Comparisons:** To isolate the policies' impact from broader trends, we compare Florida and Washington to similar states without such policies. We expect greater reductions in prescription rates and overdose mortality in the states implementing these policies, which highlights the effectiveness of the interventions in combating the opioid crisis.

Control States
It is essential to carefully select control states when conducting a difference-in-differences (DiD) analysis. Control states can act as benchmarks to better isolate the effects of opioid policies by accounting for broader trends and external factors unrelated to the interventions. Florida, Georgia, Alabama, and Oklahoma were selected as control states due to their similar regulatory environments and policy views before and after policy implementation. These states also lacked significant opioid-related policies during the study period and were free from major confounding factors, such as substantial shifts in healthcare infrastructure, that could skew opioid shipment or mortality data. Similarly, Oregon, Colorado, and Maine were chosen as control states for Washington based on analogous criteria.

Why Difference-in-Differences?
A simple pre-post analysis evaluates changes in prescription and mortality rates within a state over time. However, such an approach cannot account for broader trends or external influences that may occur concurrently with the policy. For example, national opioid awareness campaigns may independently reduce prescription rates and overdose deaths; economic changes, such as a recession, could affect opioid use differently across regions; or variations in healthcare access and reporting practices might influence observed outcomes. The DiD method effectively addresses this limitation by comparing trends in treated and control states, isolating the policies' impact under the assumption that treatment and control states would have followed parallel trends without the intervention. While no statistical method can eliminate all confounding influences, DiD provides a stronger framework for evaluating the policies' specific impact.

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 (Morphine Grams Per Capita) 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 a few counties which did not report any shipment data for opioids. Given the small population of these countries (all below 10,000 residents), we assume there are 0 shipments to them.

3.3 Mortality Data

The mortality data for this analysis is sourced from the US Vital Statistics records, which provide annual counts of drug-related and non-drug-related deaths for all U.S. counties from 2003 to 2015. This dataset includes county identifiers, years, causes of death, and death counts. To ensure reliable analysis, we focused on unintentional drug overdoses, the most consistently reported category, reducing the risk of compounding missing data issues inherent in less frequently reported categories like overdose suicides or undetermined overdoses. The data was aggregated at the county-year level to compute annual deaths by county, aligning with the study's focus on analyzing annual trends over time. These steps prepared the dataset for evaluating opioid-related mortality patterns with confidence in its relevance and reliability.

Missing values were identified during data preparation. 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). This substantial level of missing data is primarily driven by privacy restrictions.

Privacy restrictions play a major role in this issue, as data for categories with fewer than ten deaths in a given county, year, or cause of death are censored to protect individual privacy. Zero counts are also not reported, meaning counties with no drug-related deaths are absent from the dataset. These restrictions disproportionately affect counties with lower populations, where drug-related deaths are less frequent, creating significant gaps in the data.

In addition to privacy restrictions, challenges in reporting infrastructure further contribute to missing data. Smaller, rural counties often face resource constraints, such as limited healthcare access and administrative capacity, which restrict their ability to reliably track and report mortality data. These systemic challenges may increase the gaps in coverage, particularly in regions with fewer resources to maintain consistent record-keeping and reporting processes. For instance, the National Rural Health Association (2022) points out that public health systems in rural areas often operate with insufficient funding and infrastructure, which limits their capacity to collect and manage health data effectively. Similarly, the U.S. Department of Agriculture Economic Research Service (2022) reports that rural counties experience chronic disparities in healthcare access and infrastructure, which exacerbate difficulties in maintaining accurate health records and contribute to gaps in mortality data.

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 approach to address the issue of missing data begins with the evaluation of patterns within counties that do report overdose mortality statistics. A thorough analysis of the actual data revealed a positive relationship between overdose-related mortality rates and the population size of a given county. Specifically, this relationship suggests that more populous regions—such as larger metropolitan areas and their surrounding suburbs—tend to experience a higher incidence of drug overdose cases, proportional to their population size. The accompanying chart further demonstrates this trend: as the population of a county increases, so too does the frequency of overdose deaths. The chart employs a logarithmic scale for population size, rather than raw figures, in order to facilitate a clearer visual representation of this correlation - ultimately making it easier to interpret this positive pattern.

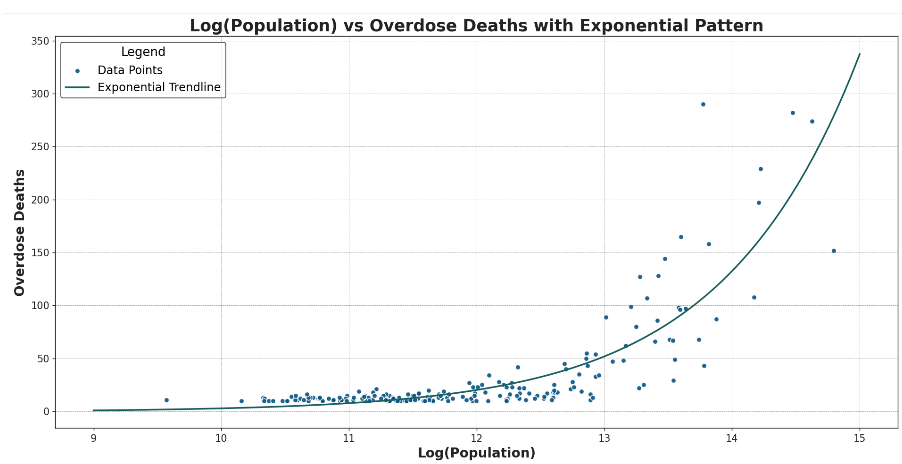

Figure 2: Relationship of Log Population and Overdose Deaths

Given the notorious positive relationship between overdose fatalities and population size and the considerable absence of mortality data for overdose deaths in missing-value counties, our team decided to implement a predictive modeling approach to estimate the missing overdose mortality figures. This estimation utilizes the population size of each county as a predictor. Specifically, we employed a Random Forest model, which was trained on actual data collected from 1,300 counties. The reason for selecting this particular model lies in its capacity to capture and quantify the nuanced relationship between population size and overdose mortality rates for counties where data is absent. The model imputes missing values by referencing counties of comparable population sizes, while simultaneously controlling for variations across state-year attributes. The chart below illustrates the predicted mortality rates against the actual observed values demonstrating that the model effectively captures and mirrors the initially observed positive trend.

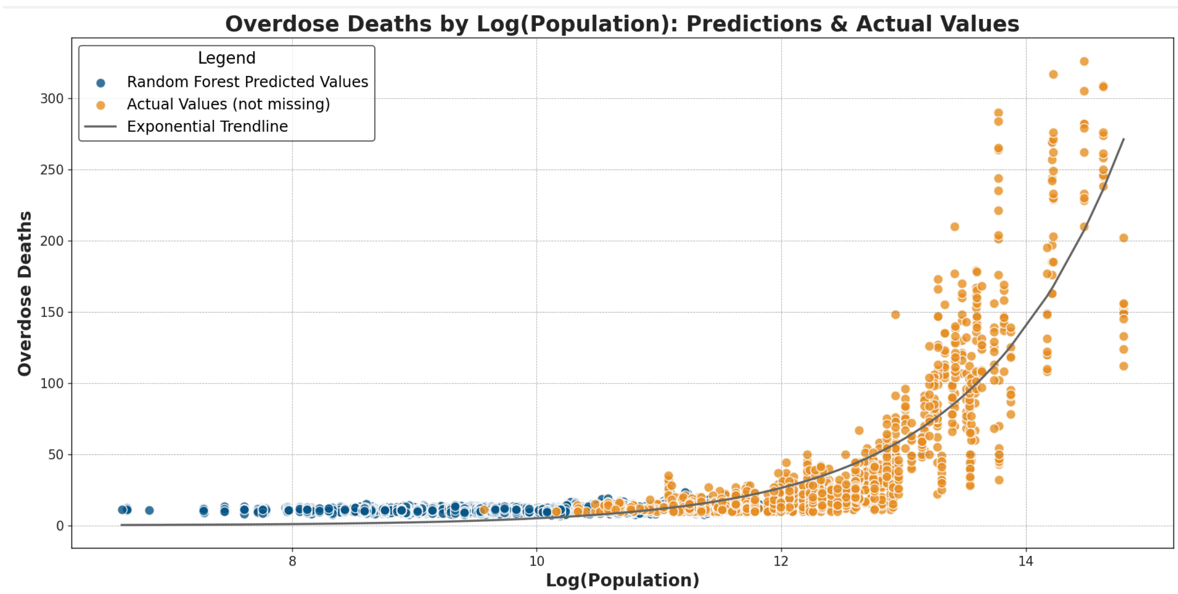

Figure 3: Actual & Predicted Overdose Deaths vs Log Population

One nuance that the model predicts fails to predict well are counties with an extremely small population. This can be seen in Figure 3 on the left side extremity of the data, where practically no actual mortality 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 these fatalities existed in the first place. It is also reasonable that the opioid crisis reverberates into these smaller communities leading to potential cases of overdose. Yet, in these low population areas, reporting restrictions for resident privacy and the potential of the non-occurrence of overdose cases(discussed in *Missing Values 3.3.1 Section*), makes overdose-related mortality difficult to observe or predict. Due to 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 counties where the population is less than 9,000 individuals will no longer be included in the subsequent steps of our analysis. The 9,000 threshold is a value obtained from the distribution of unique counties by population size which you can see below; This cutoff eliminates the bottom 15%(~ 500 counties) from all states being analyzed in our original dataset, including treated and controlled states used in the difference in difference approach.

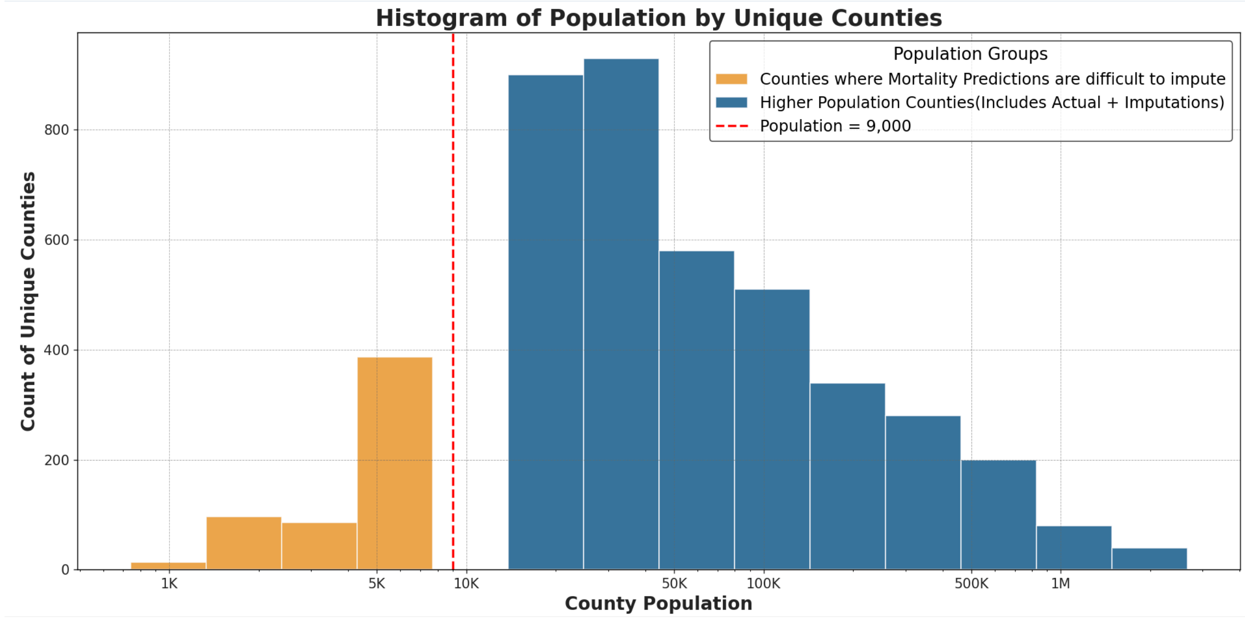

Figure 4: Histogram – Count of Unique Counties by Log Population

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 and overdose mortality rates 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.

To evaluate opioid prescription rates over time, we normalized the data by calculating the grams of morphine prescribed per capita, divided by the population of each state (illustrated in the left plots of Figures 5 and 6). Similarly, to assess overdose mortality rates, we normalized the data by computing the number of overdose deaths per 100,000 people, adjusted for the population of each state (shown in the right plots of Figures 5 and 6). These normalization techniques facilitate more accurate cross-state comparisons by controlling for population size variations.

The figures below focus on identifying significant changes in the normalized metrics following policy implementation in Washington and Florida. By examining trends in grams of morphine prescribed per capita and overdose deaths per 100,000 people, this analysis underscores the potential impact of policy changes on opioid prescription patterns and overdose mortality rates within these states.

4.1.1 Washington

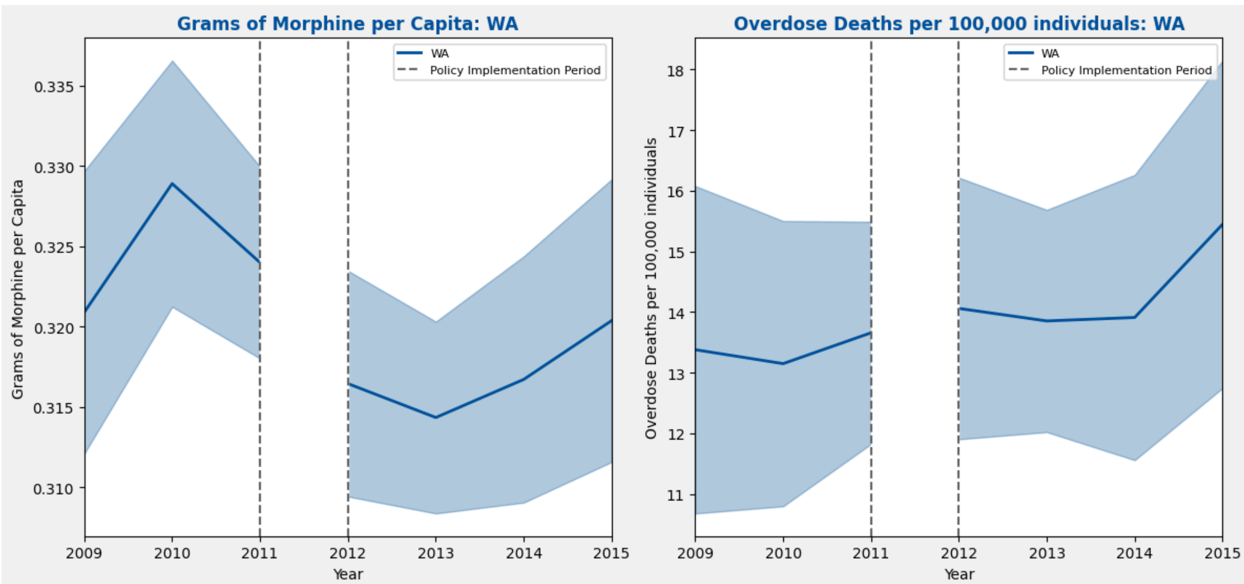

Figure 05: Pre-post Analysis for Washington

Using the normalized metrics, the year 2012 serves as the reference point for evaluating trends in opioid grams per capita and overdose deaths per capita before and after Washington's policy implementation. In the three years leading up to 2012, Grams of Morphine per capita showed an initial increase from 2009 to 2010, followed by a decline into 2011. Overdose Deaths per 100,000 individuals, however, displayed no clear pattern, with a slight decrease from 2009 to 2010, a marginal rise from 2010 to 2011. These mixed pre-policy trends suggest that external factors or random fluctuations may have influenced both opioid distribution and overdose deaths during this period.

In the post-policy period, a more consistent trend is observed. Grams of Morphine 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

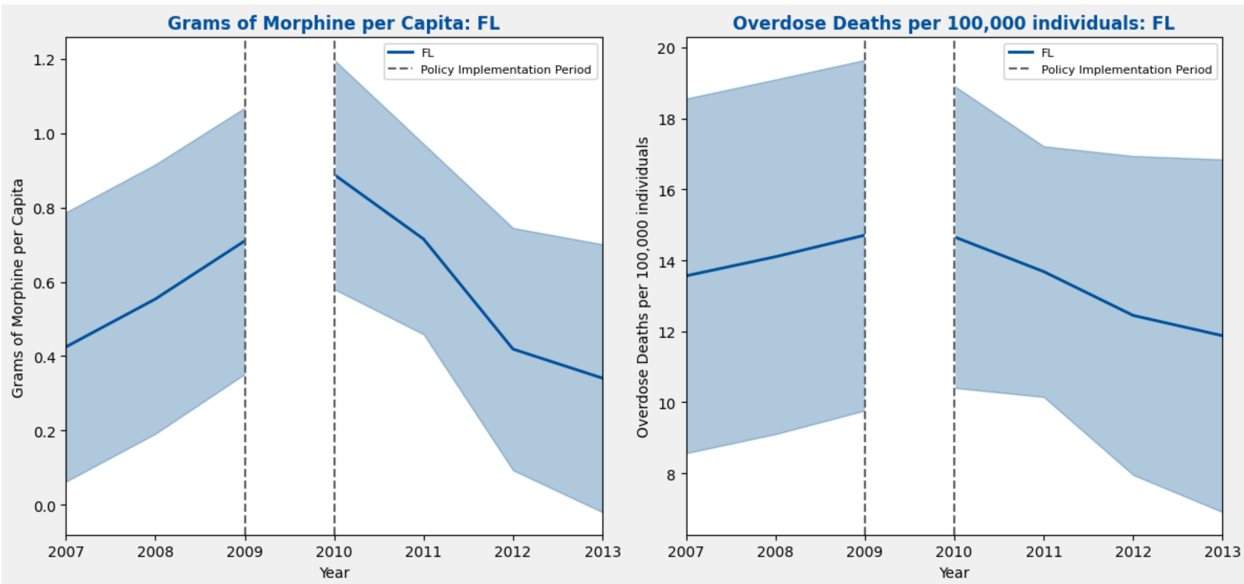

Figure 6: Pre-post Analysis for Florida

Using the normalized metrics, the year 2010 serves as the reference point for evaluating trends in opioid grams per capita and overdose deaths per 100,000 individuals before and after Florida's policy implementation. During the pre-policy period (2007–2010), the data reveal a consistent increase in Grams of Morphine per capita prescribed per capita, highlighting a growing trend in opioid distribution leading up to the policy change. Overdose Deaths per 100,000 individuals during the same period also show a parallel upward trajectory, indicating a strong association between rising opioid availability and the escalation of overdose fatalities. These patterns underscore the critical context for assessing the policy's impact on mitigating these trends.

In the post-policy period (2010–2013), a significant decline in both Grams of Morphine per capita and Overdose Deaths per 100,000 individuals is observed. Grams of Morphine per capita shows a sharp and consistent downward trend immediately after 2010, suggesting that the policy effectively curtailed opioid shipments. Similarly, Overdose Deaths per 100,000 individuals 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

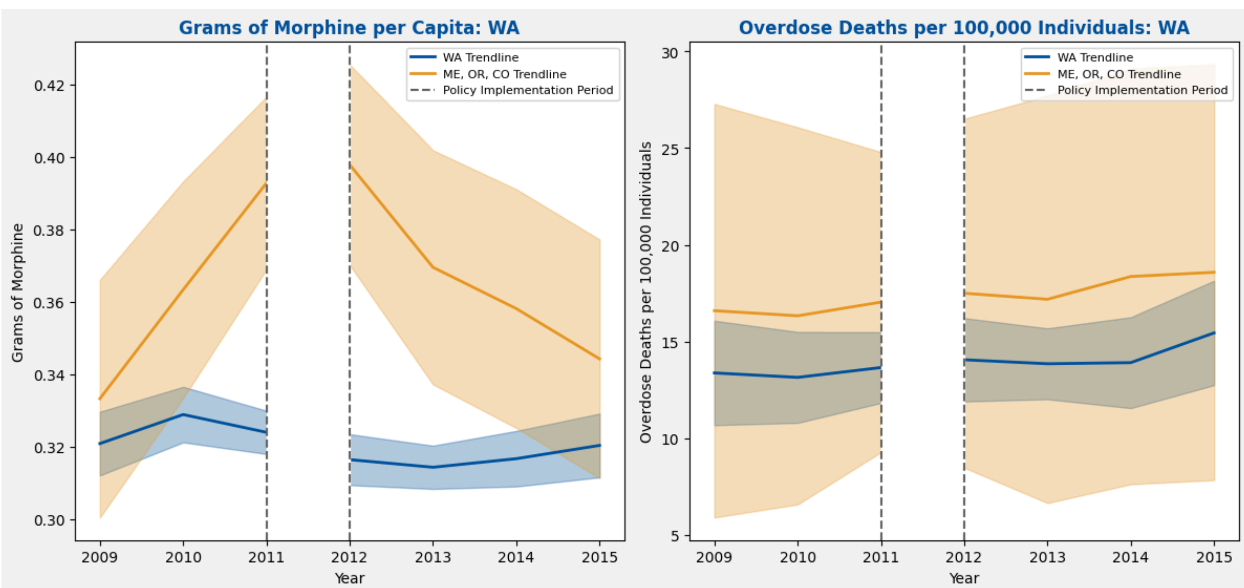

Figure 7: DiD Analysis for Opioid Consumption and Mortality Rate in Washington VS Control States Control States: Maine, Oregon, Colorado

This Difference-in-Differences (DiD) plot evaluates the impact of Washington's 2012 opioid policy by comparing trends in opioid Grams 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 Grams per capita and overdose deaths, validating the comparability of the groups before the policy change. After 2012, opioid Grams 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

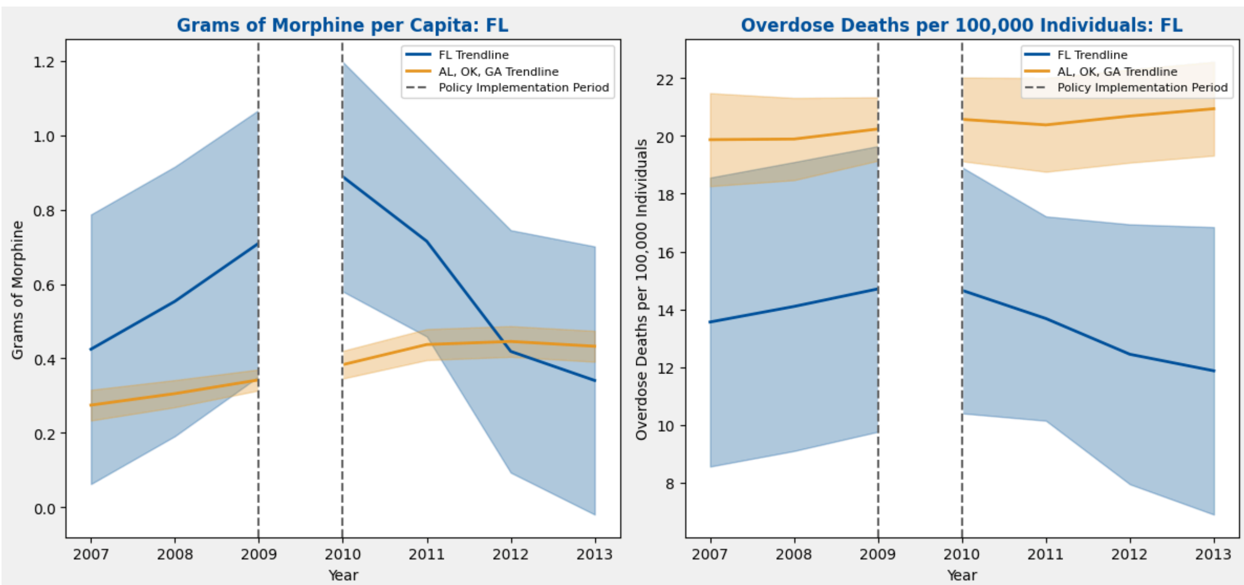

Figure 8: DiD Analysis for Opioid Consumption and Mortality Rate in Florida VS Control States
Control states: Alabama, Oklahoma, Georgia

Similarly, this Difference-in-Differences (DiD) plot compares trends in opioid Grams 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 Grams 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 Grams 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 Grams 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 Grams 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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