Practical Data Science

Assessing the Effects of Opioid Control Policies in The United States

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Report Overview

Executive Summary

The growing problem of prescription opioids in the United States has raised concerns due to the increase in addiction and overdose deaths. Given this situation, a series of policies have been implemented in various states across the United States. This research aims to examine the impact of regulations governing opioid prescriptions on two crucial aspects: the overall volume of opioid prescriptions and the incidence of overdose deaths.

Specifically, an analysis was carried out on the impact of policies restricting opioid prescriptions in the states of Texas, Washington, and Florida. To conduct this investigation, we utilized various data sources, including information on opioid prescriptions in the United States, drug-related deaths, and population data. All the sources were publicly accessible. To conduct this analysis, a Pre-Post Comparison was initially carried out to understand the differences in our key indicators before and after the implementation of the policies. However, given the limitations of this analysis, a second Difference-in-Differences analysis was conducted. This compared changes in overdose deaths and drug shipments in these states following policy changes to other states that did not alter their opioid policies. Distinct plots were used to estimate and illustrate the 'difference-in-difference' statistically, revealing variations from the year of policy change in each county.

In our analysis of the results, we have reached mixed conclusions. We find that certain state-level public policies aimed at regulating medical opioid prescriptions and reducing associated deaths can be effective, but their effectiveness varies significantly across the states and counties we studied.

In the case of Florida, our initial pre-post analysis indicated a reduction in both opioid prescriptions and overdose deaths following the implementation of opioid restriction policies. However, when we applied the "diff and diff" analysis, the reduction in the amount of morphine equivalents sent per person did not reach statistical significance. Similarly, in Washington, our pre-post analysis hinted at a decrease in morphine equivalents per capita after policy implementation, but this outcome was less conclusive when utilizing the differences-in-differences analysis. On the other hand, our analysis of Texas revealed an impact on opioid consumption in both the before and after periods, consistent with the findings from our differences-in-differences analysis.

In summary, our study underscores the variability in the effectiveness of state-level policies aimed at regulating opioids and reducing associated deaths across different states and counties. While some regions experienced significant positive outcomes, others did not display clear statistical effects. These findings emphasize the necessity for tailored approaches to address this complex issue at both the state and county levels.

Motivation

Recently, the state of prescription opioids in the United States has become more concerning. There has been a significant increase, leading to higher rates of addiction and overdose deaths. This disturbing pattern has not only triggered a widespread epidemic of opioid addiction but has also led to a troubling increase in overdose deaths related to prescription drugs. Additionally, the issue has extended beyond prescribed opioids, involving non-prescribed substances like heroin and fentanyl. This shift occurs as individuals initially caught up in prescription opioid addiction turn to illicit markets to sustain their dependency.

The objective of this research is to investigate the different ways in which regulations regulating the prescription of opioids can specifically impact two crucial factors: the overall volume of opioid prescriptions and the incidence of overdose deaths.

Research Question

"Are the regulations in Florida, Texas, and Washington effective in reducing overdose deaths and curbing drug prescriptions?"

This raises questions about the effects of opioid prescriptions, particularly in terms of how they affect the volume of prescriptions and contribute to drug overdose deaths.

Data Overview

For this evaluation, we will be using the following datasets:

Opioid Prescriptions

We will be using a dataset containing all prescription opioid drug shipments in the United States from 2006 to 2019 to gather information on opioid prescriptions. This dataset, released in 2020 by the Washington Post, was obtained through a Freedom of Information Act (FOIA) request to the US Drug Enforcement Administration.

Vital Statistics Mortality Data

To analyze trends in drug-related deaths, we will use the U.S. Vital Statistics records, covering every death in the country. It is essential to highlight that, for privacy reasons, the U.S. Vital Statistics

Agency censors certain data, omitting information when the number of individuals in a specific category is less than 10 or when counts are zero. Using annual mortality data that combines deaths over entire years enhances data integrity by preventing the impact of low death thresholds in counties. To address missing values, a specific strategy has been developed, which will be detailed in the methodology.

Population

To obtain specific population data categorized by age group for each county and each year spanning from 2006 to 2015, we acquired data from the StatsAmerica website. StatsAmerica is a service provided by the Indiana Business Research Center at Indiana University's Kelley School of Business. They furnished us with a comprehensive dataset encompassing population data categorized by age and sex. This dataset covers the entire United States, including individual states and counties, and spans from the year 2000 to 2019. The primary data source for this dataset is the U.S. Census Bureau. It appears that the StatsAmerica research group processed raw data obtained from the U.S. Census Bureau to create this dataset. This dataset offers two different classification criteria for separating age groups and gender types. We opted for this dataset because it allows for a more in-depth analysis by providing multiple demographic dimensions, rather than presenting population numbers in a collapsed format. This versatility in classification criteria is expected to enhance the thoroughness of our analysis.

Unemployment Rate

We obtained our unemployment rate data from the United States Department of Agriculture (USDA) Economic Research Service website. This website is overseen by a dedicated research group. The dataset we accessed is quite comprehensive, covering information on both unemployment rates and median household incomes for U.S. states and counties. This dataset spans a wide timeframe, from 2000 to 2022. Based on their official documentation, the research group tasked with curating this dataset collects data from a diverse array of sources. These sources encompass entities such as the U.S. Department of Labor, Bureau of Labor Statistics, Local Area Unemployment Statistics, U.S. Department of Commerce, and several others. However, for our specific analysis, we focused exclusively on the unemployment rate column. The primary reason for this choice is that while the dataset provides information on both unemployment rates and median household incomes, median household income data is only available for the year 2021. Due to this limitation, we decided to prioritize the unemployment rate column as it offers comprehensive coverage of employment status for each year, spanning from 2000 to 2022.

Methodology

Initially, three states were chosen as counterfactuals for each state under investigation. This selection process was based on a Euclidean distance analysis, with details provided in "*Appendix 1: Selection of States for Counterfactual Analysis.*"

In simple terms, we selected certain factors for all American states: the increase in unemployment rates, opioid shipments, the rise in people aged over 45, and the normalized opioid shipments per capita. Next, we calculated the Euclidean distance in these four dimensions and chose the three states with the smallest distance, using Texas, Washington, and Florida as reference points. The selected states were Texas, paired with New York, Virginia, and Idaho; Florida, paired with Delaware, Nevada, and Tennessee; and finally, Washington, paired with Massachusetts, Vermont, and Montana.

To manage missing values in Vital Statistics Mortality Data due to privacy considerations, the missing data was filled using the average mortality rate by state and year, employing the data from the most frequent cause of drug-related deaths. For further details, please refer to *"Appendix 2: Managing Missing Values in Vital Statistics Mortality Data".*

To address our research questions, we will employ two methodologies: Pre-Post Comparison and Difference-in-Differences.

Pre-Post Comparison analysis

In our 'Pre-Post Comparison' analysis, we examined the prescription drug utilization and overdose mortality in the states of Florida, Texas, and Washington. To achieve this, we performed two key calculations to assess opioid consumption and mortality rates from 2006 to 2019.

First, we calculated the annual morphine milligram equivalent shipped per capita for each county within this period. This involved dividing the total morphine equivalent usage by the county population, providing an estimate of the average morphine equivalent consumption per individual in that state.

Secondly, we calculated the average mortality rate per 100,000 people for each state from 2006 to 2015. This metric reflects the number of deaths per 100,000 individuals within a given state. Our subsequent pages will delve into the rationale behind these calculations in greater detail.

Our analysis focused on comparing these statistics just before recent policy changes were implemented and after the policies were enacted. The underlying assumption was that if the policies had remained unchanged, the states in the post-policy-change period would have exhibited similarities to their pre-policy-change conditions.

Difference-in-Difference analysis

A pre-post analysis is good, but it has limitations. Why? Because we can't see what would have happened if the policy had never been implemented. It's possible that the same decrease could have occurred without the policy. Therefore, we need another, more sophisticated way to measure the impact. One technique is the difference-in-differences analysis. The idea is to create two scenarios: in one, the policy is implemented in State A, and we measure the pre- and post-change; in the second scenario, the policy is not implemented, and we also measure the pre- and post-change. Finally, we measure the effect by taking the difference between the pre-post changes in both scenarios. If there is a change, it can be attributed to the policy. The previously selected states served as a contrafactual baseline for comparison.

IIn this analysis, we employed the 'difference-in-difference' approach to estimate the effects. . More specifically, distinct Difference-in-Difference plots were created, one for each county. These plots aimed to illustrate patterns in line trajectories aligning with the reference counties. However, they also revealed variations or gaps emerging from the year of policy change in each county.

The Differences in Differences study compares the treatment state's behavior before and after a policy change with other states having similar characteristics. However, it's important to note that Differences in Differences may not always be valid because it assumes parallel trends between the treatment state and a counterfactual state in the absence of the policy. If these trends significantly diverge, biases may impact the accuracy of estimating the policy impact. Recognizing the limitations of the Diff-in-Diff technique is crucial, as its validity relies on the presence of parallel trends between the treatment group and the counterfactual group before policy implementation, and any substantial divergence in these trends could introduce biases and potentially affect the accuracy of estimating the policy impact.

Results

Overall Scenario

As stated in this document, our analysis was conducted for three different states: Florida, Washington, and Texas, each with different interventions at different times. Despite having more than one public intervention, Florida considers 2010 as the treatment year. In the case of Washington, the treatment year is 2012, and for Texas, it is 2007. In those specific years, the average morphine milligram equivalent shipped per capita is presented in the following table:

Year	State	State Average	National Average
2006	Texas	151.88	132.7
2009	Florida	573.39	182.33
2011	Washington	389.56	209.79

Table 1: Average Morphine Milligram Equivalent Shipped per Capita

Table 1 illustrates the consumption by state and the national average to provide a comparison point. The three states were above the national average the year before each policy implementation, with Florida showing the largest difference.

Year	State	State Average	National Avg
2006	Texas	12.54	10.94
2009	Florida	14.5	10.95
2011	Washington	13.17	12.

Table 2: Average Unintentional Drug Poisoning Mortality Rate per 100,000 Population

Table 2 displays the Average Unintentional Drug Poisoning Mortality Rate per 100,000 Population for the three states in the year of policy change, alongside the corresponding national averages. We can see that once again, the states present an average higher than the national average, supporting the need to implement policies aimed at reducing opioid prescriptions in those states and, consequently, the deaths caused by them.

Pre-Post Comparison analysis

Drug prescriptions

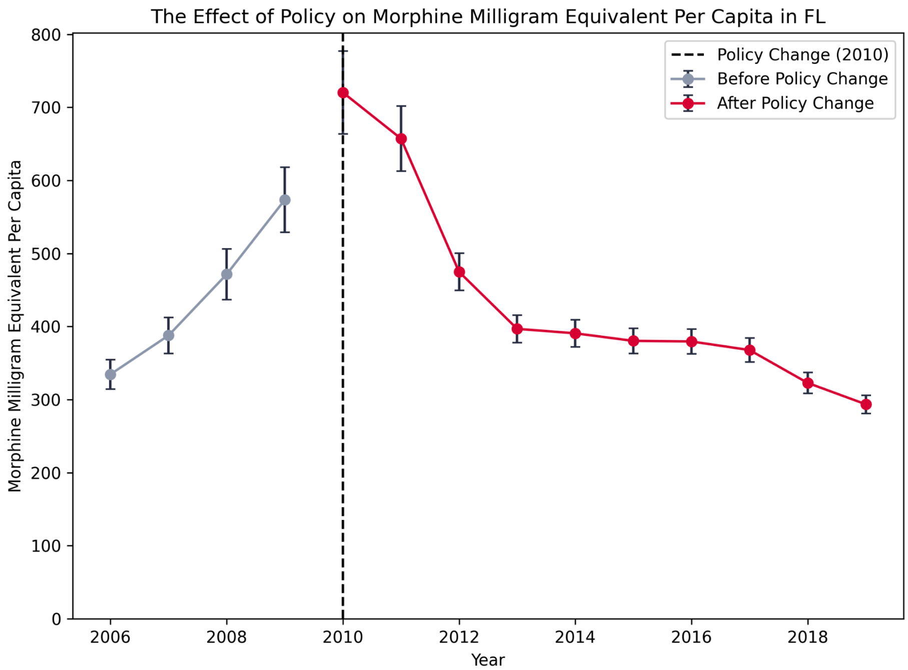

Figure 1: Evolution of Average Morphine Milligram Equivalent Shipped per Capita by Year in Florida

In Figure 1, we examine the impact of a policy implemented in Florida with the aim of addressing opioid misuse. This policy, enacted in February 2010, was in response to the proliferation of pain clinics and the excessive prescription of opioids throughout the state. The analysis presented here, known as a Pre-Post Comparison, investigates how regulatory measures influenced the consumption of morphine milligram equivalents (MME) per capita. We chose the year 2010 as a pivotal point to assess the shift in per capita MME sales patterns before and after the policy's enactment.

Before the policy came into effect (2006-2009), there was a consistent increase in morphine consumption, indicating a rising trend of opioid usage within the state. This consumption went from 334.6 MME per capita in 2006 to 573.4 in 2009. In 2010, the year the policy was implemented, morphine consumption reached its peak at 720.4 MME per capita. Following the policy's enactment (2011-2019), there was a substantial and sustained decline in per capita MME consumption, resulting in a reduction to less than half of the peak level—down to 293.6 in 2019, even lower than the figures from 2006. This decline suggests that the opioid regulation policy, after an initial adjustment period, likely had a positive impact in reducing MME consumption in Florida.

The error bars on the graph for each year represent the precision of the per capita MME mean estimates, calculated from averages across the 66-67 counties in Florida. Smaller standard errors lead to shorter error bars, indicating a greater consistency in county values relative to the mean and reflecting the policy's impact on statewide uniformity. The reduction in the length of error bars post-2010, the year of the policy change, suggests that the opioid intervention policy has been effectively implemented across the majority of Florida's counties.

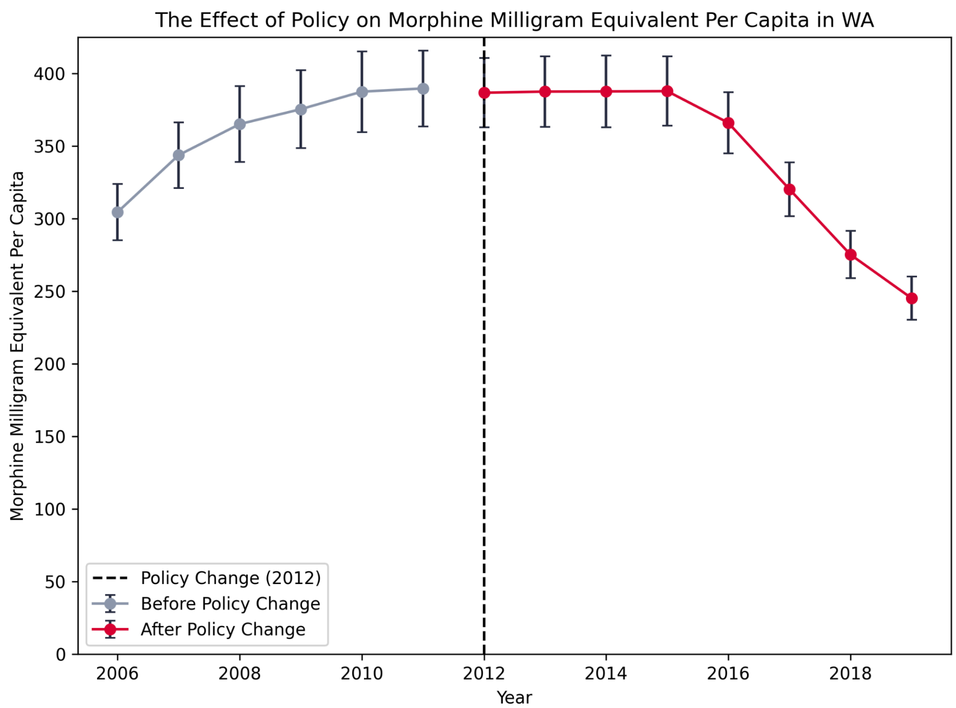

Figure 2: Evolution of Average Morphine Milligram Equivalent Shipped per Capita by Year in Washington

In Figure 2, we examine the impact of a policy introduced in Washington state to combat opioid abuse. The year 2012 is crucial in this context because it represents a significant shift in prescription regulations within the state.

Before the policy's implementation (from 2006 to 2011), Washington experienced a consistent rise in morphine milligram equivalent (MME) consumption, increasing from 304.4 in 2006 to 389.6 in 2011. However, once the policy came into effect (from 2012 to 2015), MME consumption stabilized, with minimal fluctuations between 386.6 and 387.7. This stability represented a significant departure from the previous trend of consistent growth. Subsequently, from 2016 to 2019, there was a substantial decrease in MME consumption, dropping from 365.9 to 245.2. This decline suggests that the 2012 regulations played a significant role in reversing the increasing trend observed from 2006 to 2011, contributing to a more effective control of MME consumption in Washington.

To determine whether the opioid control policy had consistent effects across all 39 counties in Washington, we incorporated error bars and conducted a comprehensive data analysis. These error bars were visibly longer when compared to previous plots for the state of Florida. Upon closer examination, it became evident that certain counties, such as Pacific, Asotin, Clallam, and Cowlitz, exhibited extremely high MME levels. Asotin County recorded the highest value, with 775.3 MME per capita. These outlier values were responsible for the longer error bars in Washington, and they persisted not only in 2019.

As a result, we can conclude that while the state of Washington as a whole experienced the effects of the policy, its impact was not uniform across every county. Some counties showed limited improvement, indicating that the policy was more effective in certain areas than in others.

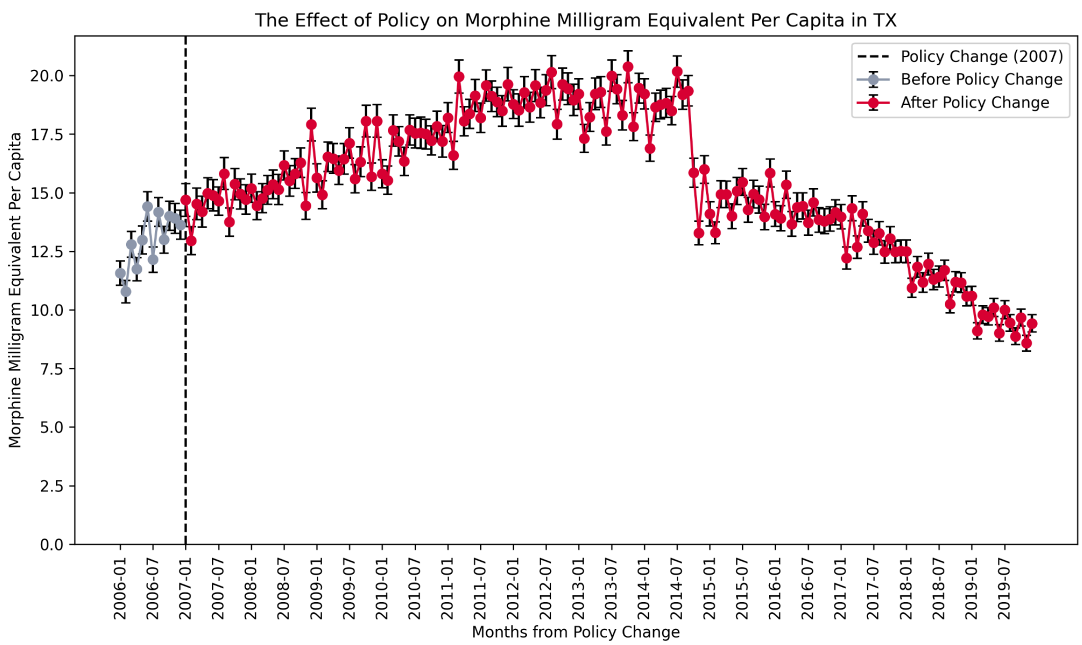

Figure 3: Evolution of Average Morphine Milligram Equivalent Shipped per Capita by Month in Texas

We conducted a comprehensive analysis of Texas, utilizing a substantial dataset spanning from January 2006 to December 2019. Our primary focus was on monthly per capita consumption of morphine equivalents (MME). A significant policy shift occurred in Texas in January 2007 when regulations on opioid prescriptions were introduced. To present our findings systematically, our graph displays MME per capita, with semi-annual intervals on the x-axis.

The data reveals a discernible pattern in Texas concerning Morphine Milligram Equivalents (MME) from January 2006 to July 2014. Initially, MME exhibited a consistent increase, starting at 11.6 in

January 2006 and reaching 13.7 in December 2006. However, following a policy change in January 2007, there was a significant uptick, reaching 20.2 MME by July 2014. By July 2014, there was a significant surge, peaking at 20.2 MME. Subsequently, there was a sharp and substantial decline in August 2014, plummeting to 19.3 MME and further dropping to 9.42 MME. This substantial decrease, almost halving the MME value from August 2014, underscores the remarkable effectiveness of the opioid policy implemented in Texas.

Overdose deaths

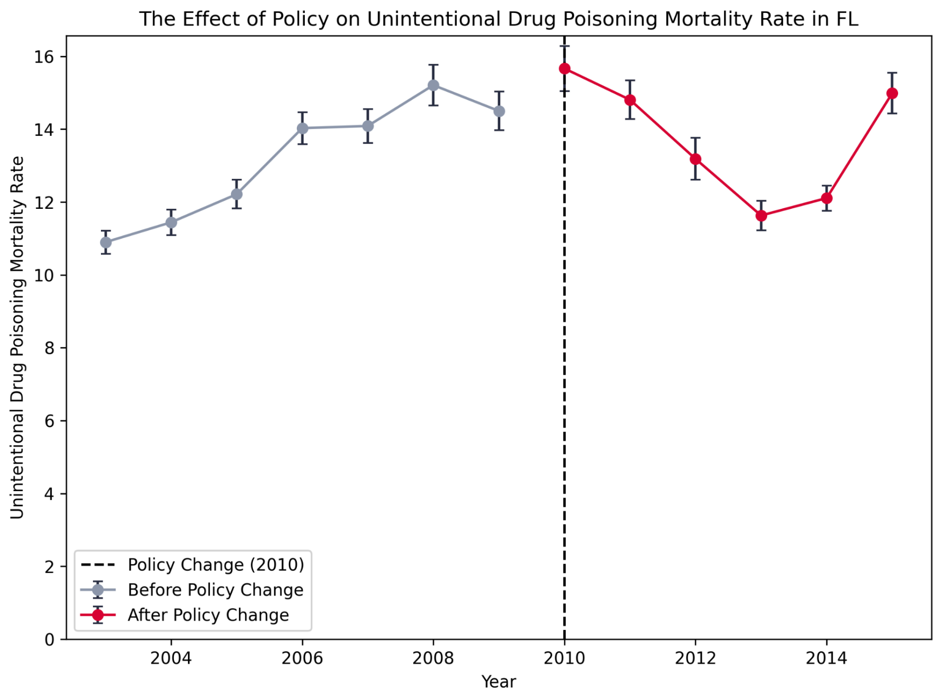

Figure 4: Evolution of Average Unintentional Drug Poisoning Mortality Rate per 100,000 Population by Year in Florida

In Figure 4, our objective is to examine the impact of Florida's opioid control policy on mortality rates related to accidental drug poisoning. We selected the year 2010 as a pivotal point for Florida due to significant policy changes around that time. When analyzing the average mortality rate per 100,000 people in Florida from 2006 to 2015, we observed an upward trend leading to the policy implementation in 2010. However, starting in 2010 (with a rate of 15.7), we noted a declining trend in mortality rates, reaching a low point in 2013 (11.6). While there was a minor increase in 2015 with a value of 15, a broader analysis of total morphine equivalents consumption and total transactions, compared to another dataset in our possession, suggests that Florida's policy intervention has continued to contribute positively to reducing opioid overdose deaths.

Additionally, in 2015, we examined the unintentional drug poisoning mortality rate in Florida and found that 51 out of 67 counties had rates equal to or lower than the mean value. This indicates the effectiveness of policy intervention in reducing mortality rates. However, two counties, Brevard and Okeechobee, reported rates exceeding 25 deaths per 100,000 people, demonstrating the need for further attention and intervention in these areas.

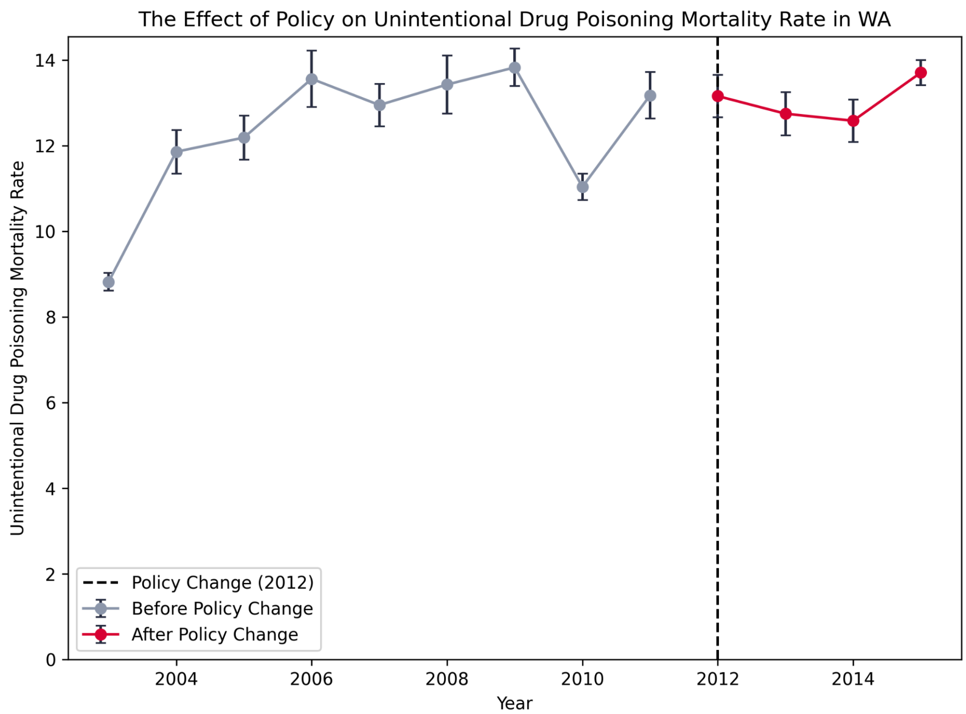

Figure 5: Evolution of Average Unintentional Drug Poisoning Mortality Rate per 100,000 Population by Year in Washington

In Figure 5, we investigate the impact of modified opioid prescription practices in the state of Washington on mortality rates resulting from accidental drug poisoning. In response to the opioid crisis, significant changes were implemented in January 2012, making this year our focal point for analysis.

The average mortality rate exhibited a predominantly increasing trend until 2012, rising from 8.8 in 2003 to 13.2. However, a decrease was observed from 2012 (13.16) to 2014 (12.6). Although there was an increase in the average mortality rate in 2015, this uptick appears to be temporary. Further analysis using another dataset revealed that the rising trend observed in 2015 is not sustained, as both the total morphine equivalent consumption amount and transaction cases have consistently decreased since 2015.

The error bars on the figure illustrate the consistent policy effects of reducing unintentional drug poisoning per 100,000 people. In 2015, 35 out of 39 counties showed rates equal to or lower than the mean mortality rate of 13.7. However, in Wallawalla, Grays Harbor, and Cowlitz counties, the number of deaths per 100,000 people exceeded 20. Consequently, we can conclude that while overall policy effects contribute to lowering the mortality rate, these specific counties still require monitoring and targeted interventions for improvement.

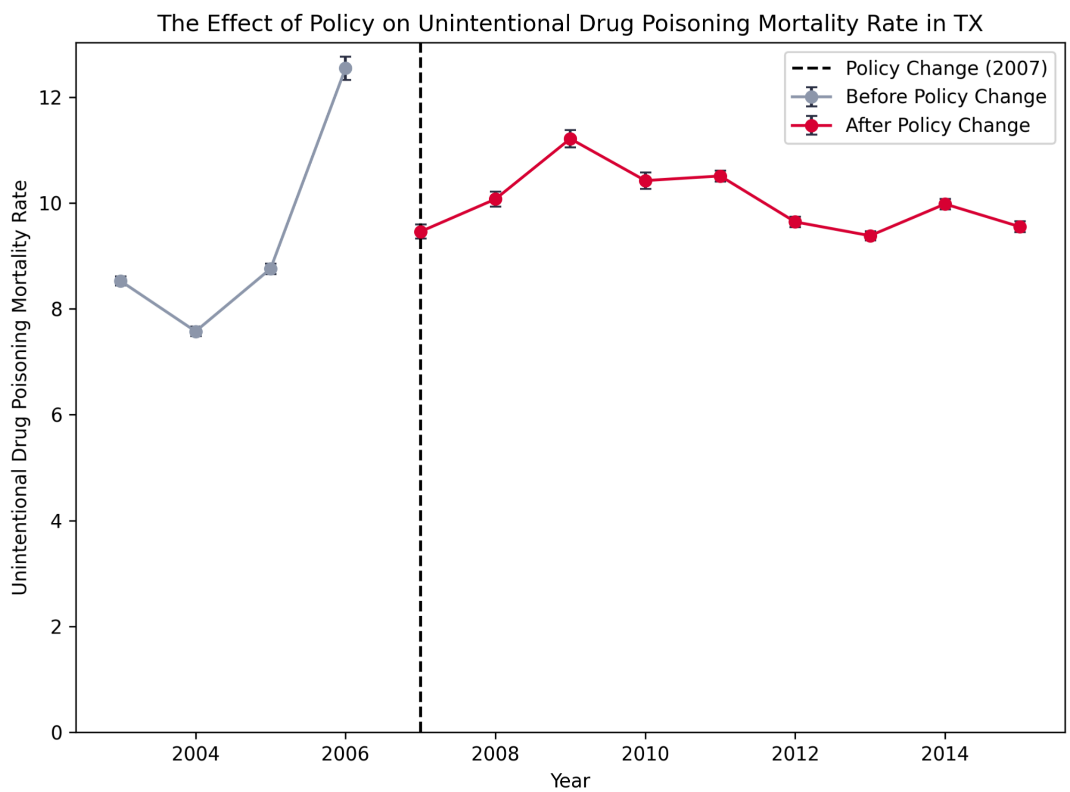

Figure 6: Evolution of Average Unintentional Drug Poisoning Mortality Rate per 100,000 Population by Month in Texas

In Figure 6, we investigate the impact of altered opioid prescription practices in Texas on mortality rates resulting from accidental drug poisoning. Significant changes were implemented in January 2007 as part of the Texas Medical Board's response to controlled substance pain treatment, and this year serves as our focal point for analysis.

In 2003, before the policy change, the average number of deaths attributed to unintentional drug poisoning in Texas stood at 8.5. However, by 2006, just prior to the policy change, this figure had increased to 12.5. Interestingly, in 2007, the year when the policy was introduced, it dropped to 9.5. Although there were slight increases in the subsequent years until 2009, there was a gradual decline from 11.2 in 2009 to 9.6 in 2015. Consequently, we can conclude that the policy in Texas contributed to a reduction in deaths caused by unintentional drug poisoning.

The error bars for Texas are significantly shorter compared to those for Florida and Washington. In 2015, out of the 224 counties, 211 reported rates equal to or lower than the mean values. This indicates that the policy had a consistently positive effect across the majority of Texas's approximately 250 counties. However, Nacogdoches, Liberty, Henderson, and Galveston counties reported more than 15 deaths per 100,000 people in 2015, significantly exceeding the average value of 9.55. This suggests a need for further targeted policy changes and investigations in these specific areas.

While the previous graphs provide some understanding of the influence of policies to control opioid prescriptions in the states of Texas, Washington, and Florida, it is essential to consider that Pre-Post Comparison analyses assume that if policies had not changed, these states in the post-change period would have exhibited similarities to how they appeared in the pre-change period. This assumption is made without considering other factors that may have influenced the observed results. We recognize that the real world is complex, and just comparing before-and-after periods may not fully capture all the factors at play.

To address this situation, in the next section, we will perform a Difference-in-Difference analysis that seeks to mitigate the impact of these unconsidered factors, thus providing a more robust assessment of the effects of opioid control policies in the selected states.

Difference-in-Difference analysis

The Differences in Differences (Diff-in-Diff) study utilized states similar to those under investigation as counterfactuals. This analytical approach entails not only comparing the treatment state in the periods before and after a policy change but also assessing how it fares in comparison to other states with similar characteristics during the same time frame. This comparative analysis allows us to understand whether observed changes are specifically attributed to the policy or if they are part of broader trends, such as global decreases in drug consumption.

By conducting this comparison, the aim is to factor in external influences. However, it's important to acknowledge that the Diff-in-Diff method isn't always valid. This methodology assumes that, in the absence of the policy, the treatment state and the counterfactual state would have followed the same trajectory, which isn't always the case. This assumption is referred to as the parallel trends assumption.

It is crucial to recognize that the validity of the Diff-in-Diff technique hinges on the presence of parallel trends between the treatment group and the counterfactual group before the policy's implementation. If these trends diverge significantly, the estimation of the policy's impact may be subject to biases.

Drug prescriptions

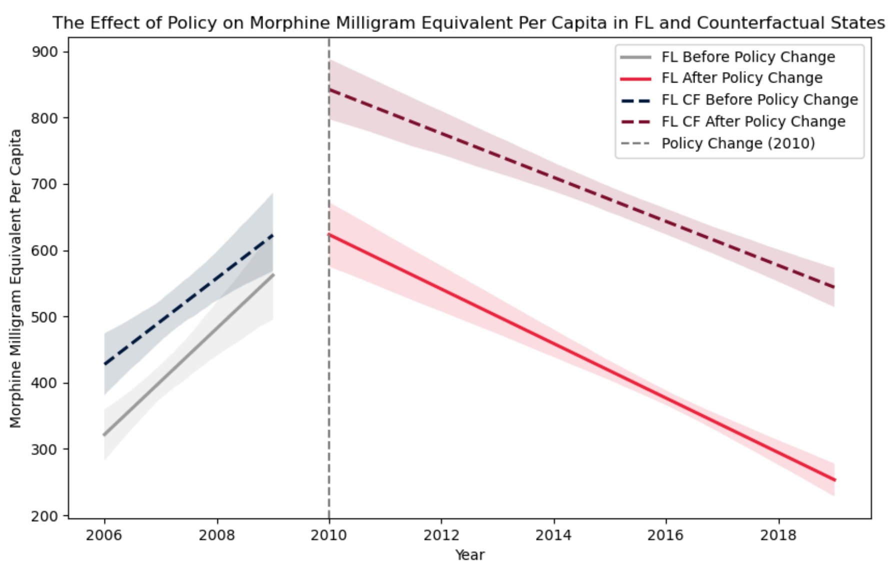

Figure 7: Trend of Morphine Milligram Equivalent Shipped per Capita in Florida Before and After the Policy

In Figure 7, the initial impression suggests a significant impact of the policy implemented in Florida on reducing the Morphine Milligram Equivalent Shipped per Capita. However, upon closer examination and comparison with its counterpart states, the observed effect appears less substantial. This can be attributed to the similarity in the variation depicted in both graphs. Nevertheless, the slope of Florida's trend exhibits a more abrupt variation, suggesting a modest impact of the policy implemented in 2010. This nuanced interpretation indicates that while there may be a discernible effect, it might be relatively smaller than initially perceived.

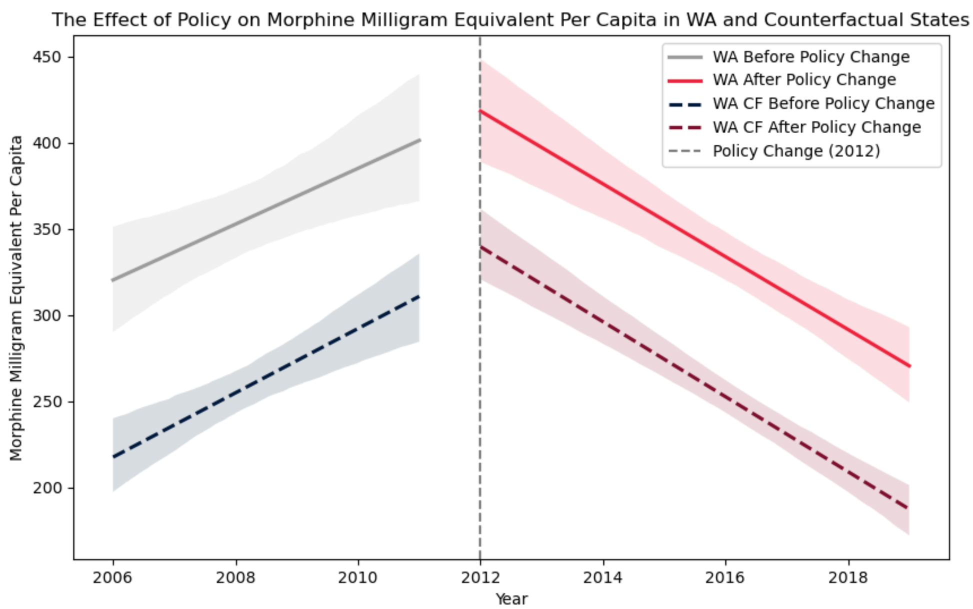

Figure 8: Trend of Morphine Milligram Equivalent Shipped per Capita in Washington Before and After the Policy

Upon reviewing Figure 8 for Washington, a comparable trend emerges. Initially, there appears to be a decline in opioid shipments, yet when contrasted with its counterpart, the observed effect is parallel. While the data initially implies a reduction in opioid shipments following the policy implementation in Washington, the comparison with the hypothetical scenario suggests that the impact might not be as significant as initially assumed. Acknowledging this resemblance in variation between the two conditions becomes crucial for a nuanced evaluation of the policy's effectiveness. The findings for Washington remain somewhat inconclusive. This is mainly attributed to the fact that both the control and treatment groups displayed similar trends both before and after the policy implementation.

In Figure 9, the trend of morphine shipped per capita in Texas before and after the implementation of the policy in 2009 is presented. It is essential to note that, given the availability of a limited information period before the policy's application, monthly data was selected for calculations. This accounts for the more detailed scale of the graphical representation, as we are working with monthly data in this case.

At first glance, a significant and pronounced effect is observed after the policy's implementation in the reduction of Morphine Milligram Equivalent shipped per capita in Texas. This decrease is more conspicuous compared to the counterpart states used as a reference. This result encouragingly suggests that the policies implemented in Texas to prevent indiscriminate opioid consumption have had a positive and effective impact.

The visible reduction in morphine consumption per person after the policy's application indicates that regulatory measures have been successful in controlling the prescription and distribution of opioids in the state. However, it is crucial to consider other factors that could influence this trend and acknowledge that reality is complex. In this context, the analysis of Difference-in-Differences could offer a more profound understanding by comparing these trends with states that did not implement changes in their opioid policies.

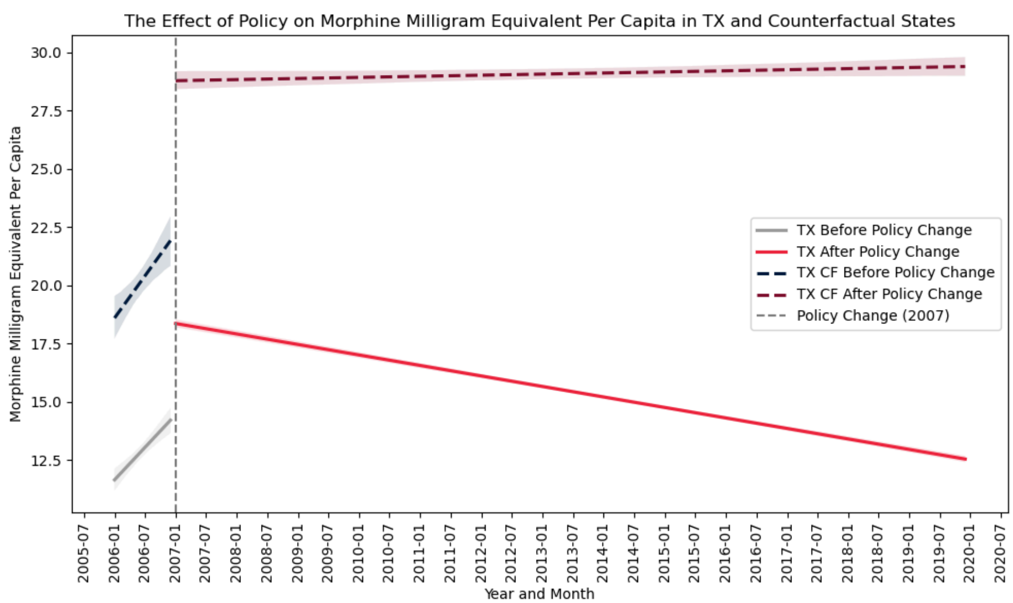

Figure 9: Trend of Morphine Milligram Equivalent Shipped per Capita in Texas Before and After the Policy

Overdose deaths

When analyzing Figure 10, we can observe the effect of the policies on the reduction of drug-related mortality in Florida. A distinct impact of the policy on the unintentional drug poisoning mortality rate per 100,000 population in Florida becomes evident. While the trend in the comparison states remains stable after the analyzed year (2010), Florida exhibits a significant decline in the variable. This reduction implies a positive influence of the implemented policies in Florida on decreasing the unintentional drug poisoning mortality rate, signifying a favorable response to the measures taken.

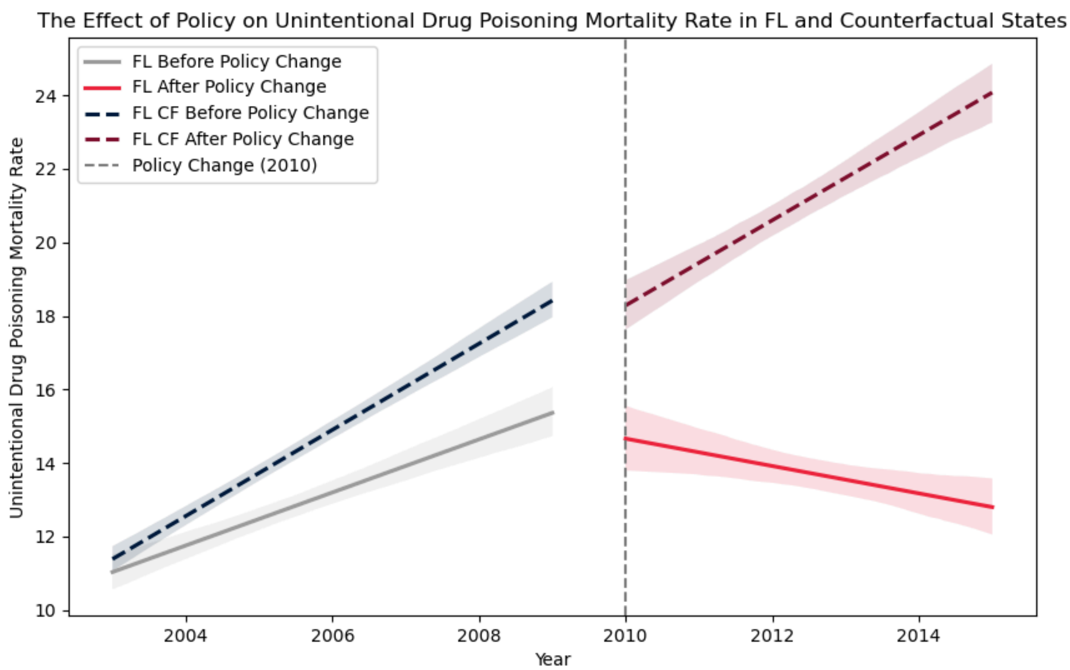

Figure 10: Trend of Unintentional Drug Poisoning Mortality Rate per 100,000 Population in Florida Before and After the Policy

In the case of Figure 11, we can analyze the situation in Washington. At first glance, it seems that Washington's counterpart states may not necessarily be the most suitable concerning the Mortality Rate related to drugs variable. In this way, we do not observe a clear effect in reducing the Unintentional Drug Poisoning Mortality Rate per 100,000 Population. While this variable does not decrease, there appears to be a certain deceleration in its growth.

This lack of a clear decrease could suggest that the policies implemented in Washington may not have had such a pronounced impact on reducing the mortality rate due to accidental drug poisoning. It is important to consider that the absence of a decline does not necessarily indicate that the measures are ineffective, as a slowdown in growth could still be interpreted as a positive effect by preventing more significant increases in the mortality rate.

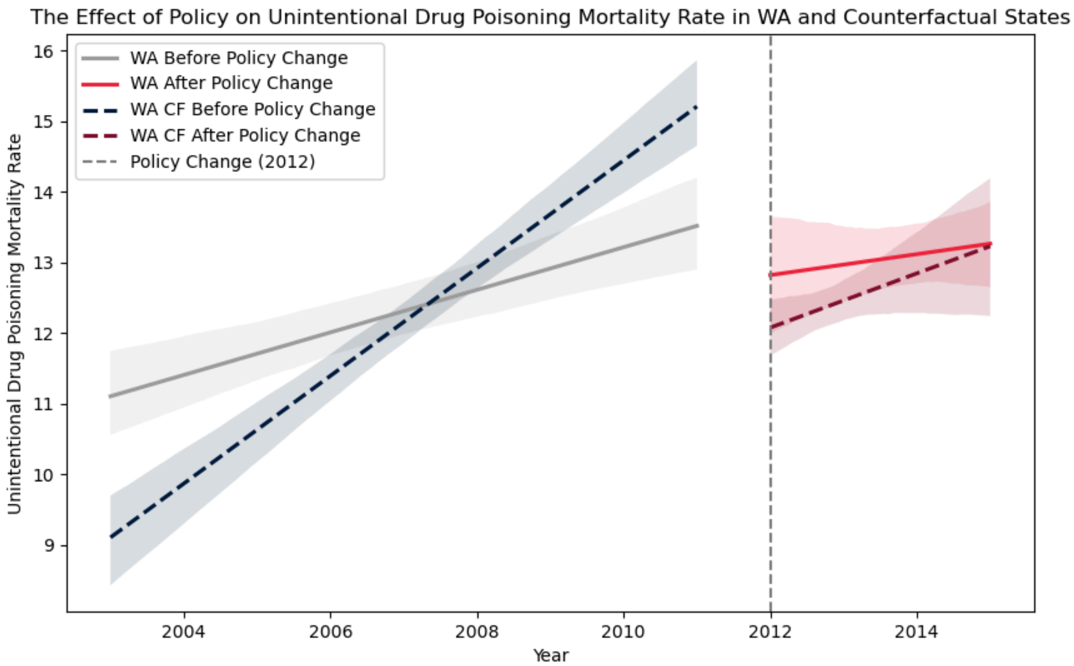

Figure 11: Trend of Unintentional Drug Poisoning Mortality Rate per 100,000 Population in Washington Before and After the Policy

Finally, when analyzing the state of Texas in Figure 12, we can observe a breakpoint after the treatment year of 2007. While there is also a deceleration in the variable Unintentional Drug Poisoning Mortality Rate per 100,000 Population for the counterpart states, the decrease in Texas is more pronounced. Therefore, we can assert that the public policy implemented in Texas does seem to have an effect in reducing drug-related mortality.

This significant reduction in the Unintentional Drug Poisoning Mortality Rate per 100,000 Population in Texas post-2007 suggests a positive impact of the implemented policies. The observed trend indicates that the measures taken in Texas have been successful in curbing the unintentional drug poisoning mortality rate, highlighting the potential effectiveness of the implemented public health interventions. Further analysis and monitoring will be essential to assess the long-term sustainability and overall success of these policies.

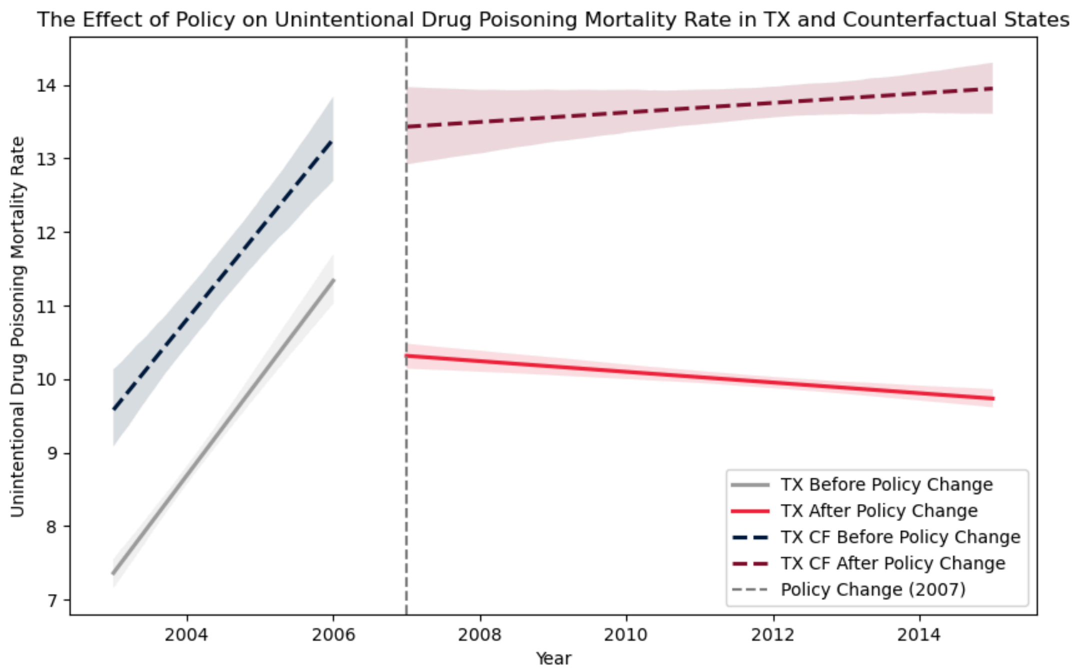

Figure 12: Trend of Unintentional Drug Poisoning Mortality Rate per 100,000 Population in Texas Before and After the Policy

Conclusions

In conclusion, our research provides detailed insights into the impact of state-level policies designed to regulate opioid prescriptions and mitigate associated deaths. Focusing on Florida, Washington, and Texas, our analysis employed a combination of Pre-Post Comparison and Differences-in-Differences methodologies.

The findings reveal varying degrees of effectiveness across the states under examination. In Florida, the initial implementation of opioid restriction policies demonstrated a significant reduction in both opioid prescriptions and overdose deaths, as indicated by the pre-post analysis. However, the differences-in-differences analysis revealed that the decrease in morphine equivalents sent per person was not statistically significant.

For Washington, the post-implementation period showed a subtle deceleration in the growth of variables, as observed in the pre-post analysis. Although the differences-in-differences analysis did not yield a clear result, a discernible effect in reducing unintentional drug poisoning mortality rates was evident.

In contrast, the state of Texas exhibited no apparent impact on opioid consumption in the periods before and after policy implementation. However, the differences-in-differences analysis indicated a stabilization in overdose-related deaths, suggesting a potential positive effect of the policy.

These mixed conclusions underscore the complex nature of the opioid crisis and the varied effectiveness of state-level interventions. While certain policies demonstrated positive outcomes in specific aspects, it is crucial to acknowledge the disparities in impact across states. The utilization of diverse analytical approaches has facilitated a more comprehensive understanding of the multifaceted challenges posed by opioid control policies. Further research and an extended observation period may contribute to refining our understanding and enhancing the effectiveness of future policy implementations.

Future work

While our study provides a comprehensive analysis of opioid consumption per capita and average mortality rates per 100,000 people in every county from 2006 to 2015, it's important to acknowledge potential areas for improvement.

Firstly, our use of Euclidean distance to identify comparable states for Texas, Florida, and Washington may have limitations, as it cannot consider all the influencing factors in state selection.

Moreover, our analysis incorporates additional variables such as population, the percentage of people over 45 years old, and unemployment rates. However, these variables alone may not offer a complete understanding of the situation. Therefore, it would be beneficial to conduct further analyses with additional potential socio-economic factors, such as educational attainment, income per capita, and annual counts of mental health patients, as these factors may be correlated with opioid usage and could provide more insight.

Furthermore, expanding our selection of comparable states to include more diverse options would enable a more thorough and precise difference-in-difference analysis. This would help us better determine whether the opioid policy interventions have indeed been effective or not.

Additionally, although we chose "unintentional deaths" as the primary correlated cause of death related to opioid abuse due to its high percentage (around 70% of all related causes of deaths), we still had to rely on the average mortality rate per state to fill in values for every county and year when computing the average mortality rate per 100,000 people. This method may introduce discrepancies with the actual mortality rate. For future research, it might be beneficial to explore alternative metrics that can better reflect opioid overdose death counts. Moreover, considering that the data for Florida, Texas, and Washington during the period from 2006 to 2015 did not consistently cover information from all counties, even though it included almost all counties, it might be necessary to acquire additional data to ensure comprehensive county-level coverage in our analysis.

Appendices

Appendix 1: Selection of States for Contrafactual Analysis

The accurate measurement of a treatment is often challenging due to the impossibility to observe both the treatment group with treatment and without it simultaneously. To estimate potential outcomes, we seek a group resembling the treatment group. While various techniques like synthetic control group and propensity scores exist for this purpose, they fall beyond the scope of our analysis. Instead, we propose a simpler yet effective method to identify states before policy implementation.

We utilized milligrams purchased per capita for each county, normalized by its standard deviation and mean. We also considered the percentage increase between 2006 and the policy implementation year, the percentage rise in individuals aged 45 and above, and the percentage change in the unemployment rate. Our aim was to identify socioeconomic variables associated with opioid consumption. The unemployment rate reflects the county's economic conditions, the age group over 45 is considered due to health deterioration with age, and using morphine bought per capita helps control for population size.

To establish similarities in trends where policies were not implemented, we examined percentage changes. Variables not within the range of zero to one were normalized for consistency in our four-dimensional space.

Appendix 2: Managing Missing Values in Vital Statistics Mortality Data

In Vital Statistics Mortality Data, we face the challenge that, due to privacy issues, the U.S. Vital Statistics Agency censors some data. This implies that we have NA values for most causes of death in the states under study. To address this situation, we have developed a strategy consisting of 2 parts:

Selection of the most frequent drug-related cause of death

Firstly, we identify the drug-related cause of death with the highest data completeness. Initially, we observe four causes of drug-related deaths in our database. However, if we require each record to have the complete number of deaths for every cause, a significant portion of our data is eliminated. For example, in the case of the three states FL, TX, and WA, we have a total of 4,586 rows, representing a combination of county/year. Out of this total, only 1,078 have values for the most frequent cause of death, 'Unintentional Drug Poisoning Deaths.' On the other hand, only 23 rows have complete values for all four causes of death of interest

For this reason, we decided to only use the cause of death with the highest prevalence, namely "Unintentional Drug Poisoning Deaths." To confirm if our decision makes sense, we calculate, for the 23 rows that do have these 4 complete causes of death, the percentage of deaths corresponding to this main cause. In each state, we find that this main cause represents more than 70% of the total samples related to drug deaths, as shown in Figure 10. Therefore, we consider using only the cause of death "Unintentional Drug Poisoning Deaths" as an appropriate strategy.

Cause of Death	FL	TX	WA
All other drug-induced causes	7%	7%	6%
Suicide Drug Poisonings Deaths	15%	12%	14%
Undetermined Drug Poisonings Deaths	6%	7%	6%
Unintentional Drug Poisoning Deaths	**72%**	**74%**	**74%**
Total	**100%**	**100%**	**100%**

Figure 10: Distribution of deaths due to drug-related causes by state for the period 2005 - 2013 for the states of FL, TX, WA.

Filling Missing Data

Finally, to handle the remaining missing records, we calculate the mortality rate per 100,000 inhabitants for the available data and then determine the average mortality rate for the county's state and year. With this value, we fill in the missing values for counties and years.