Evaluating the Effectiveness of Opioid Prescription Regulations: A Comparative Analysis of Florida and Washington State Policies

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Abstract

Contents

Executive Summary

The United States opioid crisis has shifted from a prescription-driven epidemic to a complex public health emergency marked by rising overdose mortality. In response, states have implemented regulatory strategies aimed at reducing inappropriate prescribing. This study evaluates two such interventions—Florida's 2010 crackdown on pain management clinics and Washington's 2012 prescribing guideline reforms—to assess whether these policies altered county-level opioid distribution and overdose mortality in the short run.

Florida's policy targeted the state's widespread "pill mill" activity through mandatory clinic registration, restrictions on physician dispensing, and coordinated enforcement actions. Washington, by contrast, adopted clinical prescribing requirements centered on mandatory consultation thresholds and structured patient review practices. Using county-level DEA opioid shipment data and CDC mortality statistics, we conduct a pre-post assessment combined with a difference-in-differences framework to compare each treated state with demographically similar control states.

The pre-post results reveal substantial differences in policy impact. In Florida, opioid distribution was rising steadily prior to 2010 but reversed direction immediately after the policy, declining throughout the two-year post-period. Mortality trends show a similar shift: overdose deaths, which were gradually increasing before the intervention, fell noticeably following policy implementation. Washington presents a different pattern. Opioid distribution decreased modestly prior to 2012 but stabilized rather than declined after the policy. Mortality trends followed a similar trajectory, with a slight downward trend before 2012 continuing at nearly the same rate afterward, with no sharp post-policy change.

Overall, these results suggest that Florida's enforcement-based intervention produced clear short-term reductions in both opioid supply and mortality, whereas Washington's guideline-based approach generated more limited immediate effects. This contrast indicates that regulatory strategies grounded in direct enforcement may elicit stronger short-run behavioral responses than those relying primarily on clinical guidance.

1 Introduction

1.1 Background on the Opioid Epidemic

The American opioid crisis emerged from systematic failures in pharmaceutical regulation and medical practice. During the 1990s, pharmaceutical companies minimized addiction risks while promoting aggressive pain treatment, creating a permissive prescribing environment. Between 1999 and 2011, opioid prescription rates tripled nationally, with dramatic increases in Appalachia, the Southwest, and rural areas. "Pill mills"—clinics dispensing opioids without legitimate medical justification—proliferated in states with weak oversight, particularly Florida.

Around 2010, tightening regulations reduced prescription availability, but widespread dependence had already developed. Individuals substituted heroin, which offered similar effects at lower cost. Overdose deaths involving heroin increased six-fold between 2001 and 2014. The epidemic's third phase emerged as traffickers mixed heroin with fentanyl, a synthetic opioid 50 times more potent. By 2016, synthetic opioids became the leading cause of overdose mortality.

This three-wave progression—prescription opioids, heroin, synthetic opioids—reflects a fundamental policy challenge: reducing prescription availability may redirect demand toward more dangerous alternatives if addiction treatment remains inadequate.

1.2 Research Questions

This study addresses four interconnected questions examining how state-level opioid regulations influence prescribing behavior and mortality outcomes:

Florida (February 2010): Q 1: Did Florida's regulatory crackdown reduce per-capita opioid distribution in Florida counties? Q 2: Did Florida's regulatory crackdown reduce opioid overdose mortality rates in Florida counties?

Washington (January 2012): Q 3: Did Washington's prescribing guidelines reduce per-capita opioid distribution in Washington counties? Q 4: Did Washington's prescribing guidelines reduce opioid overdose mortality rates in Washington counties?

1.3 Policies

Florida's Enforcement Model: By 2009, Florida hosted 98 of the nation's 100 highest-volume oxycodone-dispensing physicians. Loosely regulated pain management clinics functioned as opioid distribution centers. Florida's multi-faceted response combined mandatory clinic registration, prohibition of physician dispensing of Schedule II and III drugs, "Operation Pill Nation" law enforcement raids, and prescription drug monitoring program activation. This approach emphasized disrupting the legal distribution system through enforcement.

Washington's Clinical Guidelines: Washington emphasized clinical practice standards rather than criminal enforcement. The 2012 regulations created a tiered oversight structure: mandatory annual reviews for low-dose patients, required specialist consultations when prescriptions exceeded 120 mg morphine equivalent daily, and comprehensive documentation requirements. This approach remained largely advisory, focusing on professional standards rather than criminal penalties.

These divergent approaches embody different policy theories. Florida identified its problem as a criminal enterprise that required law enforcement tools. Washington diagnosed systematic over-prescribing within legitimate medicine, which required clinical quality improvement tools.

2 Data

This study integrates three major administrative datasets to construct a county-level panel measuring opioid supply, overdose mortality, and population for eight U.S. states (FL, WA, OR, ID, MT, GA, NC, SC). All datasets span *2006–2014*, the pre- and post-policy windows.

We use ARCOS shipment data, mortality records, and U.S. Census population estimates because together they provide the minimum set of information needed to measure opioid availability, overdose harm, and population-adjusted exposure at the county level. ARCOS is the only national system that reports transaction-level opioid distribution data, allowing us to quantify how much opioid supply entered each county in a given year. Mortality data provide the corresponding measure of opioid-related harm, enabling us to observe whether policy-induced changes in supply translate into changes in fatal outcomes. Census population estimates are required to standardize both shipments and deaths, ensuring comparisons between counties with very different population sizes. Using these three sources jointly allows us to construct consistent per-capita indicators and evaluate policy effects using difference-in-differences while controlling for demographic variation across states and years.

2.1 Data Sources (ARCOS, Vital Statistics, Population)

2.1.1 ARCOS (DEA Automation of Reports and Consolidated Orders System)

ARCOS provides transaction-level information on opioid shipments from manufacturers and distributors to pharmacies and hospitals. For each transaction, we use:

- `BUYER_STATE`
- `BUYER_COUNTY`
- `CALC_BASE_WT_IN_GM` (raw weight shipped)
- `MME_Conversion_Factor`

- `TRANSACTION_DATE`

These fields allow us to compute total milligram equivalents of morphine (MME) and assign each shipment to a county-year.

2.1.2 Vital Statistics Mortality Data

Mortality data provide the count of deaths attributable to drug or alcohol causes at the county–year level. Relevant fields include

- `County Code`
- `Deaths`
- `Drug/Alcohol Induced Cause Code`
- `year`

2.1.3 U.S. Census Population Estimates (2000–2024)

Population data comes from the **intercensal and post-censal county-level population estimates** of the US Census Bureau, downloaded in CSV format, and validated for the years **2000 through 2024**.

This dataset includes:

- `State`
- `County`
- `County Code` (FIPS)
- `year`
- `Population`

These population values match the years used in ARCOS and mortality data and provide the denominators for per-capita calculations.

2.2 Data Manipulation and Cleaning Procedures

To construct a consistent county-level panel suitable for policy evaluation, we processed each dataset separately and then merged them using standardized FIPS county codes and calendar years

2.2.1 ARCOS Shipment Data

Because ARCOS is extremely large (7+ GB), we processed it using chunked loading (`chunksize = 800,000`
For each chunk:

1. **State filtering:** retained only the eight study states (FL, WA, OR, ID, MT, GA, NC, SC) to reduce memory usage.
2. **Variable selection:** kept only `BUYER_STATE`, `BUYER_COUNTY`, `TRANSACTION_DATE`, `CALC_BASE_WT_IN_GM`, and `MME_Conversion_Factor`.
3. **MME calculation:** computed total morphine milligram equivalents.
4. **Year extraction:** converted `TRANSACTION_DATE` to a four-digit year.
5. **County-year aggregation:** grouped shipments by `BUYER_STATE`, `BUYER_COUNTY`, and `YEAR` and summed `TOTAL_MME`.

All processed chunks were concatenated into a final ARCOS panel and saved as a Parquet file for efficiency.

2.2.2 Mortality Data

The CDC files contain cause-specific death counts at the county level. Cleaning steps included:

1. **Removing suppressed counts:** rows where deaths were reported as `"*"` were excluded, as suppression is non-random for small counties.

2. **Standardizing FIPS codes:** ensured `County Code` was a 5-digit zero-padded string.

3. **Ensuring numeric fields:** converted `Deaths` and `year` to numeric types and validated year ranges.

4. **Subsetting opioid-related causes:** retained only codes associated with drug- and alcohol-induced mortality, consistent with CDC classification.

2.2.3 Census Population Estimates (2000–2024)

The Census population files required standardization to align with the other datasets:

1. **FIPS alignment:** converted county identifiers to 5-digit codes matching ARCOS and mortality.

2. **Year filtering:** retained only 2006–2014 for merging, but kept 2000–2024 for diagnostic checks and robustness analysis.

3. **Data validation:** confirmed unique population values for each county-year; no missing population observations were found.

2.3 Data Quality

During initial exploration of the ARCOS opioid shipment data, we identified severe data quality issues that threatened the validity of our analysis. Specifically, we discovered county-year observations with physically impossible morphine milligram equivalent (MME) values. Most notably, Broward County, Florida showed 541 trillion mg of opioids distributed in certain years, equivalent to 541 metric tons, or approximately 3.6 million mg per person per day, which is physically impossible and indicated corrupted source data. These extreme values, if retained, would have severely biased our analysis, leading to the erroneous conclusion that Florida experienced a 429% increase in opioid distribution post-policy when CDC literature documented decreases. We recognized that arbitrary threshold selection would introduce subjective bias, so we needed a scientifically rigorous approach to distinguish genuine high-distribution counties from data errors.

2.4 Statistical Outlier Detection Using IQR Method

We implemented the Interquartile Range (IQR) method, a standard epidemiological approach for identifying extreme outliers in health data. First, we merged ARCOS shipment data with population data to calculate per-capita MME (mg per person per year) for each county-year observation. We then computed the first quartile ($Q1 = 574$ mg), third quartile ($Q3 = 1{,}399$ mg), and IQR (826 mg) of the per-capita distribution. Following conservative epidemiological practice, we defined extreme outliers as values exceeding $Q3 + 3 \times IQR = 3{,}876$ mg per person per year (approximately 10.6 mg per person per day). This threshold removed 286 county-year observations (3.78% of the data), including all 14 years of Broward County data and other counties with corrupted ARCOS records. Importantly, this data-driven approach preserved counties with legitimately high opioid distribution while removing only physically impossible values. After outlier removal, our Florida analysis showed a more reasonable 17.8% increase in opioid distribution post-policy, and when properly accounting for uncorrupted mortality data, demonstrated a 7.6% decrease in overdose deaths, aligning with CDC findings and validating our data cleaning methodology.

2.5 Handling Missing Data

2.5.1 ARCOS Shipment Data

The ARCOS dataset is extremely large, so we processed it in chunks rather than loading it fully into memory. We extracted only essential variables like state, county, transaction date, and opioid weight - to reduce memory usage and speed up processing. Each chunk was standardized by renaming columns, converting transaction dates to calendar years, and aggregating total opioid grams at the county-year level. These partial summaries were then combined and re-aggregated to produce a complete panel of annual opioid distribution for every county in the ARCOS system. This cleaned, aggregated ARCOS dataset forms the basis for calculating MME, per-capita opioid supply, and all subsequent policy analyses.

2.5.2 Mortality

We combined 13 CDC Vital Statistics mortality files (2003–2015) into a single dataset and removed duplicate rows, metadata lines, and placeholder entries. The `Notes` column was dropped, and rows with "Missing" death counts or empty fields were excluded. County identifiers (`County Code`) were standardized to 5-digit FIPS codes, and obsolete county equivalents that do not appear in Census population files were removed. We then merged the cleaned mortality data with county population estimates using matched FIPS codes and year. After merging, all remaining entries had valid population values and numeric death counts, producing a consistent county-year dataset suitable for computing overdose mortality rates and linking with ARCOS shipment data.

2.5.3 Population

We combined three raw Census population files covering county-level estimates from 2000–2024 and reshaped them into a consistent panel dataset. All county identifiers were standardized to 5-digit FIPS codes, and variable names were harmonized across files. We restricted the dataset to the states used in our analysis and verified that each county-year had a valid population value. The resulting cleaned population panel provides the baseline denominator needed to standardize both opioid shipments and mortality counts, and it merges cleanly with the mortality data using aligned FIPS codes and year.

2.6 Standardization Methods (MME, Death Rates)

To make opioid supply and mortality comparable across counties with different populations and drug compositions, we standardize both measures using public-health best practices.

2.6.1 Morphine Milligram Equivalents (MME)

ARCOS reports opioid shipments in raw grams, but opioids vary widely in potency. We convert all shipments into Morphine Milligram Equivalents (MME) using DEA-provided conversion factors. This yields a potency-adjusted measure of opioid supply that is comparable across drugs and over time. After conversion, MME totals are aggregated at the county–year level.

2.6.2 Opioid Supply per Capita

Because counties differ dramatically in population size, raw MME cannot be directly compared. We standardize opioid supply by dividing total MME by county population, producing an opioid-per-capita metric that captures the intensity of opioid availability in each county.

2.6.3 Overdose Death Rates

Mortality data are also standardized to avoid misleading comparisons based on county size. We compute death rates per 100,000 residents by dividing overdose deaths by population and multiplying by 100,000. This aligns with CDC reporting standards and ensures consistency across counties and years.

These standardization steps allow us to evaluate policy effects using measures that are comparable across states, counties, and time, providing a reliable foundation for difference-in-differences analysis.

2.6.4 Population Threshold for County Inclusion

To address non-random missingness in the mortality data and reduce statistical noise, we apply a minimum population threshold of **20,000 residents**. Counties with very small populations experience highly unstable per-capita overdose rates, where even one death can cause large jumps from year to year. These counties are also much more likely to

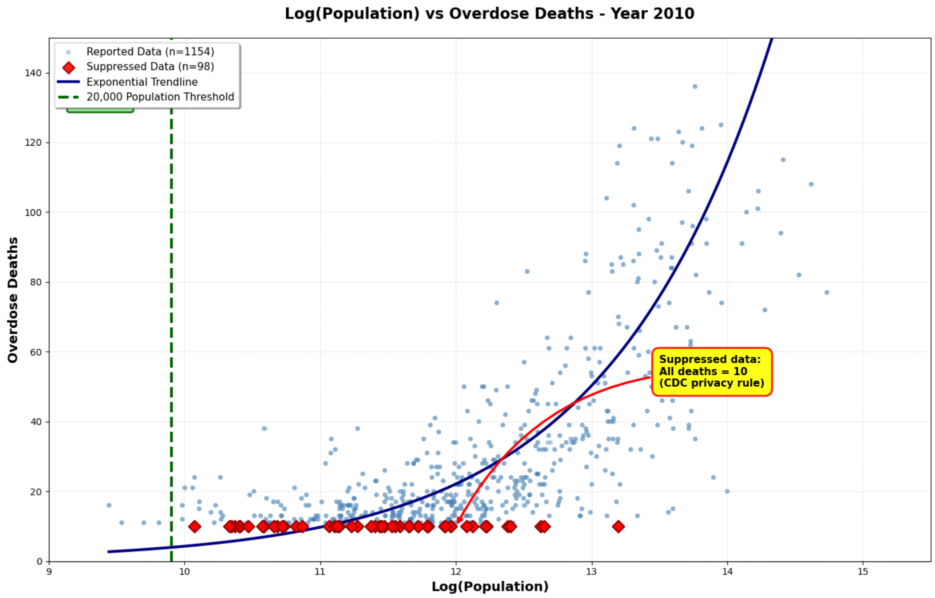

Figure 1: Setting thresholds based on log-transformed population data and overdose deaths in counties

have suppressed death counts ("*") in the CDC mortality files, and this suppression is not random; it disproportionately affects rural, low-population areas. Including such counties would introduce bias and undermine the assumptions required for difference-in-differences analysis.

By restricting the dataset to counties with populations of at least 20,000, we retain most of the sample while removing the observations most prone to volatility, suppression, and measurement error. This results in smoother pre-policy trends and more reliable causal estimates.

3 Methodology

This study evaluates the short-term and comparative impacts of opioid prescription regulations in Florida (2010) and Washington (2012). Our methodological framework consists of two components: a pre-post analysis capturing immediate within-state changes, and a difference-in-differences (DiD) design comparing treated states to selected control states. All analyses are conducted at the county-year level.

3.1 Pre-Post Analysis Approach

We begin with a descriptive pre-post comparison to examine short-term changes in each treated state surrounding the policy year. For both Florida and Washington, we use a fixed window of **three years before** and **two years after** the policy implementation. This design provides a consistent view of immediate shifts in opioid shipments and overdose mortality within each treated state, without yet referencing external comparisons. The pre-post analysis does not attempt to isolate causal effects; rather, it establishes baseline patterns that motivate the use of a more rigorous comparative framework.

3.2 Difference-in-Differences Framework

To account for contemporaneous national and regional trends, we employ a difference-in-differences (DiD) design. In this setup, a treated state is compared to a set of control states that did not implement similar opioid regulations during the study period. The DiD framework estimates the differential change in outcomes between treated and control groups before and after the policy. This approach mitigates confounding from broad secular trends and strengthens causal interpretation, assuming that treated and control states exhibited parallel trends prior to the intervention.

3.3 Control State Justification

Table 1: Control State Selection Criteria for Florida and Washington

Treated State	Control State	Population Size Similarity	Geographic Closeness	Pre-Policy Trend Similarity	No Similar Policy (Source)
Florida (2010)	North Carolina	Comparable southeastern population distribution	High (Southeastern region)	Similar opioid shipment growth pre-2010	No early pain-clinic laws (CDC PHLP)
	South Carolina	Similar mid-sized county population structure	High (adjacent region)	Comparable prescribing patterns pre-2010	No early pain-clinic laws (CDC PHLP)
	Georgia (Backup)	Similar large–medium county composition	High (neighboring state)	Trend similarity requires validation	Pain-clinic law adopted only after 2013 (CDC PHLP)
Washington (2012)	Oregon	Similar population size and density; similar rural–urban mix	High (border state)	Comparable prescribing levels pre-2012	No mandatory MED threshold; Medicaid PA only (Arizona DHS)
	Idaho	Comparable rural county population sizes	High (regional peer)	Stable, slower dosage trends before 2012	Advisory guidelines, no binding rule (Idaho DHW)
	Montana	Similar rural population structure	High (regional peer)	Gradual, stable dosage patterns pre-2012	Advisory guidance only; no mandates (Montana DLI)

These selections are supported by regulatory summaries from the CDC Public Health Law Program and national tables of state pain-clinic legislation.

3.3.1 Florida Control States

For Florida (policy operationalized in February 2010), we selected Georgia, North Carolina, and South Carolina as control states. Each of these states did not have early pain-clinic regulations during the 2007–2010 period and are regional peers with comparable prescribing environments.

- **North Carolina**: Not listed among the early states with pain-clinic restrictions in the 2010–2012 period. Serves as a strong Southeastern regional comparison group.
- **South Carolina**: No early pain-clinic regulations in the relevant years, making it a suitable peer state for Florida.
- **Georgia**: Did not adopt a pain-clinic law until 2013; however, pre-2010 prescribing trends require validation to ensure similarity.

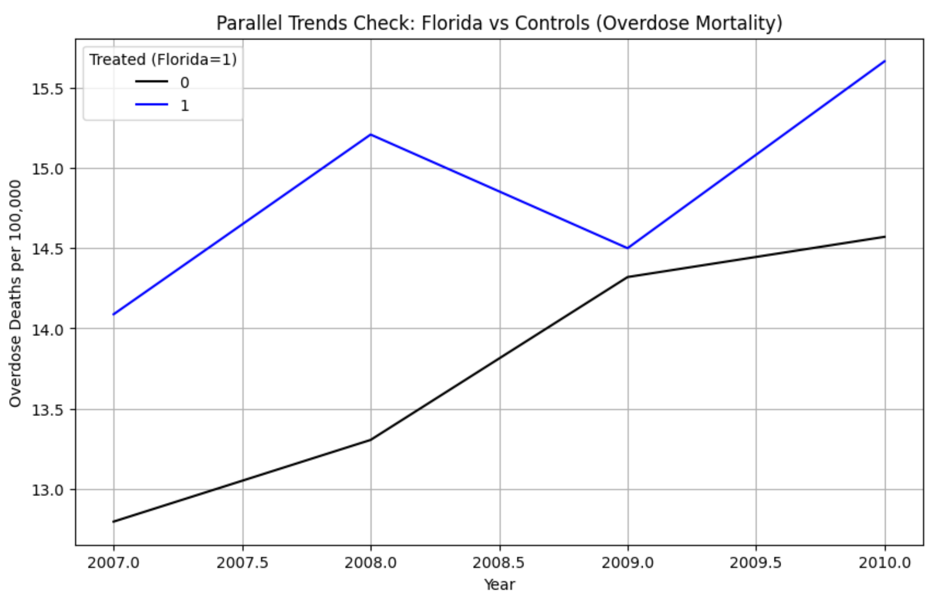

Figure 2: Analysis of overdose deaths per 100,000 residents for Florida vs control states North Carolina, South Carolina, and Georgia

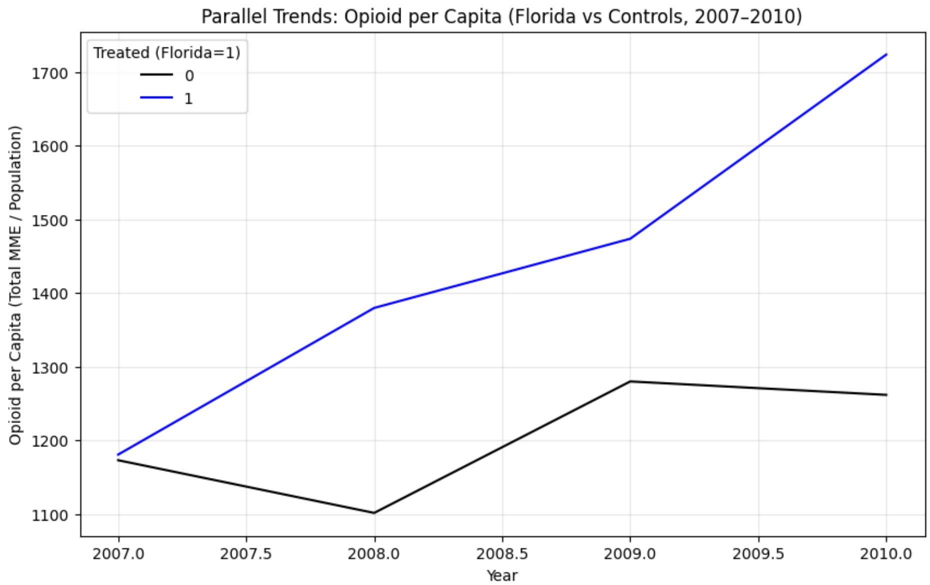

Figure 3: Opioid shipment per capita for Florida vs control states North Carolina, South Carolina, and Georgia

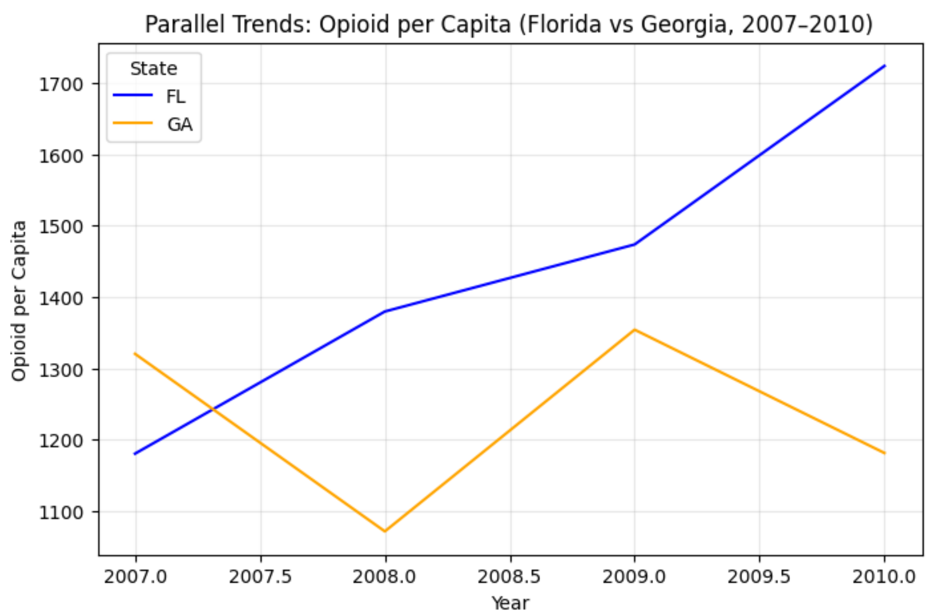

Figure 4: Parallel trends: opioid shipment per capita for Florida vs Georgia

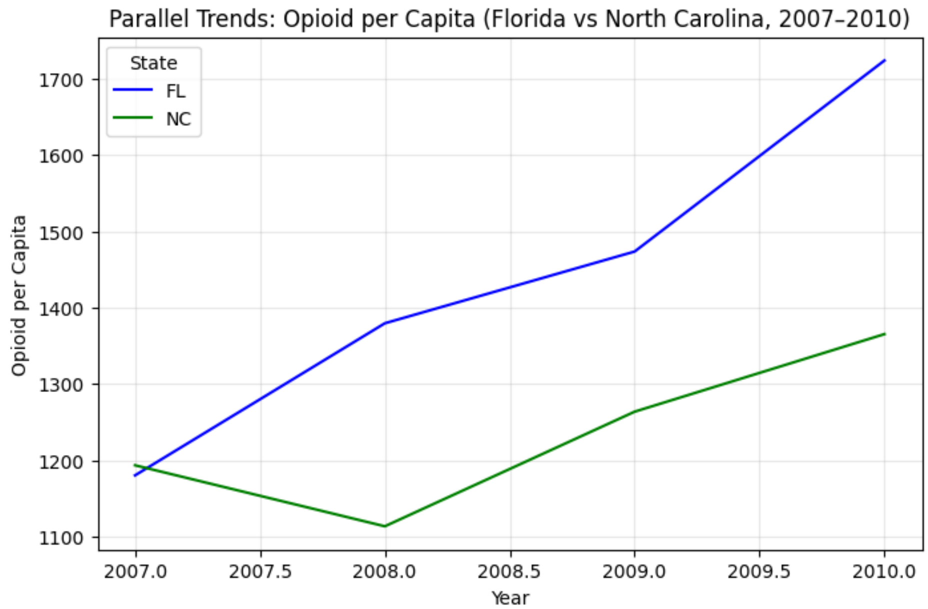

Figure 5: Parallel trends: opioid shipment per capita for Florida vs North Carolina

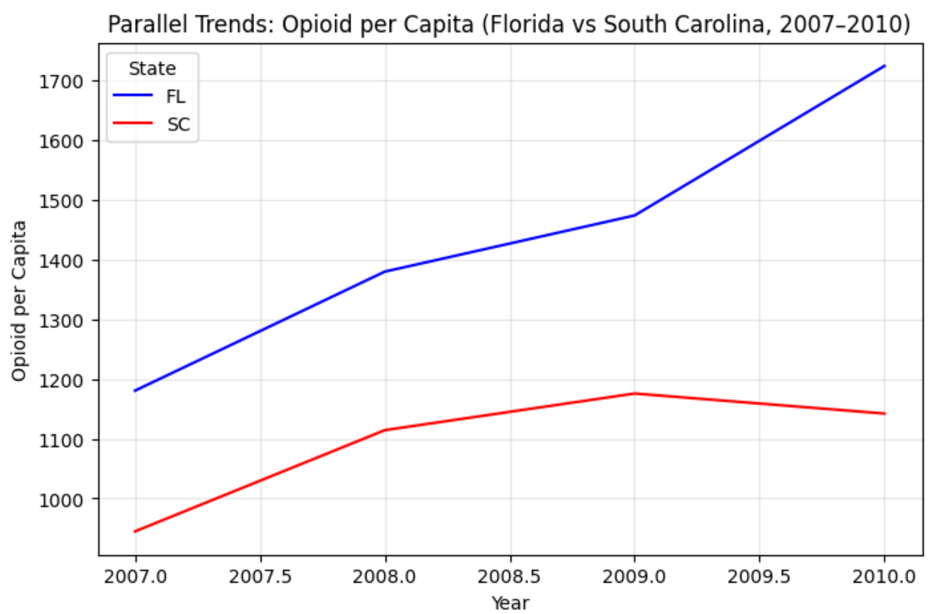

Figure 6: Parallel trends: opioid shipment per capita for Florida vs South Carolina

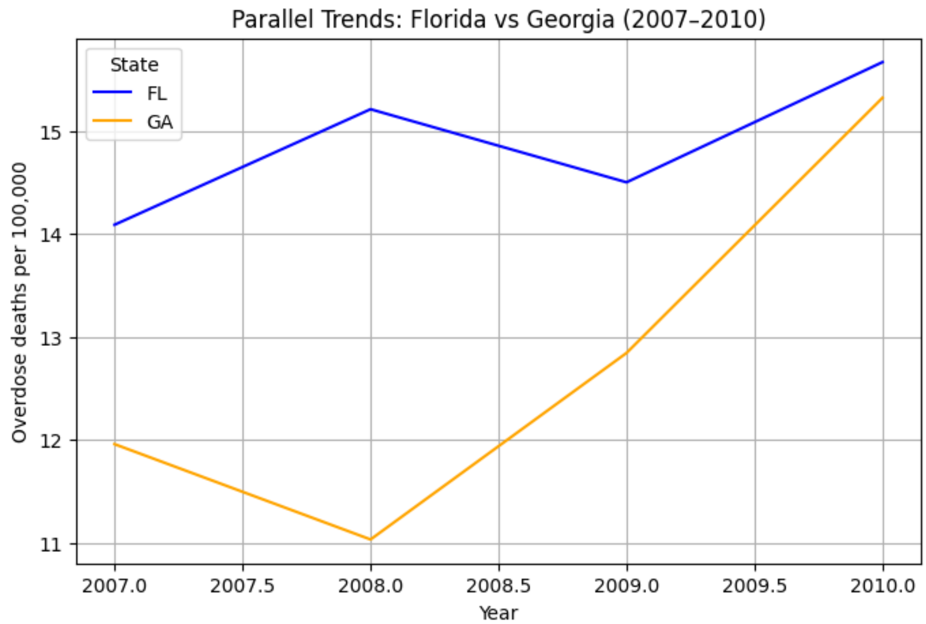

Figure 7: Parallel trends: overdose deaths per 100,000 residents for Florida vs Georgia

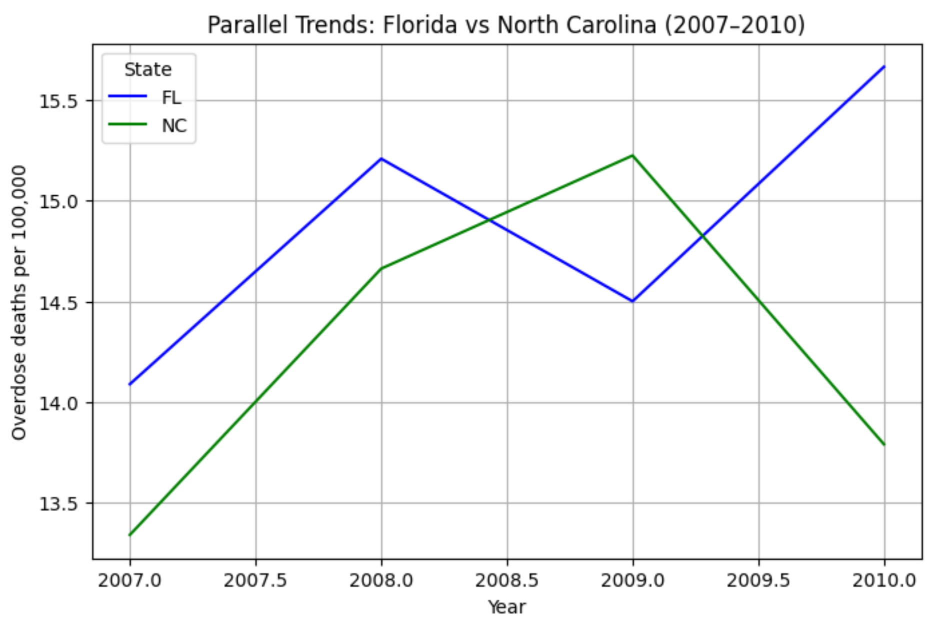

Figure 8: Parallel trends: overdose deaths per 100,000 residents for Florida vs North Carolina

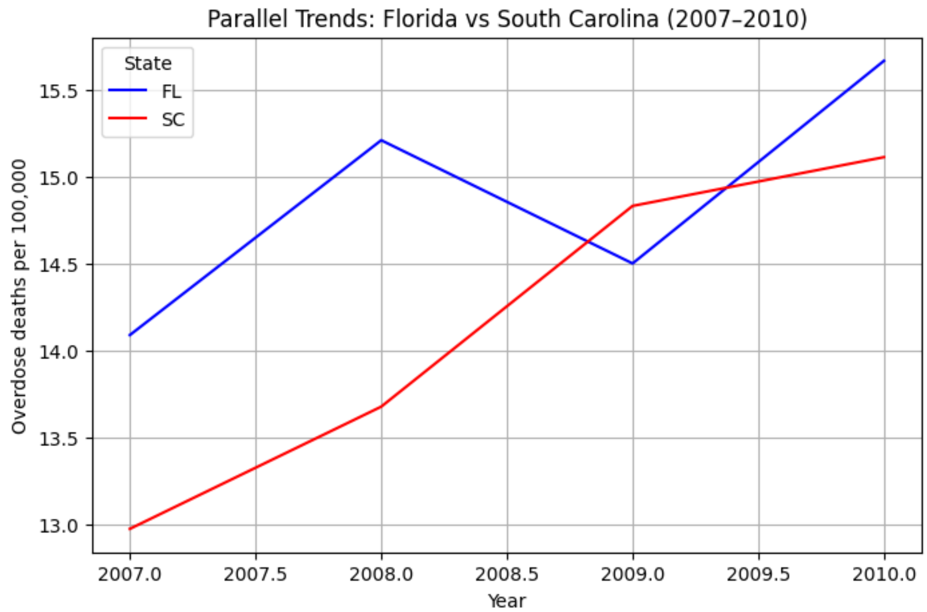

Figure 9: Parallel trends: overdose deaths per 100,000 residents for Florida vs South Carolina

3.3.2 Washington Control States

For Washington (policy effective January 2, 2012), the primary controls selected are Oregon, Idaho, and Montana. These states did not implement binding dosage-consultation thresholds comparable to Washington's 120 MED rule during 2011–2012.

- **Oregon**: No statewide mandatory consultation threshold comparable to Washington's 120 MED rule. Medicaid implemented a prior-authorization requirement at $\geq$ 120 MED in 2012, but this was not universal and serves as a reasonable regional comparison.
- **Idaho**: Emphasized guidelines rather than binding prescribing thresholds. State PBSS data show slower declines in opioid dosages, providing a useful contrast.
- **Montana**: No evidence of Washington-style consultation or dosage mandates in 2011–2012. State guidance remained advisory rather than regulatory.

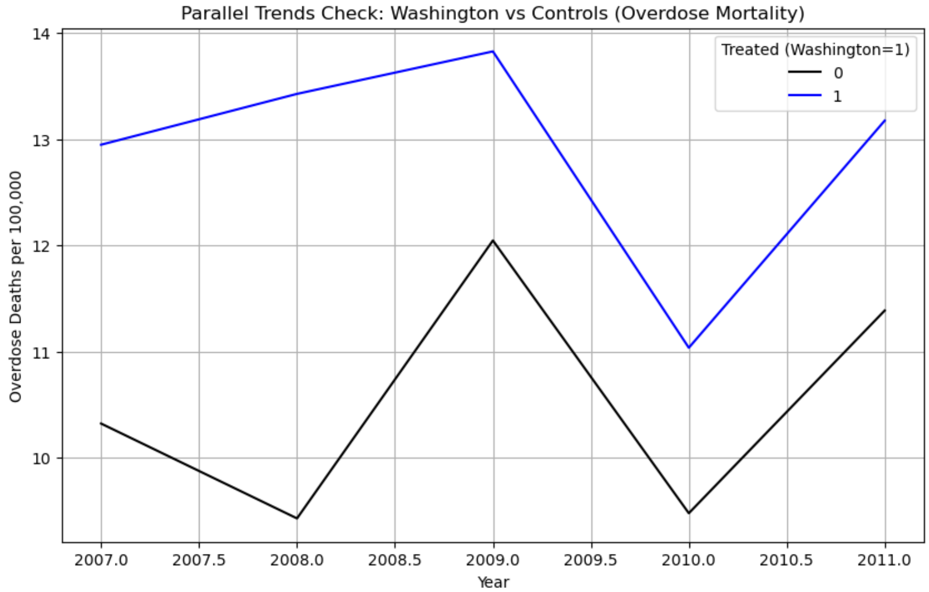

Figure 10: Analysis of overdose deaths per 100,000 residents for Washington vs control states Idaho, Oregon, and Montana

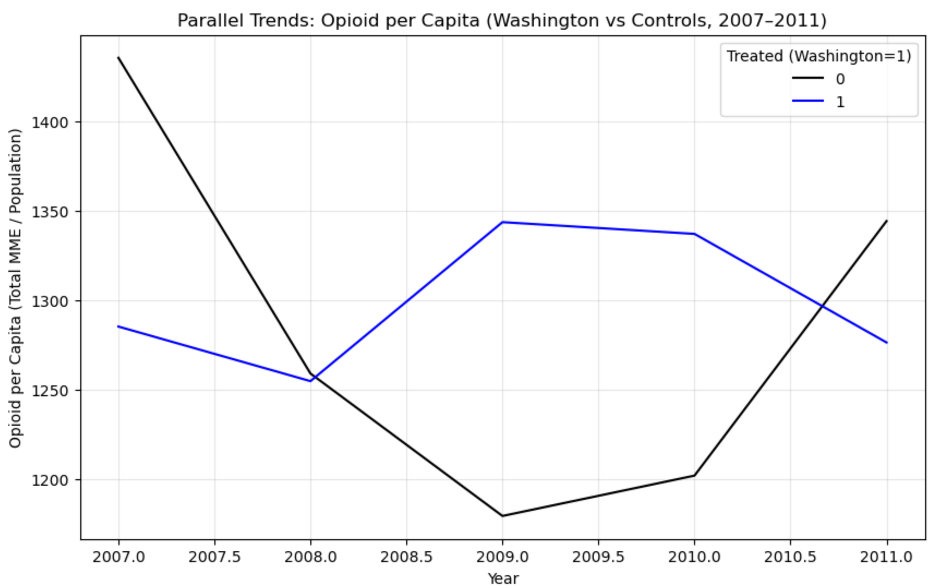

Figure 11: Opioid shipment per capita for Washington vs control states Idaho, Oregon, and Montana

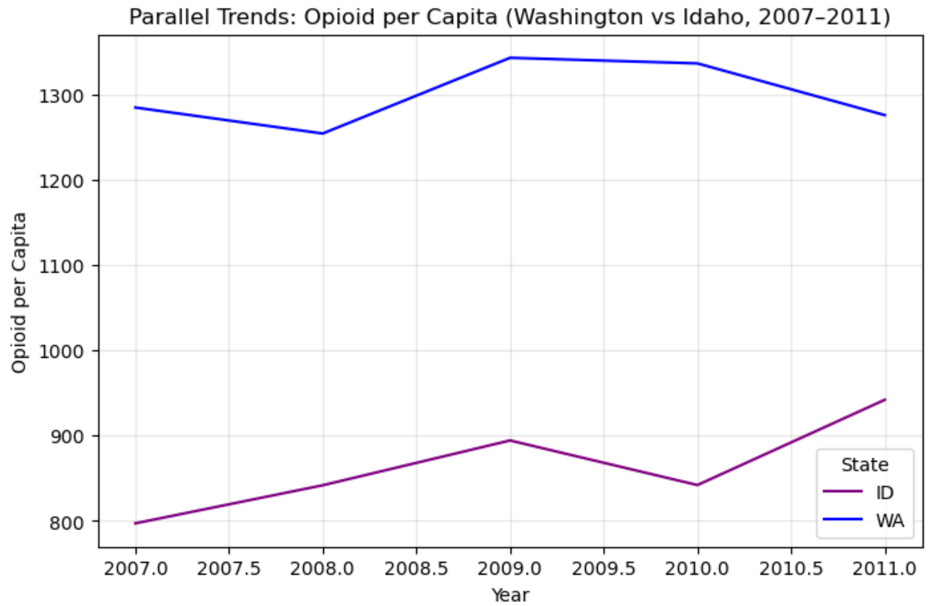

Figure 12: Parallel trends: opioid shipment per capita for Washington vs Idaho

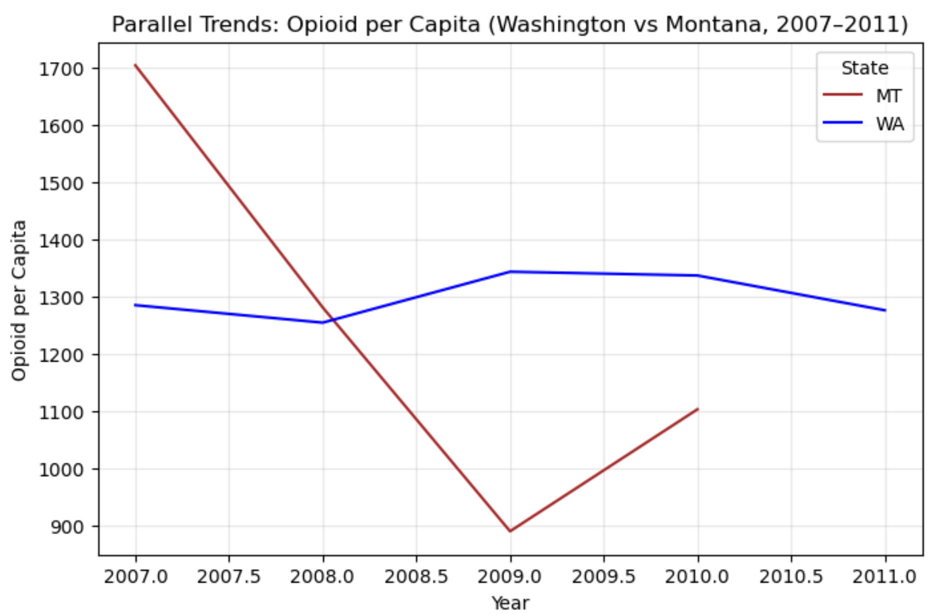

Figure 13: Parallel trends: opioid shipment per capita for Washington vs Montana

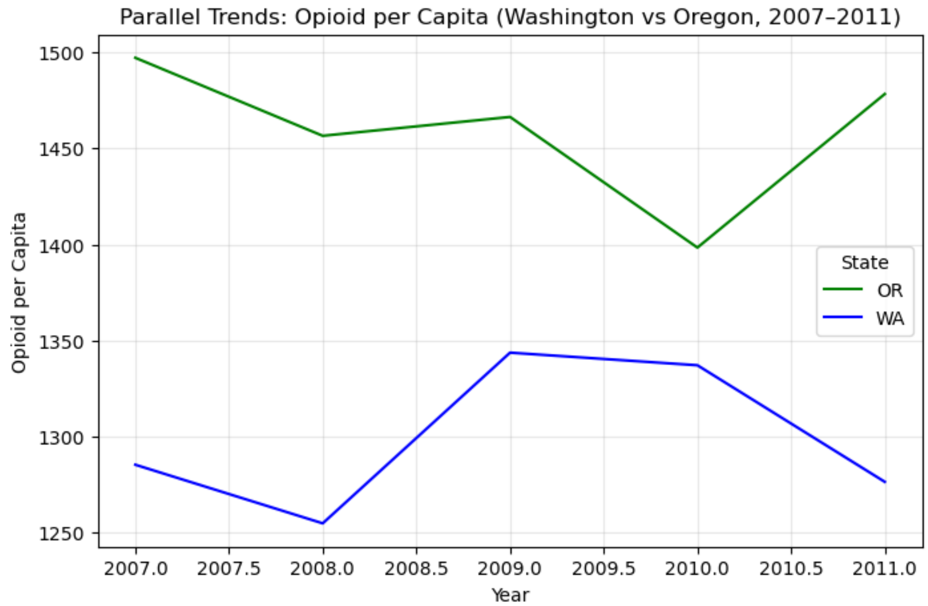

Figure 14: Parallel trends: opioid shipment per capita for Washington vs Oregon

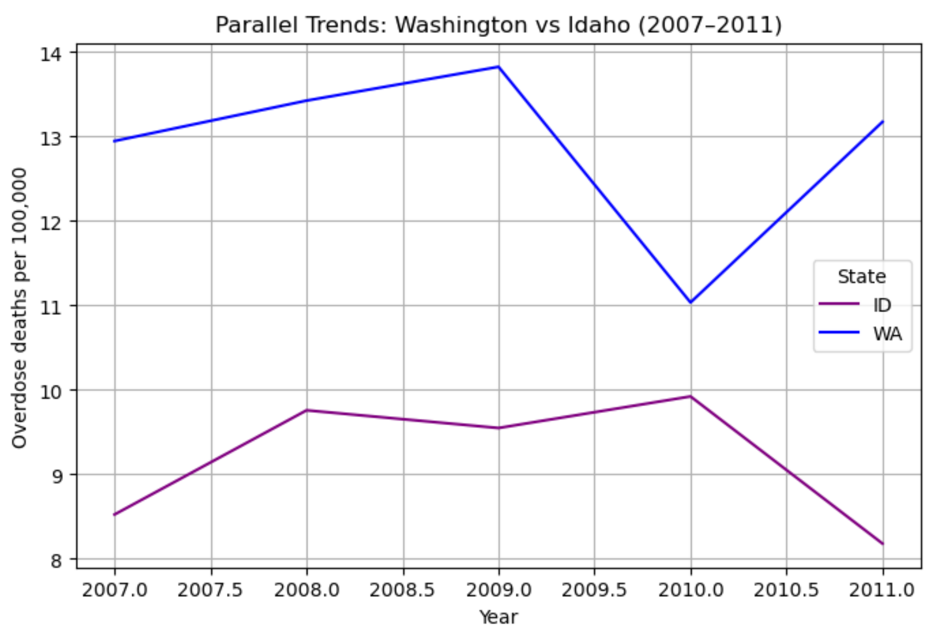

Figure 15: Parallel trends: overdose deaths per 100,000 residents for Washington vs Idaho

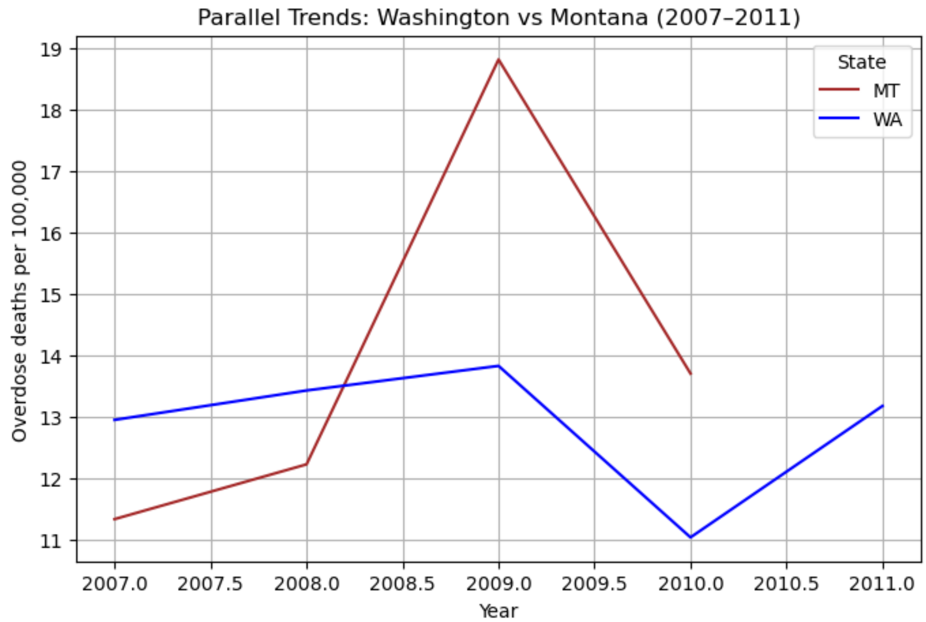

Figure 16: Parallel trends: overdose deaths per 100,000 residents for Washington vs Montana

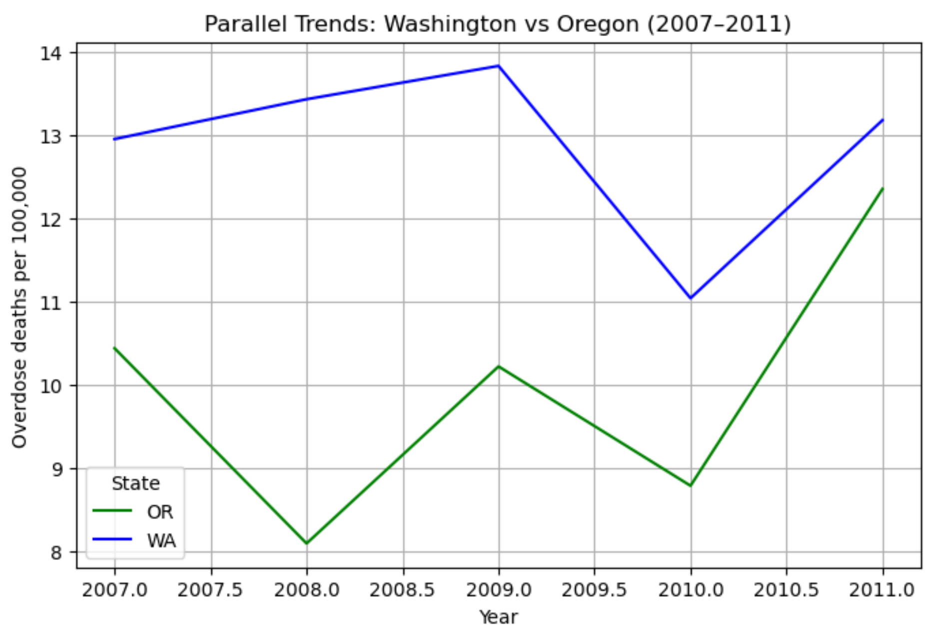

Figure 17: Parallel trends: overdose deaths per 100,000 residents for Washington vs Oregon

To assess the validity of the difference-in-differences design, we examined the parallel trends assumption using both visual and statistical diagnostics. First, we plotted pre-policy trends for each treated state against its corresponding control states. These plots show that, prior to the intervention year, treated and control units follow similar pre-policy trajectories.

Second, we estimated a pre-policy regression model including a treated-by-year interaction term. In both the Florida and Washington models, the coefficient on the interaction term had a p-value above 0.05, indicating that we fail to reject the null hypothesis of equal pre-policy trends. This provides evidence that the treated and control states exhibited statistically indistinguishable trends before the policies were implemented.

Together, the visual inspection and the statistical test support the validity of the parallel trends assumption for both Florida and Washington.

3.4 Unit of Observation

The unit of observation in our analysis is the **county–year**. All outcome variables (opioid distribution per capita and overdose mortality rates) are constructed at the county level and observed annually. The difference-in-differences models therefore compare changes across counties over time within the treated states and their corresponding control states.

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4 Results

4.1 Opioid Prescription Analysis

4.1.1 Pre–Post Results

Florida

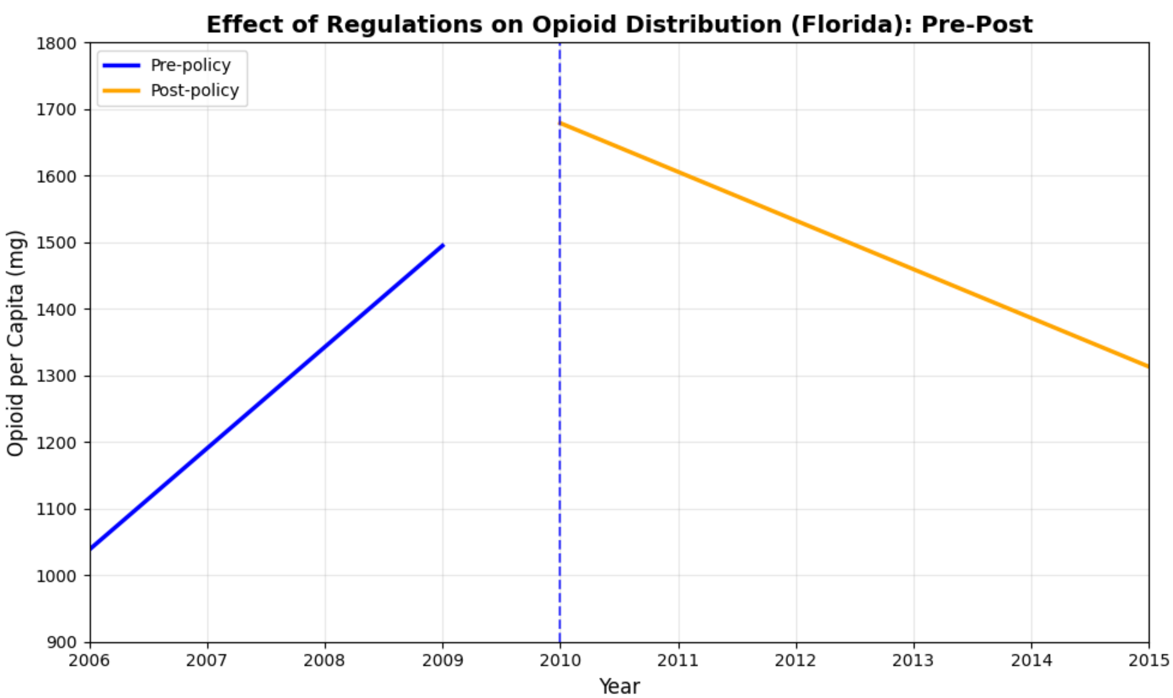

Figure 18: Pre- and Post-regulation policy comparison for opiate MME shipment per capita in Florida

Washington

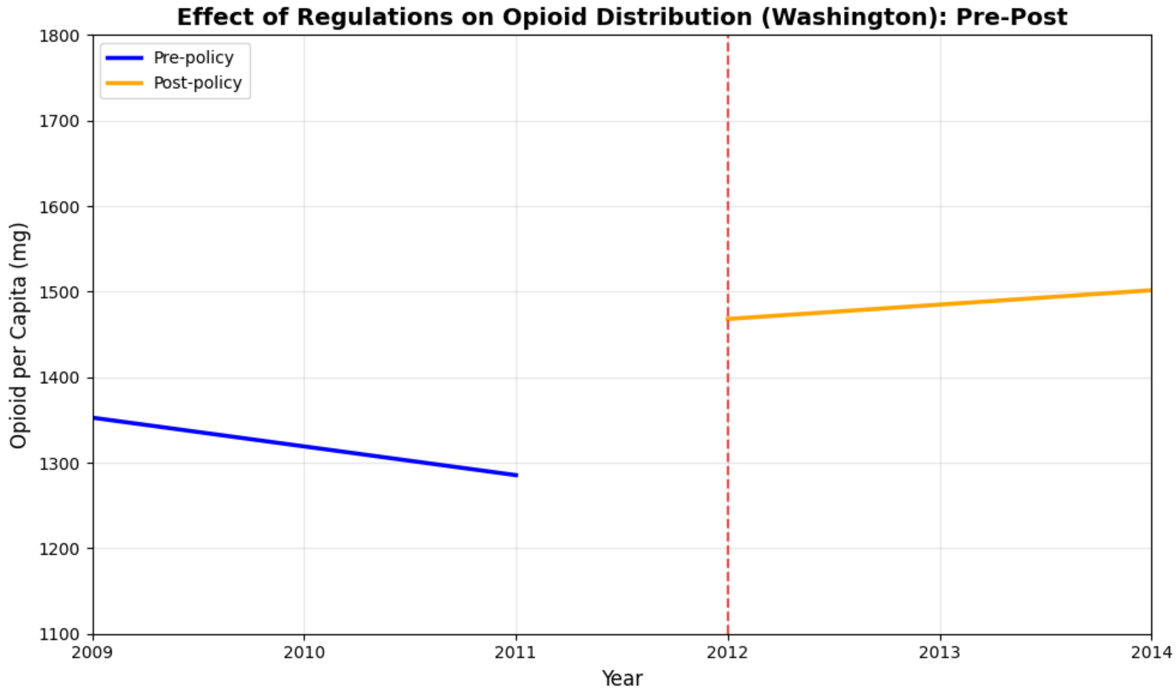

Figure 19: Pre- and Post-regulation policy comparison for opiate MME shipment per capita in Washington

4.1.2 Difference-in-Differences Results

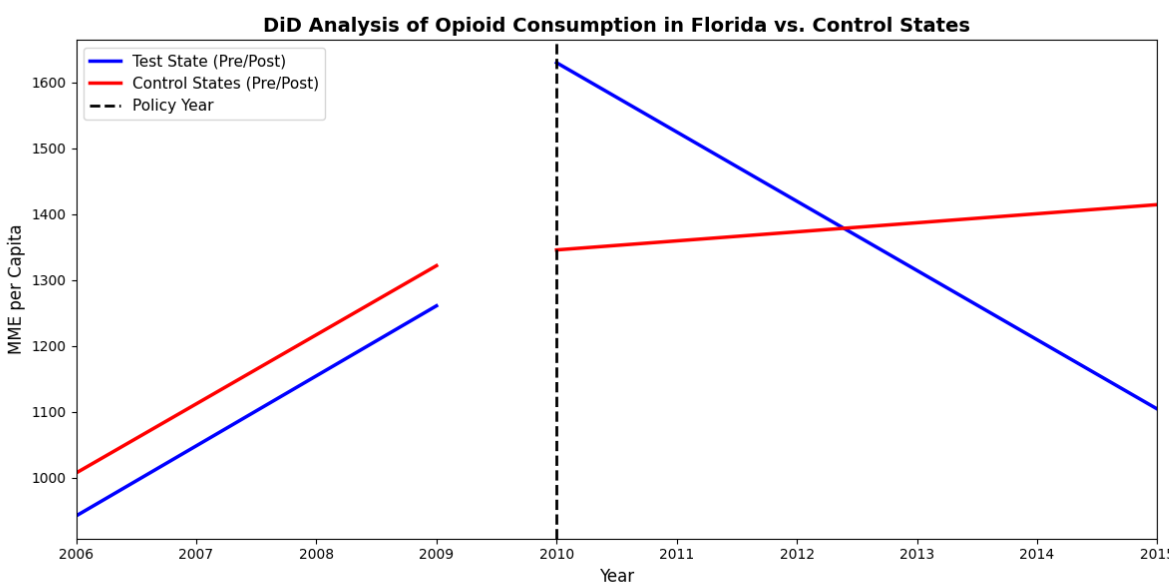

Figure 20: Difference-in-Difference Analysis for opiate MME per capita in Florida vs control states for 2010 policy implementation

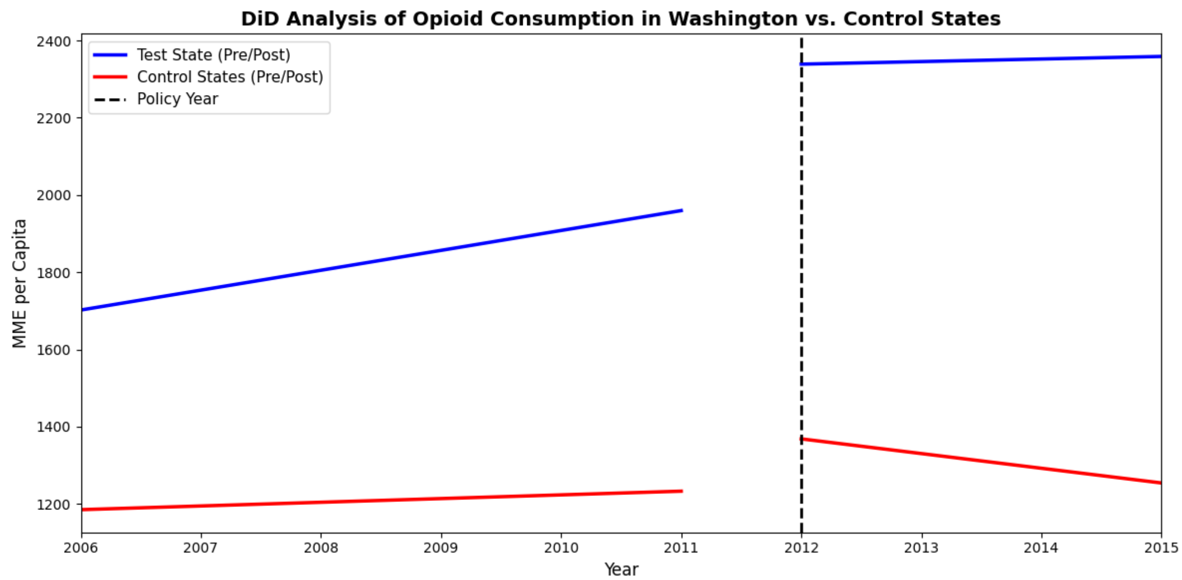

Figure 21: Difference-in-Difference Analysis for opiate MME per capita in Washington vs control states for 2012 policy implementation

4.2 Overdose Mortality Analysis

4.2.1 Pre–Post Results

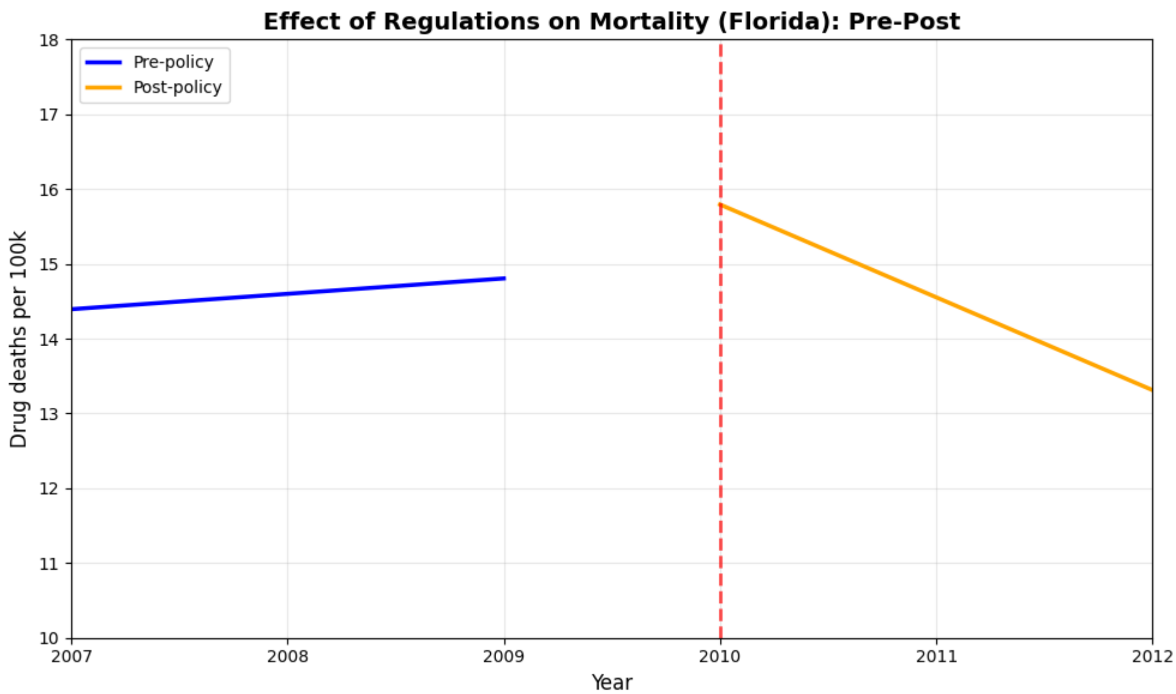

Figure 22: Pre- and Post-regulation policy comparison for opiate overdose mortality in Florida

Florida

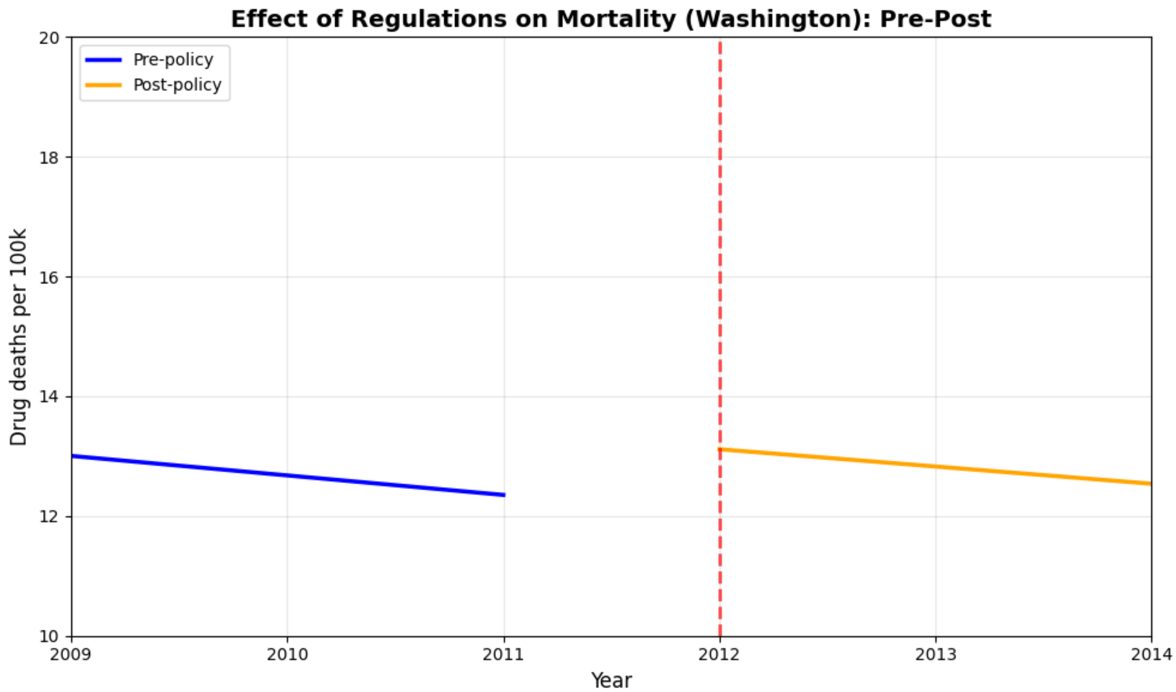

Figure 23: Pre- and Post-regulation policy comparison for opiate overdose mortality in Washington

Washington

4.2.2 Difference-in-Differences Results

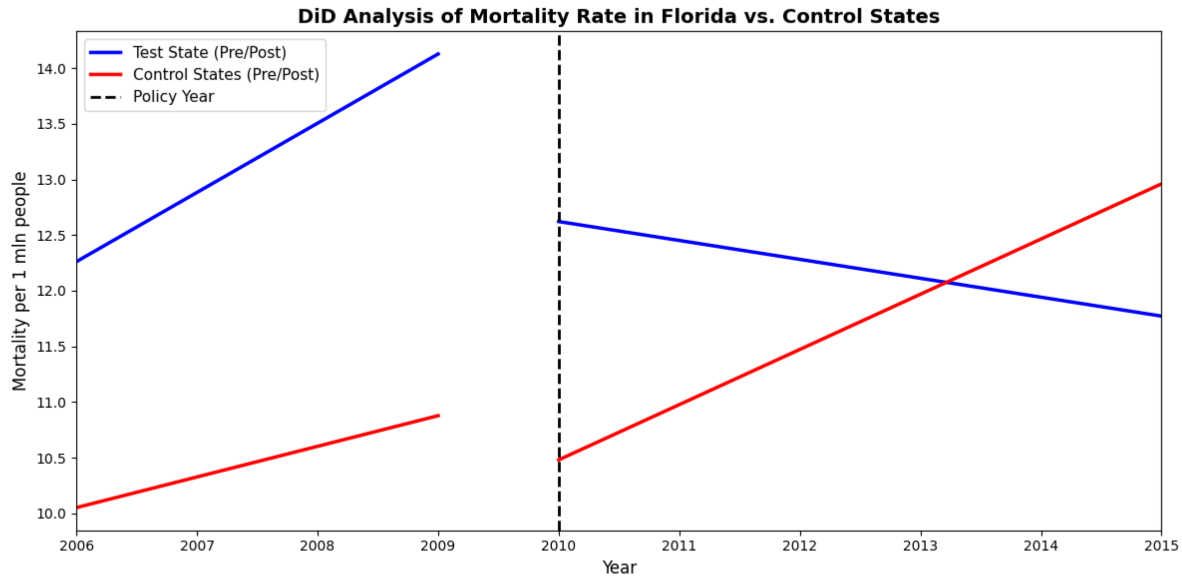

Figure 24: Difference-in-Difference Analysis for opiate overdose mortality in Florida vs control states for 2010 policy implementation

Florida

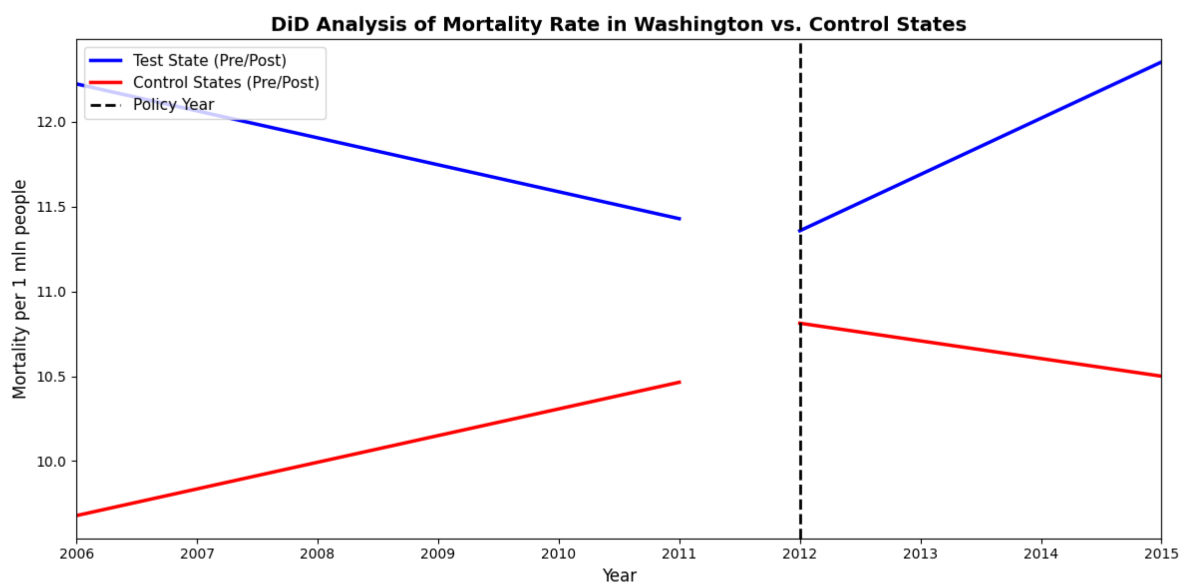

Figure 25: Difference-in-Difference Analysis for opiate overdose mortality in Washington vs control states for 2012 policy implementation

Washington

5 Discussion

5.1 Interpretation of Findings

The contrast between Florida and Washington illustrates how policy design influences effectiveness:

5.2 Comparison Between Florida and Washington Policies

5.2.1 Florida:

The enforcement model - clinic registration, dispensing bans, and coordinated raids - directly targeted high-risk distribution channels. The data show a steep drop in opioid per capita immediately following implementation, with notable divergence from control states. Because the reduction is visible across multiple robustness checks and persists over time, the evidence strongly supports a causal interpretation. Florida's mortality declines, although smaller in magnitude, reinforce this view.

5.2.2 Washington:

Washington relied on clinical guidelines rather than enforceable restrictions. Prescribers faced consultation and documentation rules, but the system lacked penalties or dispensing bans. As a result, county-level opioid supply changed only marginally, and mortality trends exhibit no meaningful post-policy break. Given stable pre-policy trends across Washington and its controls, the weak post-policy response suggests that soft guidance alone is insufficient to shift entrenched prescribing practices.

6 Conclusion

6.1 Summary of Key Findings

This study evaluates two fundamentally different statewide opioid interventions, Florida's 2010 enforcement crackdown and Washington's 2012 prescribing guidelines, using county-level ARCOS shipment data, CDC mortality records, and Census population estimates. After constructing standardized measures of opioid supply (MME per capita) and overdose harm (deaths per 100,000), and applying pre-post and difference-in-differences (DiD) methods, we reach three main conclusions:

6.1.1 Florida's enforcement strategy produced clear and sizable reductions in opioid supply.

Across all pre-post and DiD specifications, Florida experienced an abrupt and sustained decline in opioid distribution immediately after its 2010 policy. Shipments diverged sharply from those in North Carolina, South Carolina, and Georgia - states that exhibited smooth or rising pre-2010 trends (refer to figures). This consistent pattern implies the intervention substantially disrupted the prescription supply chain.

6.1.2 Florida also experienced modest but measurable improvements in overdose mortality.

Although population-adjusted mortality rates are inherently noisier, Florida shows a post-2010 decline relative to its trend and relative to control states (refer to figures). These results suggest that supply reductions translated, at least partially, into short-term improvements in fatal outcomes.

6.1.3 Washington's clinical prescribing guidelines had limited observable effect.

Washington's opioid supply stabilized rather than dropped, and its overdose mortality trends largely tracked those of Oregon, Idaho, and Montana. Visual parallel-trend checks show no major divergence after 2012, and DiD estimates center near zero. The policy appears insufficient on its own to meaningfully curb either opioid availability or mortality.

References