Practical Data Science

Assessing the Effects of Opioid Control Policies in The United States

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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 will be 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 are 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. Linear regression and distinct plots were used to estimate and illustrate the 'difference-in-difference' statistically, revealing variations from the year of policy change in each county.

Regarding the results, we have arrived at mixed conclusions. Our analysis indicates that certain state-level public policies designed to regulate medical prescriptions of opioids and subsequently reduce associated deaths appear to be effective in some cases. However, it is essential to emphasize that the degree of effectiveness varies considerably across the states we examined.

Firstly, it is important to note that the conclusions we have drawn are preliminary and subject to potential changes in our final report. Thus far, our findings suggest that the policy intervention in Florida has demonstrated positive results. In the case of Texas, while there is some initial evidence suggesting effectiveness, it's worth mentioning that Texas started with the lowest levels of both morphine consumption and mortality rates. Consequently, further investigation is required to confirm whether the policy has indeed made a significant impact in this state.

Regarding Washington, our team has not uncovered convincing evidence that the policy has successfully reduced morphine consumption per capita. We are currently revisiting our counterfactual analysis and working towards providing a more robust and definitive conclusion on this matter.

Motivation

Recently, the state of prescription opioids in the United States has become more concerning. There has been a notable 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 important to note 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. One notable aspect of this dataset is that it offers two different classification criteria for separating age groups and sex 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. It's worth noting that, as per their documentation, the research group responsible for maintaining this dataset draws data from various sources, including the U.S. Department of Labor, Bureau of Labor Statistics, Local Area Unemployment Statistics, U.S. Department of Commerce, and others. This dataset contains a total of 97 columns, excluding the state or county identification code. 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.*" 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 computed the annual morphine consumption per capita for each state during this timeframe. This involved dividing the total morphine usage by the state's population, offering an estimate of the average morphine consumption per person 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

Later, a more sophisticated analysis was conducted to address certain limitations of the pre-post comparison approach. The 'difference-in-difference' method was employed. Instead of solely comparing the states of Florida, Texas, and Washington before and after the policy changes, an investigation was conducted to determine whether there were more significant changes in overdose deaths in these states following the policy changes compared to other states that did not alter their opioid policies. The previously selected states served as a contrafactual baseline for comparison.

In this analysis, a linear regression was included to estimate the 'difference-in-difference' statistically. 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.

Results

Pre-Post Comparison analysis

Drug prescriptions

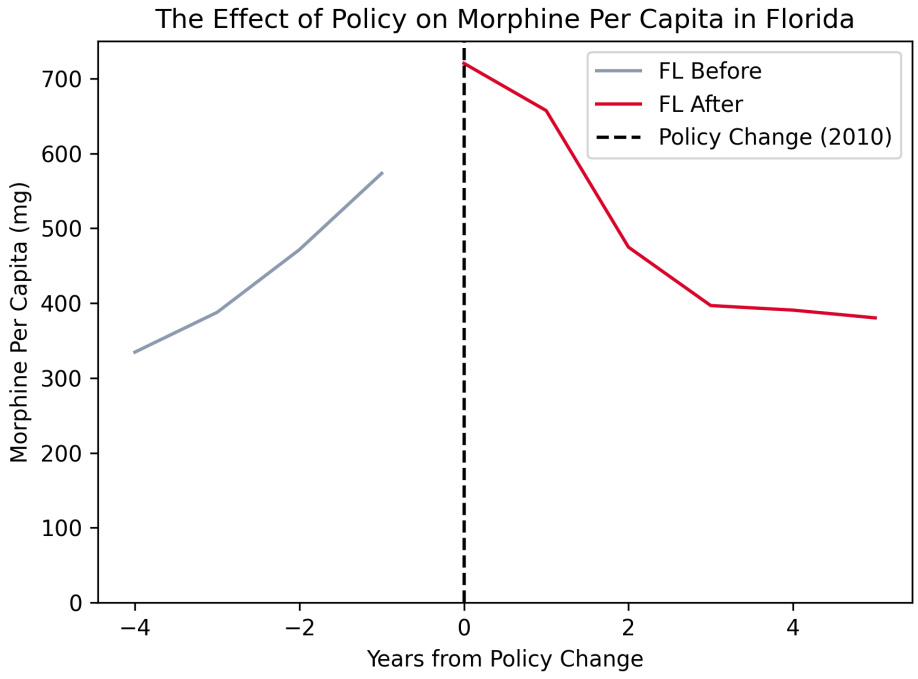

Figure 1: Evolution of Average Morphine Milligram Equivalent Shipped per Capita by Year in Florida

In Figure 1, we can infer the effects of the policy implemented in Florida to address opioid abuse. The implementation of this policy in February 2010 was carried out in response to the proliferation of pain clinics in the state and the excessive prescription of opioids. This Pre-Post Comparison analysis focuses on examining how this series of regulatory measures affected morphine consumption per capita. We used the year 2010 as a breakpoint to answer the question: How did the pattern of morphine sales per person change before and after the implementation of these policies?

During the period prior to the policy implementation (2006-2009), there was a continuous increase in morphine consumption, indicating a concerning upward trend in opioid use in the state. In the year of policy implementation (2010), the data revealed the highest per capita morphine consumption, which represents the peak level. Subsequently, after the policy implementation (from 2011 to 2015), there was a consistent downward trend in the ratio of morphine milligrams sold per person, starting from 2011. This decrease suggests that, after an initial adjustment period, the opioid control policy might be having a positive impact on reducing morphine consumption in the state.

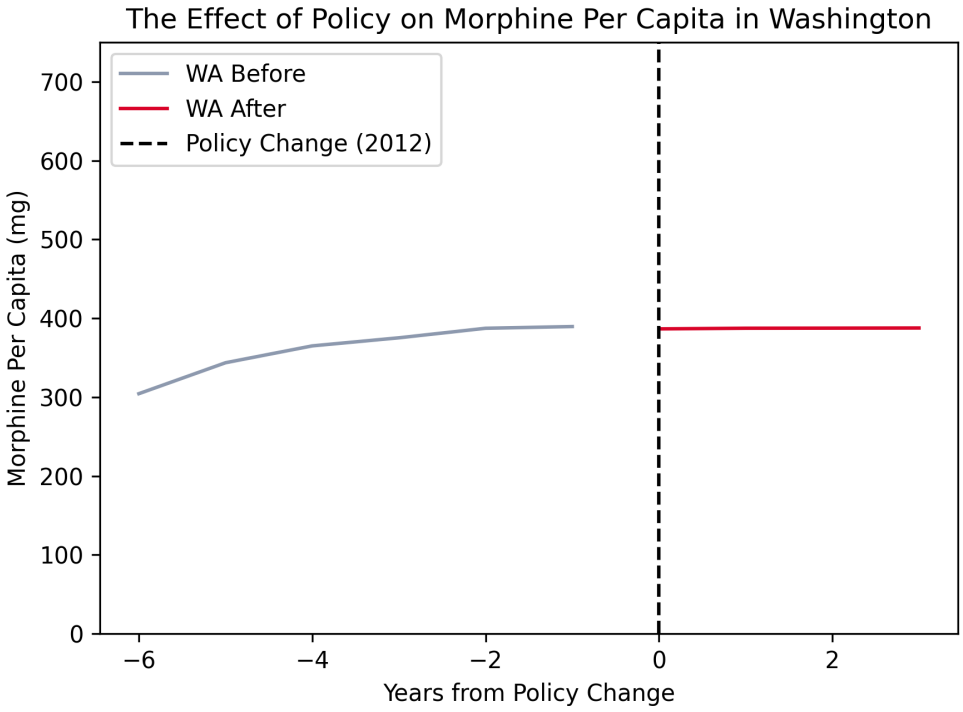

Figure 2: Evolution of Average Morphine Milligram Equivalent Shipped per Capita by Year in Washington

In Figure 2, we can analyze the effects of the policy implemented in the state of Washington to address opioid abuse. We can consider the year 2012 as pivotal for Washington in its efforts to tackle opioid abuse, marking a significant change in prescription regulations.

During the period prior to the policy implementation (2006-2011), there was a gradual increase in morphine consumption. After the implementation (2012-2015), the trend shows some stability, and there is no significant change in the evolution of the average morphine shipped per person. This could suggest that the regulations implemented in 2012 may have contributed to better control of morphine consumption in the state of Washington.

Overdose deaths

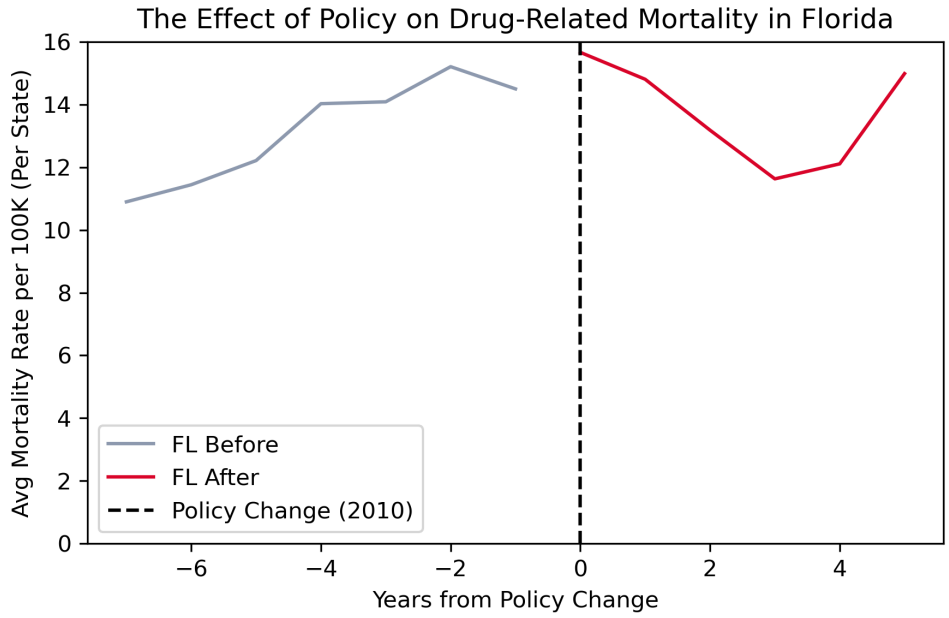

Figure 3: Evolution of Unintentional Drug Poisoning Mortality Rate per 100,000 Population by Year in Florida

In Figure 3, we aim to understand the impact of Florida's opioid control policy on mortality rates from accidental drug poisoning. Once again, we use the year 2010 as a breakpoint for Florida, considering the changes in its policies around that time. When analyzing the average mortality rate per 100,000 people in Florida from 2006 to 2015, we observed primarily an upward trend leading up to the implementation of the policy in 2010. However, starting from the year of the policy change, 2010 (with a rate of 15.66), we observed a decreasing trend in mortality rates, reaching a low point in 2013 (11.63). While there was a minor uptick in 2015 with a value of 14.98, when we analyze the broader patterns in both total morphine consumption and total transactions, as compared to another dataset we possess, it becomes evident that Florida's policy intervention continues to contribute positively to the reduction of opioid overdose deaths.

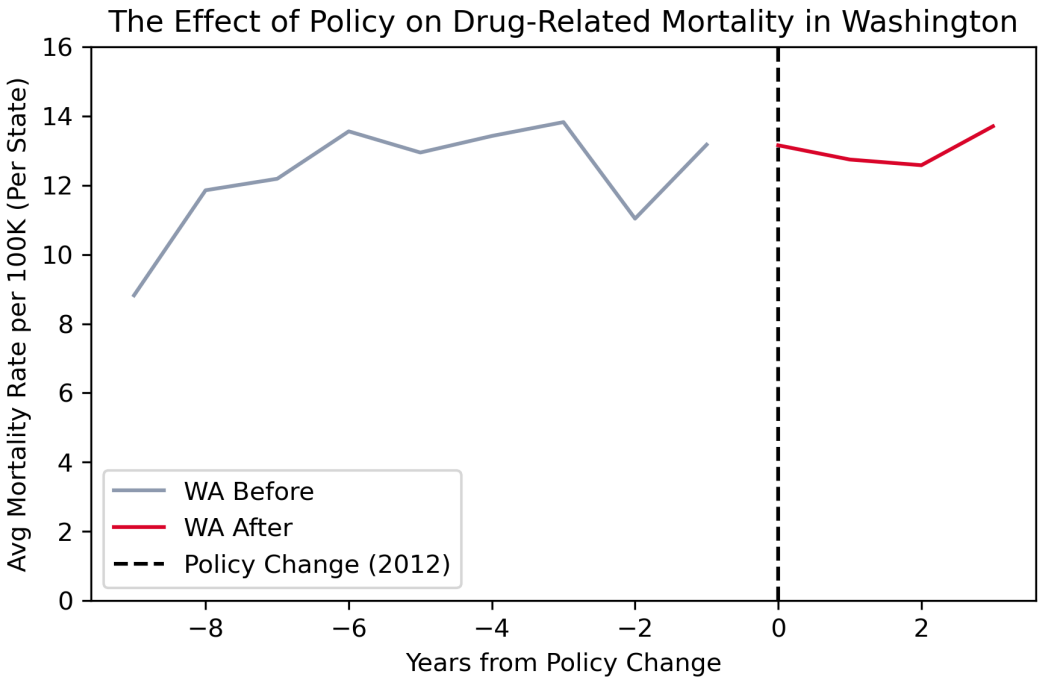

Figure 4: Evolution of Unintentional Drug Poisoning Mortality Rate per 100,000 Population by Year in Washington

In Figure 4, we examine the implications of modified opioid prescription practices in the state of Washington on mortality rates from accidental drug poisoning. Significant changes were implemented in January 2012 as part of Washington's response to the opioid crisis, making this year our breakpoint for analysis.

The average mortality rate exhibited predominantly increasing trends until 2012. However, a decrease was observed from 2012 (13.16) to 2014 (12.58). Although there was an increase in the average mortality rate in 2015, it's important to note that this rise appears to be temporary. We conducted additional analysis using another dataset and discovered that the increasing trend observed in 2015 is not sustained. This is evident because both the total morphine consumption amount and transaction cases have consistently decreased since 2015.

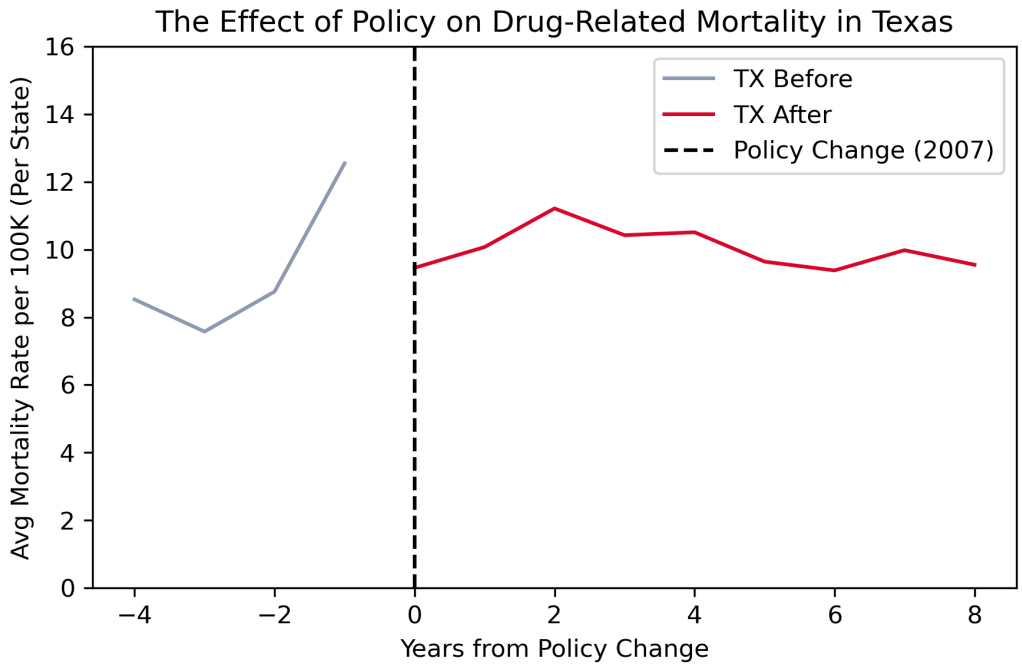

Figure 5: Evolution of Unintentional Drug Poisoning Mortality Rate per 100,000 Population by Year in Texas

In Figure 5, we explore the effects of modified opioid prescription practices in the state of Texas on mortality rates from accidental drug poisoning. Significant modifications were introduced in January 2007 as part of the Texas Medical Board's response to pain treatment with controlled substances, marking this year as our focal point for analysis.

Prior to 2007, the data indicates a varying pattern in mortality rates, with notable fluctuations in the years leading up to the pivotal policy changes. Post-2007, there is a mix of increasing and decreasing rates. However, on average, it appears that the rates have decreased since 2007.

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

Drug prescriptions

As is stated through this document, our analysis was conducted for three different states: Florida, Washington and Texas which have different interventions in different times. Florida, despite having more than one public intervention, has 2010 as the treatment year; in the case of Washington the year is 2012; and Texas in 2007. In those edge years, the average Morphine Bought (MB) per capita in milligrams (mg) in the states is shown in the next table:

Year	State	Avg. MB (mg)	National avg	Policy effect	P-value
2006	Texas	151.88	132.7	-0.54*	0.002
2009	Florida	573.39	182.33	-188.15	0.000
2011	Washington	389.56	209.79	-19.88	0.28

*The data for Texas was treated biweekly in a 36 months span from January 2006 to December 2008.
Note: The averages were picked in the last year without implementation.

Table 1: Morphine Milligram Equivalent Shipped per Capita

The table above illustrates the consumption by state and the National average to have a comparison point. The three states were above the national average the year before each policy implementation, Florida with the largest difference. After conducting the econometric analysis only in two places the data showed evidence of quantity changes due to the policy implemented, Florida, with the largest decrease of 188 mg per capita less from 2010 to 2019, and Texas with -0.54 mg per capita less from January 2007 to December 2008. The next plots illustrate the before and after the policy was implemented.

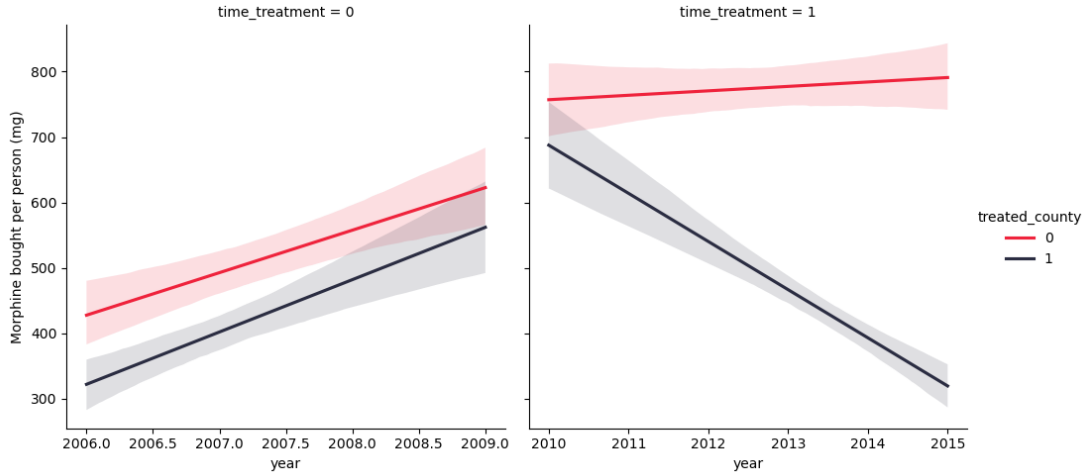

Figure 7: Annual Trend of Morphine Milligram Equivalent Shipped per Capita in Florida Before and After the Policy
Note: Confidence Intervals at 95%.

As we can see in the figure above the control group chosen and the state of Florida followed similar trends, however after the treatment the state of Florida commenced falling consistent with our regression analysis.

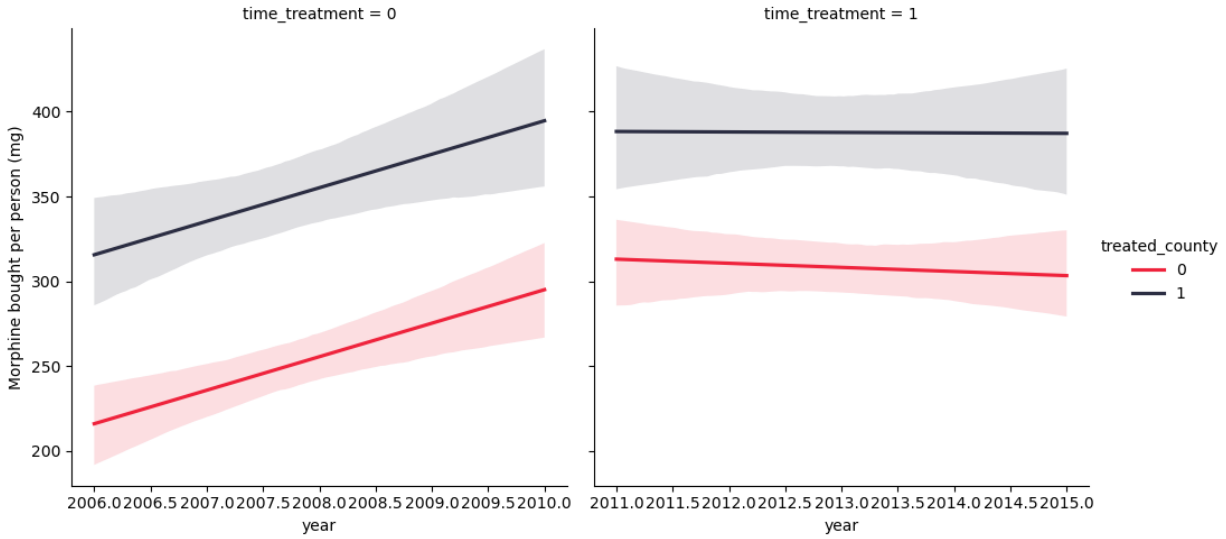

Figure 8: Annual Trend of Morphine Milligram Equivalent Shipped per Capita in Washington Before and After the Policy
Note: Confidence Intervals at 95%.

With Washington the results are not clear. First because both control and treatment presented the same trends before and after the policy implementation. However, this is consistent with our regression analysis where we found lack of evidence to support that the policy effect was different from zero.

In the case of Texas, the amount of data was limited as the starting year was 2006 for the opioid dataset. For that reason the analysis conducted was more granular and the time unit was biweekly. The figure below shows the changes before and after the policy implementation.

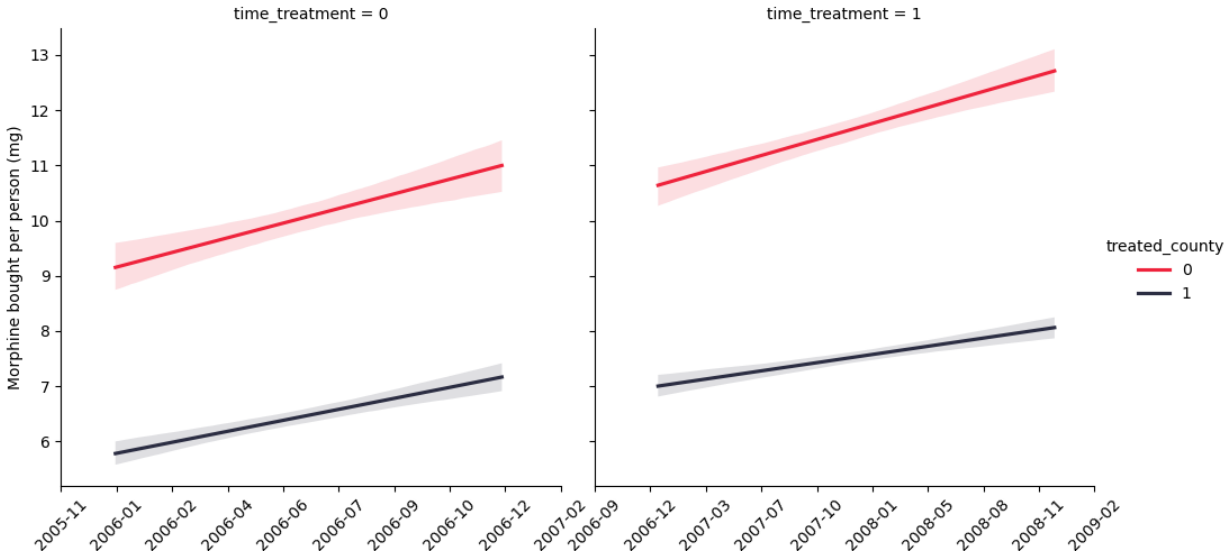

Figure 9: Annual Trend of Morphine Milligram Equivalent Shipped per Capita in Texas Before and After the Policy
Note: Confidence Intervals at 95%.

The slope change is subtle after the policy implementation and this can be caused for the same granularity that we are considering. More often than not, policies need years to be not just fully implemented but to start seeing results derived from the implementation. In the case of Texas, we consider a small effect in the two following years of the implementation. Nonetheless, even if the change is subtle it can be relevant in proportional terms. Recalling table 1, Texas was the state with less Morphine mg bought per capita meaning that even small changes are relevant in terms of percentage changes.

However, our study seeks to answer if the policies influenced the overdose deaths too. To tackle these questions the same analysis was conducted with mixed results. First, we present the same table as we did for Morphine Bought per capita (mg).

Overdose deaths

Overdose Mortality Rates for 100,000 inhabitants

Year	State	Mortality rate (100k)	National Avg	Policy effect	P-value
2006	Texas	12.54	10.94		
2009	Florida	14.5	10.95	-4.86	0.000
2011	Washington	13.17	12.	0.8	0.07

Note: We are still working in Texas and we might change Washington counterfactuals

The table shows similar results as table 1. Texas is the state with the smallest mortality rate, is followed by Washington and finally, Florida. The policy effect measure only was conducted for Washington and Florida for data availability.[1] To follow the same path of analysis we conducted trends visualizations for our control and treatment states shown below.

[1] We are still working on Texas data and we are going to change our Washington counterfactuals for mortality.

Conclusions

In conclusion, the application of a Pre-Post Comparison analysis revealed significant insights into the impact of opioid control policies in the states of Florida, Texas, and Washington. Particularly, the implementation of policies in Florida in 2010 led to a substantial reduction in morphine consumption per capita, demonstrating the effectiveness of regulatory measures in curbing opioid prescriptions. Similarly, Washington's policy changes in 2012 appeared to stabilize morphine consumption, suggesting a successful intervention. However, the analysis for Texas, with policy changes in 2007, showed a more nuanced picture, with a subtle decrease in morphine consumption. While Pre-Post Comparison analyses provide valuable insights, the complexity of real-world factors requires further investigation.

In the case of the analysis on overdose deaths, in Florida, opioid control policies in 2010 led to a significant reduction in mortality rates. Changes in Washington in 2012 initially showed a decline until 2014, with a temporary increase in 2015. However, further analysis revealed that this increase was not sustained. In Texas, modifications in 2007 resulted in mixed patterns of mortality rates, but overall, rates decreased after 2007.

The subsequent application of a Differences-in-Differences analysis addressed some limitations of the initial approach, yet the conclusions remain similar. The econometric analysis indicated that Florida experienced the most significant reduction in morphine consumption, followed by Texas. However, the results for Washington were inconclusive, suggesting the need for a more comprehensive examination and possibly a longer observation period.

The comprehensive analysis presented here underscores the importance of employing diverse methodologies to comprehend the multifaceted impact of opioid control policies, urging continued research for a more nuanced understanding and effective policy implementation.

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.

Finally, we need to enhance our difference-in-difference analysis. Contrary to our initial expectations, we obtained dissimilar results and trend lines for Washington. As a result, we are currently in the process of reevaluating our analysis approach. For now, we have included the difference-in-difference analysis and tables specifically for morphine consumption per capita to illustrate the policy effects in Florida, Texas, and Washington.

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.

Appendix 3: Regression results

The following regressions were conducted to determine the effect of the policies implemented in our three states of analysis. The three variables used were time_treatment, 1 if the policy is already in place, 0 if not; treated_county, 1 if the county was part of one of the three states selected, 0 if not; treatment, 1 if the two variables listed before are 1, 0 if not. Now we list our two first states and their regression considering first Morphine Milligrams bought per capita.

Florida

Drug Shipments

OLS Regression Results

Dep. Variable:	Morphine Milligrams per capita		
		R-squared:	0.129
Model:	OLS Adj.	R-squared:	0.127
Method:	Least Squares	F-statistic:	87.56
Date:	Nov 2023	Prob (F-statistic):	7.65e-53
		Log-Likelihood:	-12985.
No. Observations:	1781	AIC:	2.598e+04
Df Residuals:	1777	BIC:	2.600e+04
Df Model:	3		
Covariance Type:	nonrobust		

	coefficients	std err	t	P>|t|	[0.025	0.975]
Intercept	524.8642	16.884	31.086	0.000	491.749	557.979
time_treatment	249.2436	21.755	11.457	0.000	206.575	291.912
treated_county	-82.5352	27.598	-2.991	0.003	-136.663	-28.408
treatment	**-188.1512**	35.553	-5.292	0.000	-257.881	-118.422

Omnibus:	522.793	Durbin-Watson:	0.228
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1544.227
Skew:	1.497	Prob(JB):	0.00
Kurtosis:	6.441	Cond. No.	7.12

Mortality Rate

OLS Regression Results

Dep. Variable:	Mortality rate	R-squared:	0.279
Model:	OLS	Adj. R-squared:	0.278
Method:	Least Squares	F-statistic:	229.0
Date:	Nov 2023	Prob (F-statistic):	1.31e-125
		Log-Likelihood:	-5395.2
No. Observations:	1781	AIC:	1.080e+04
Df Residuals:	1777	BIC:	1.082e+04
Df Model:	3		
Covariance Type:	nonrobust		

	coefficients	std err	t	P>|t|	[0.025	0.975]
Intercept	17.0153	0.238	71.479	0.000	16.548	17.482
time_treatment	4.1431	0.307	13.508	0.000	3.542	4.745
treated_county	-2.5587	0.389	-6.576	0.000	-3.322	-1.796
treatment	-4.8692	0.501	-9.714	0.000	-5.852	-3.886

Omnibus:	907.404	Durbin-Watson:	1.132
Prob(Omnibus):	0.000	Jarque-Bera (JB):	13395.838
Skew:	2.027	Prob(JB):	0.00
Kurtosis:	15.809	Cond. No.	7.12

Washington

Drug Shipments

OLS Regression Results

Dep. Variable:	Morphine Milligrams per capita		
		R-squared:	0.095
Model:	OLS	Adj. R-squared:	0.093
Method:	Least Squares	F-statistic:	39.95
Date:	Nov 2023	Prob (F-statistic):	1.49e-24
		Log-Likelihood:	-7369.3
No. Observations:	1147	AIC:	1.475e+04
Df Residuals:	1143	BIC:	1.477e+04
Df Model:	3		
Covariance Type:	nonrobust		

	coefficients	std err	t	P>|t|	[0.025	0.975]
Intercept	255.7441	7.702	33.204	0.000	240.632	270.856
time_treatment	52.4871	10.871	4.828	0.000	31.158	73.817
treated_county	99.4086	13.192	7.536	0.000	73.526	125.291
treatment	**-19.8812**	18.643	-1.066	0.286	-56.460	16.697

Omnibus:	75.342	Durbin-Watson:	0.250
Prob(Omnibus):	0.000	Jarque-Bera (JB):	88.764
Skew:	0.663	Prob(JB):	5.31e-20
Kurtosis:	3.313	Cond. No.	6.33

Mortality Rate

OLS Regression Results

Dep. Variable:	Mortality rate	R-squared:	0.006
Model:	OLS	Adj. R-squared:	0.003
Method:	Least Squares	F-statistic:	2.077
Date:	Nov 2023	Prob (F-statistic):	0.102
		Log-Likelihood:	-2692.7
No. Observations:	1010	AIC:	5393.

Df Residuals:	1006	BIC:	5413.
Df Model:	3		
Covariance Type:	nonrobust		

	coefficients	std err	t	P>|t|	[0.025	0.975]
Intercept	13.4345	0.205	65.378	0.000	13.031	13.838
time_treatment	-0.6926	0.281	-2.466	0.014	-1.244	-0.142
treated_county	-0.4754	0.323	-1.470	0.142	-1.110	0.159
treatment	0.8057	0.451	1.786	0.074	-0.080	1.691

Omnibus:	322.728	Durbin-Watson:	1.460
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1143.681
Skew:	1.522	Prob(JB):	4.50e-249
Kurtosis:	7.231	Cond. No.	6.49

Texas

Drug Shipments

OLS Regression Results

Dep. Variable:	Morphine Milligrams per capita		
		R-squared:	0.071
Model:	OLS	Adj. R-squared:	0.071
Method:	Least Squares	F-statistic:	820.8
Date:	Nov 2023	Prob (F-statistic):	0.00
		Log-Likelihood:	-1.1012e+05
No. Observations:	32053	AIC:	2.202e+05
Df Residuals:	32049	BIC:	2.203e+05
Df Model:	3		
Covariance Type:	nonrobust		

	coefficients	std err	t	P>|t|	[0.025	0.975]
Intercept	10.0730	0.103	98.247	0.000	9.872	10.274
time_treatment	1.6001	0.126	12.739	0.000	1.354	1.846
treated_county	-3.6011	0.145	-24.803	0.000	-3.886	-3.317
treatment	-0.5421	0.178	-3.046	0.002	-0.891	-0.193

Omnibus:	23124.861	Durbin-Watson:	0.274
Prob(Omnibus):	0.000	Jarque-Bera (JB):	557183.940
Skew:	3.219	Prob(JB):	0.00
Kurtosis:	22.384	Cond. No.	8.42