Preliminary Report [Technical]

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Introduction

Since 1999, healthcare providers in the United States began prescribing opioids at large as pain relievers with the assurance of pharmaceutical companies that such pain relievers are not addictive. This soon proved problematic as the increased opioid prescriptions and the addictive nature of drugs led to the widespread abuse of opioids and nearly quadrupled drug overdose-related deaths across the United States (NCSL, 2019). To address this public health concern, several states have introduced prescription drug limitations and monitoring programs to enforce stricter rules on the prescription of opioids. This study aims to analyze the causal effect these policy changes had on mortality rates due to drug overdose. We examine three different states that implemented such policy changes: Florida, which went into effect in February 2010, Texas, which went into effect in January 2007, and Washington, which went into effect in January 2012. Furthermore, for Florida and Washington, we will analyze the effect the policy change had on drug prescriptions. We hope to deliver results that can inform policymakers about the effectiveness of such policies to prevent future drug overdose deaths and help combat the opioid crisis in the United States.

Data & Methodology

We utilized two types of data: prescription opioid shipments data and U.S. mortality data. The *opioid prescriptions* data set, released by the Washington Post in 2020, contains all prescription oxycodone and hydrocodone, both opioids, medication shipments in the United States from 2006 to 2014. We use this data to analyze the changes in the opioid prescription for Florida and Washington and their respective comparison states. The *mortality data* contains statistics on every death in the United States (although some are missing for privacy reasons) and the data set includes a variable that informs us about the general form of death. This data set is provided by the US Vital Statistics system. We utilize this data set to analyze the changes in drug-related mortality rates in Florida, Texas, and Washington. In addition to these two data sets, we also need to obtain data on the population for each county and year. Both the absolute number of opioids delivered and the number of deaths are not meaningful for analysis unless they are normalized by the population of each county in each year, because more populated counties are anticipated to have more opioid prescriptions as well as a higher absolute number of deaths. Thus, we obtain census data on the population for all states we study from the U.S. Census Bureau.

Based on these data sets, we conduct a difference-in-difference analysis. We choose this methodology as – given adequate comparison states – it enables us to infer causal relationships between the policy introduction and mortality rate. Moreover, it aids in comparing our results to previous research in the field which often employs difference-in-difference analyses (e.g., Dowell et al., 2016).

To conduct a difference-in-difference analysis for the three states we want to study, each of these three states (all of which have introduced drug-control policies) has to be compared to a set of *comparison states* which have not enacted similar policies. Our goal is to find comparison states that are a) similar to the three states studied before the policy was introduced as well as b) are expected to behave similarly to the states studied after the policy has been introduced. If we identify such states, we can treat them as good proxies for the counterfactuals of a state not having introduced a drug control policy. Any states that enacted drug control policies were manually excluded as they cannot constitute a good counterfactual. We then choose five comparison states from the remaining states for each of our baseline based on similarity metrics that are related to a) political orientation (as politics has a major influence on public policies) b) physical proximity to the state, and c) general demographics based on data from. We choose these similarity metrics as it is the political system that can enact and enforce drug control policies. Thus, states with generally similar political orientations might behave more similarly than states in which the population votes differently. Furthermore, we expect states that are close together geographically to be more comparable than states that are far apart. Finally, we use demographic characteristics for similarity matching as it is related to the distribution of causes of death, e.g, states with older populations might have more natural and fewer drug-related deaths than states with younger populations or vice versa. After finding five potential comparison states for Florida, Texas, and Washington, we perform exploratory data analysis to examine the drug-related mortality trends of each of these comparison states in relation to the baseline to narrow down to three states per baseline. The final comparison states chosen for each state are listed in the table below:

State	**Comparison States**
FL	GA, IL, MS
TX	GA, IL, KS
WA	CA, IL, KS

After collecting all necessary data sets, we continue onto clean the data on hand. The geographic unit of observation for our analysis is a county and the temporal unit is a year, therefore, we will aggregate our data, if needed, to reflect shipments, mortality, and population on a per county per year basis. Consequently, the census data does not need additional cleaning or grouping as it is comprehensive and contains the absolute population for each county per year. The only change we made is to remove footnotes and extra columns in the Excel tables that helped the interpretation of the data but hindered the automated data reading.

As for the shipments data, we extract only the necessary columns to reduce computational overhead and correct the data types. Next, we have to calculate a standardized measure for the "amount of opioids". Neither the number of pills nor the absolute weight of a shipment can be used, as both ignore the strength. Consequently, we choose to calculate the opioid quantity as

$$opioid\_qty \ = dosage\_unit * strength * MME\_conversionfactor$$

Which multiplies the opioid dosage unit by its strength and converts it to Morphine-milligrams-equivalent. Then we group it by county and year for each state, summing the "opioid_qty".

In contrast to the drug shipments data, the mortality data requires extensive preprocessing, as it contains the absolute number of deaths for drug-related as well as alcohol and non-drug-related causes for the entire United States. Thus, we only filter the data set for the state we need and subset by death cause. We consider the following codes/causes to be considered "drug-related":

Code	**Cause**
D1	Drug poisonings (overdose) Unintentional
D2	Drug poisonings (overdose) Suicide
D4	Drug poisonings (overdose) Undetermined
D9	All other drug-induced causes

The mortality data also includes a significant amount of missing values. Since any death count under ten in a given year in a county under a given death code is redacted from the original data set, we lose a significant number of counties from the data set. This only worsens after subsetting for the four drug-related death categories, to a point where we are only left with 43 out of 254 counties for Texas. We tried to mean-impute the mortality rate for the missing counties and death codes by the mean mortality rate in all other counties in a given year but found the imputation to significantly bias our results, as for some states almost 90% of the data had to be imputed. The missing data issues were specifically prevalent for deaths coded as "D9" as only a few counties reported D9. Given its description, however, D9 should be part of our analysis. Thus, considering the amount of missing data, we conclude that we do not have a reasonable basis to impute death data on a per drug code per year per county basis, so we drop any observations with missing values instead.

Finally, the cleaned data sets need to be combined with the census data to calculate the number of opioids shipped *per capita* as well as the mortality *rate*. As our unit of observation is one county per year, we use the (State, County, Year) variables as a join key to merge the data sets. Subsequently, we can calculate – for each county in each state per year – the ratios of interest: the mortality *rate* and the number of opioids shipped *per capita*. These will be used for both the pre-post as well as the difference-in-differences analysis. For each state we study, we concatenate the state's data with its comparison states data, such that the final data set for each analysis is one data frame. Some summary statistics for these data are displayed in the tables in Appendix A.

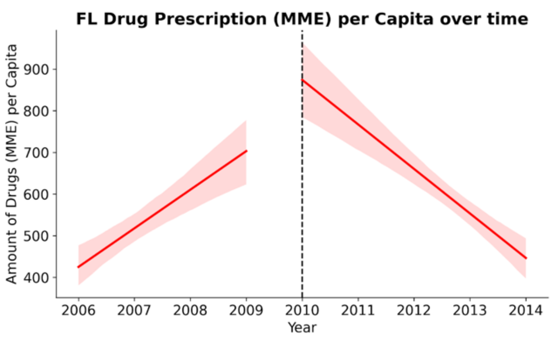
Based on this data we will create pre-post and difference-in-differences plots. To further quantify the effect that the policies had, will perform a difference in differences regression.

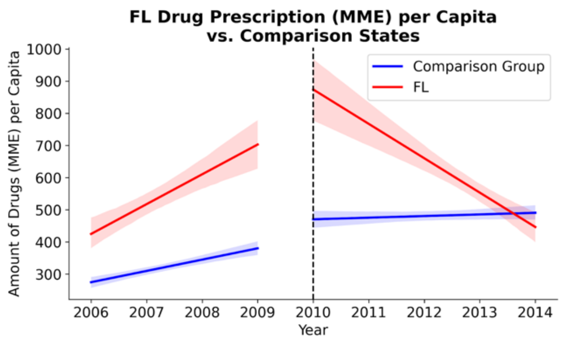
Analysis

For each policy change, a pre-post analysis and a difference-in-difference analysis are carried out. We look at how policy changes influence both opioid shipments and overdose deaths in Florida, but just overdose deaths in Texas and Washington.

Florida

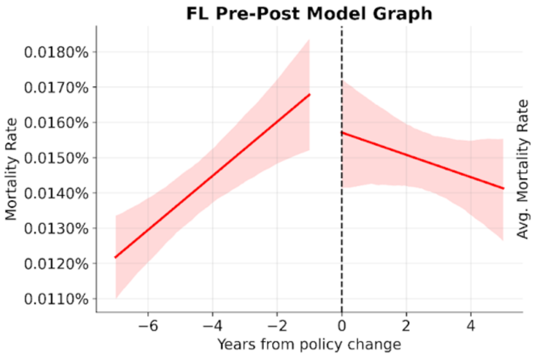
Shipments Data

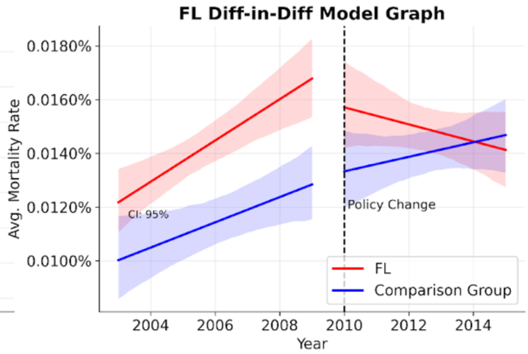




The number of opioids shipped per capita in Florida decreased significantly after the drug control policy was introduced. Comparing this data to the comparison state shows that generally, after 2012, the increase in opioids per capita started to slow down. For Florida, however, this decrease was more drastic than for the comparison states which indicates that the policy did cause this reduction in opioid prescriptions. This can be explained by the fact that the policy enforces stricter rules and monitoring around prescribing opioids so physicians have to be more rigorous and cannot prescribe as many opioids as before.

Mortality Data

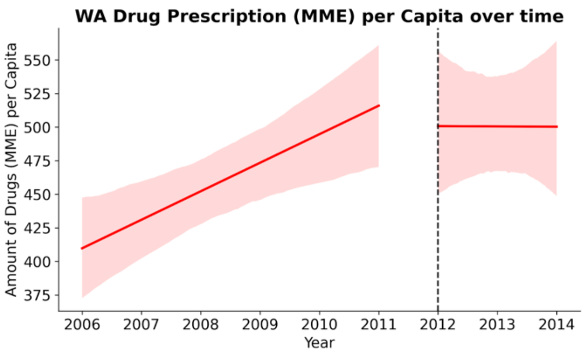


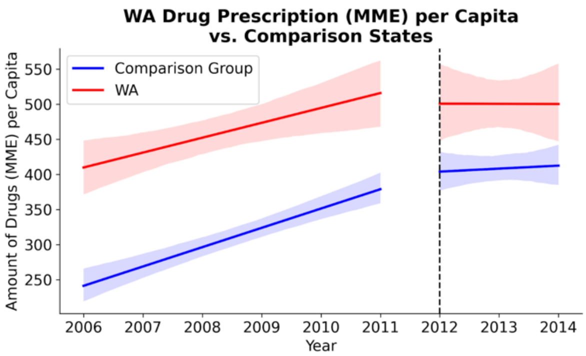


The pre-post analysis indicates that the mortality rate decreased after FL introduced the policy. However, to make sure that this change cannot just be attributed, we use the difference-in-differences plot to compare this change against the average change in all comparison states. The plot might indicate that the policy was effective in reducing drug-related mortality if we only consider the trendlines since the mortality in the comparison states kept climbing after 2010 whereas the trend reversed in Florida. However, if we also consider the 95% confidence intervals around the regression lines, we cannot conclude that the policy had an effect: the confidence intervals are so wide that the post-policy trend in Florida could still be increasing while the trend in the comparison states decreases!

Washington

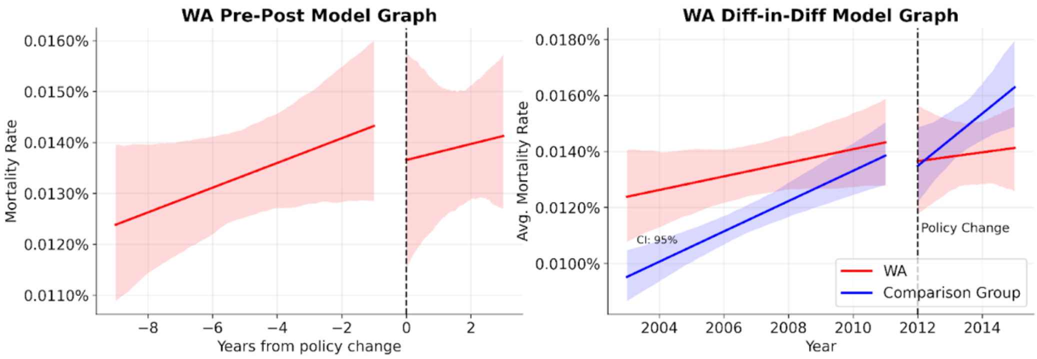
Shipments Data





The pre-post analysis of prescribed opioids in Washington might indicate that the policy had an effect: Before 2012, Washington saw a steady increase in opioids shipped per capita, while the trend stagnated after 2012. However, this has to be compared against the trend in the comparison states. The difference-in-differences analysis indicates that the comparison states saw the same stagnation – but without introducing a drug control policy. This leads us to conclude that the enactment of the policy in Washington did not cause a decline in prescribed opioids, but maybe another factor (one that also affected the comparison states) influenced the trend in shipped opioids per capita.

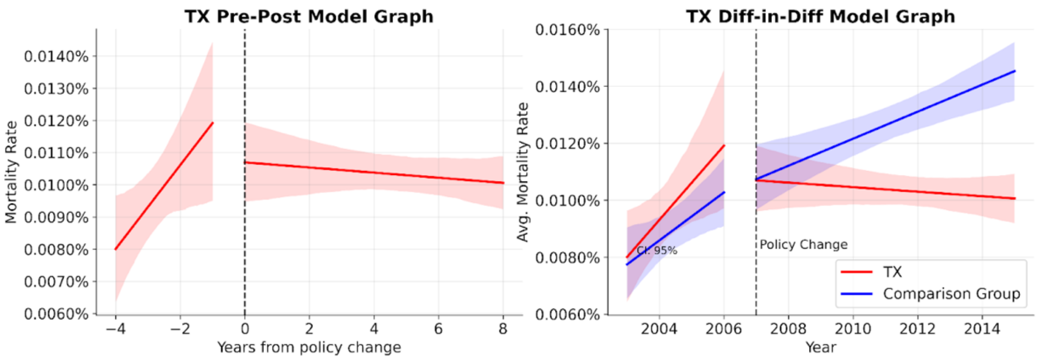
Mortality Data



As for the mortality data, the pre-post plot already indicates that there was no severe effect on the drug-related mortality rate (although the estimates are subject to more uncertainty than for the other states). Comparing this trend to the results of the difference-in-difference analysis shows that we cannot conclude that the policy was effective. The confidence intervals for the post-policy trends in mortality rate overlap. While we can be 95% confident that the trend in the comparison states did not reverse (i.e. the slope is greater than zero), for Washington the width of the confidence interval does not indicate a clear change in trend.

Texas

Mortality Data



For Texas, judging from the pre-post plot, the mortality reduced after the introduction of the policy as the trend changed from a sharp increase to a slight decrease over time. Once again, we have to compare this effect against several comparison states to make any causal claims. While the rate of change of mortality rate reduced for both Texas and the comparison states, the mortality rate is decreasing in TX after the introduction of the policy. Comparing this against the rather steady and unchanged increase in mortality for the comparison states indicates that the policy might have caused a decrease in drug-related deaths.

To quantify the effects of the policies with more detail, we fit a difference-in-differences regression model. We create two binary dummy variables for a) the introduction of the policy (zero before policy was introduced and one after), and b) the treatment state (one for treatment state, zero otherwise). We then regress the mortality rate and number of opioids per capita on the year of policy introduction (normalized to zero being the year that the policy has been introduced), the two dummy variables, and all possible interactions between these three. The estimated coefficients for the two regression models for Florida are shown in the tables below.

	coef	std err	t	P>|t|
Intercept	0.0001	8.69e-06	15.309	0.000
post	1.81e-07	1.1e-05	0.016	0.987
policystate	4.238e-05	1.3e-05	3.265	0.001
post*policystate	-1.857e-05	1.66e-05	-1.116	0.265
year	4.695e-06	2.13e-06	2.200	0.028
year*post	-1.995e-06	3.05e-06	-0.654	0.513
year*policystate	2.979e-06	3.04e-06	0.980	0.327
year*post*policystate	-8.844e-06	4.56e-06	-1.939	0.053

Table 1: Regression of FL mortality rate

	coef	std err	t	P>|t|
Intercept	2.706e+07	9.15e+06	2.956	0.003
post	3.169e+06	1.08e+07	0.292	0.770
policystate	2.815e+08	2.51e+07	11.223	0.000
post * policystate	1.174e+07	2.97e+07	0.396	0.692
year	2.283e+06	3.34e+06	0.684	0.494
year * Post	-2.074e+06	4.09e+06	-0.507	0.612
year * policystate	4.043e+07	9.17e+06	4.409	0.000
year * post * policystate	-9.689e+07	1.12e+07	-8.635	0.000

Table 2: Regression of FL opioid shipments

For these regression models the coefficient of the interaction between year and the two dummy variables is the most interesting one. It represents the difference in differences for three just stayed after the policy has been introduced compared to control states before the policy change. We can see that for Florida both of these estimated coefficients are negative, indicating a decline in mortality rate and number of opioids shipped respectively. For the regression of the mortality rate the coefficient is not significantly different from zero. However, this does not necessarily indicate that there is no effect: the estimate of the coefficient represents the difference in differences after one year, not at the end of the time period we study.

Overall, assuming that the comparison states are adequate counterfactuals of our states studied, we do see that the drug control policies caused a reduction in drug-related mortality only for Texas. For Florida, while the general trend indicates an effective policy, the confidence intervals around our estimates do not permit a clear conclusion. Finally, for Washington, the data suggest that the policy did not affect either the number of opioids prescribed per capita or the drug-related mortality rate.

We have to acknowledge that fitting our models on a per-year basis only leaves us with very few data points for the time after the respective drug control policies were enacted, especially for Washington and Florida. This might also explain the wide confidence intervals around our estimates. Further evidence for this hypothesis for the case of Florida is that previous research in the field suggests that the drug control policies introduced in Florida were indeed effective in reducing drug-related mortality (Kennedy-Hendricks et al., 2016). The same has been suggested for the entire United States generally (Dowell et al., 2016; Dart et al., 2015).

Conclusion & Limitations

In this report, we combined data on opioid shipments and drug-related mortality to study whether drug control policies that were introduced in three states caused a reduction in mortality. So far, it seems like introducing drug control policies causes a decrease in the drug mortality rate for only Texas. However, for Florida, the policy was also effective in reducing the number of opioids shipped per capita. This confirms previous research in the field, which indicates that drug control policies can be an effective measure to reduce drug related mortality in the United States.

This study is subject to several limitations. The difference-in-differences approach relies heavily on choosing accurate representations for the unobservable counterfactuals. While we did our best to find a sound methodology of choosing comparison states, and the diagrams indicate that the pre-policy trends in the comparison states are indeed similar to the ones in our states studied, we can never be fully certain that the comparison states are accurate proxies of the counterfactuals. Additionally, given that many counties did not report data for all death codes as some absolute counts per category are below 10, this analysis only applies to the counties that did report data. Given that the imputation strategy we tried failed in producing accurate results, this limitation might prevent findings from generalizing across the entire US. Finally, the uncertainty attached to our estimates might stem from the fact that we have too little data after the years of the policy introductions. This might prevent us from finding an effect even if it is present.

References

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2. Dowell, D., Zhang, K., Noonan, R. K., & Hockenberry, J. M. (2016). Mandatory provider review and pain clinic laws reduce the amounts of opioids prescribed and overdose death rates. *Health Affairs*, *35*(10), 1876-1883.
3. Kennedy-Hendricks, A., Richey, M., McGinty, E. E., Stuart, E. A., Barry, C. L., & Webster, D. W. (2016). Opioid overdose deaths and Florida's crackdown on pill mills. *American journal of public*

Appendix

A. Summary Statistics

	Florida	Comparison State GA, IL, MS
Observations	458	821
Mean of Mortality Rate%	0.01470	0.01438
STD of Mortality Rate%	0.00622	0.00919
Minimum Mortality Rate%	0.00390	0.00266
Maximum Mortality Rate%	0.04082	0.09815
Number of Counties	43	

	Texas	Comparison State GA, IL, KS
Observations	432	748
Mean of Mortality Rate%	0.01031	0.01372
STD of Mortality Rate%	0.00546	0.00918
Minimum Mortality Rate%	0.00144	0.00305
Maximum Mortality Rate%	0.04274	0.09815
Number of Counties	56	

	Washington	Comparison State CA, IL, KS
Observations	198	863
Mean of Mortality Rate%	0.014	0.014
STD of Mortality Rate%	0.005	0.009
Minimum Mortality Rate%	0.004	0.004
Maximum Mortality Rate%	0.031	0.098
Number of Counties	21	

Preliminary Report [Non-Technical]

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Introduction

Over the last two decades, the use and abuse of prescription opioids have skyrocketed in the United States, resulting in a massive increase in opioid addiction, reflected in prescription as well as non-prescription opioid overdose deaths, as people who became addicted to opioids due to prescriptions turn to illegal markets to feed their addiction.

To address this public health concern, several states have introduced drug control policies to crack down on clinics and physicians who prescribe large numbers of opioids. These policies require more rigorous reporting on opioids prescribed as well as a periodic review of the opioid treatment to ensure every prescription stems from a medical need. Three states that have introduced such policies are Florida, Texas, and Washington. While more than 30 states across the US have introduced similar policies, this study will focus on these three. The goal of this study is to assess whether the introduction of such policies caused a decrease in drug-related mortality as well as the number of opioids prescribed. This information is valuable to policymakers to gauge which measures are most effective in combating the opioid crisis and preventing unnecessary deaths.

Data & Methodology

For each state, this report analyzes the overdose-related mortality rates for different counties across several years. As the mortality rate is defined as the ratio of drug-induced deaths divided by population of each county, we employ data from the US vital statistics office on overdose deaths as well as data from the U.S. Census Bureau on the population per county per year. For Florida and Washington in particular, we also analyze the effect the policy has on drug shipments based on a data set that was collected by the Washington Post.

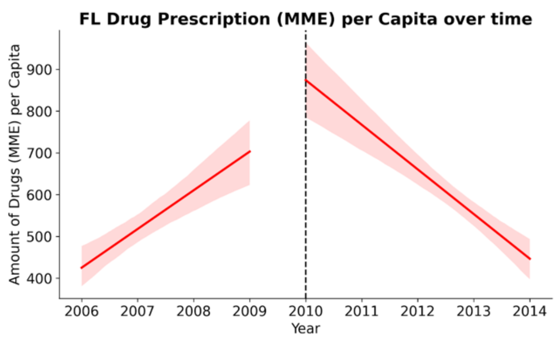
To gauge whether the policy caused a change in drug mortality rates (and the observed change was not only due to chance), we need to employ statistical methods from the field of causal inference. Fundamentally, for any given state, we need to observe two versions of reality: one in which the policy has been introduced and one in which the policy has not. The actual effect of the policy can then be calculated as the difference between these two versions of reality. Note, however, that this problem is inherently impossible to solve, as for each state we can only observe the reality that has occurred, that is, for Florida, Texas, and Washington, the version in which the policy has been introduced. To compare these two separate versions of reality, we need to choose a set of comparison states. These comparison states are considered a good proxy for the version of reality in which the policy has not been introduced. Ideally, they are as similar as possible to the three states we study in pre-policy trends in shipments and mortality *and* have to be expected to behave similarly to our states studied had the policies not been introduced. We pick three comparison states for each state we observe based on similarities metrics quantifying political orientation, geographic proximity, and general demographics as well as on pre-policy graphical trends of the change in mortality or prescription rates over time. We choose these similarity metrics because the political orientation of a state significantly influences the policies that are enacted. Moreover, we expect states that are closer together geographically to be more similar. Finally, the demographic characteristics of a state might influence the causes of deaths that occur. After choosing comparison states, we calculate the difference of the trends between the states with drug policies in place and our comparison states. This procedure is known as a difference-in-differences analysis.

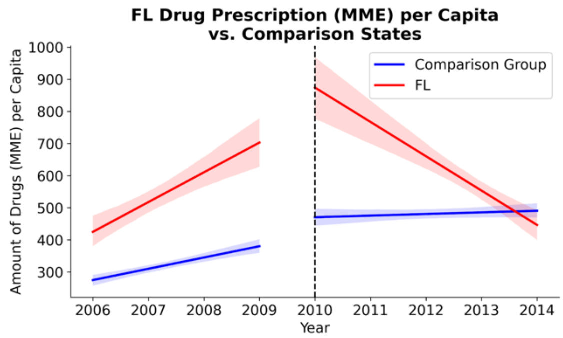
Results

For all three states Florida, Texas, and Washington, the mortality rate and prescription drug shipments increase before the introduction of the policy, however, the change of these trends post-policy differ by state. Looking at the comparison states of Florida, Texas, and Washington, we observe a rise in both mortality rates and drug shipments that are similar to our states of interest before and after the introduction of the policy. The before-policy year increase in both mortality rate and drug shipments is, in fact, also part of why we chose these states in the first place. The post-policy year increases are also consistent with our expectations since none of these comparison states have introduced opioid limitation policies.

Florida

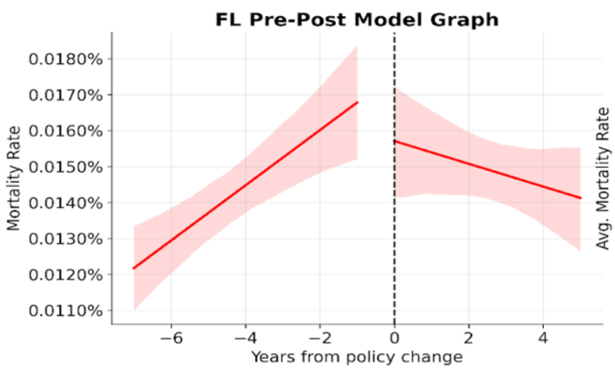
Shipments Data

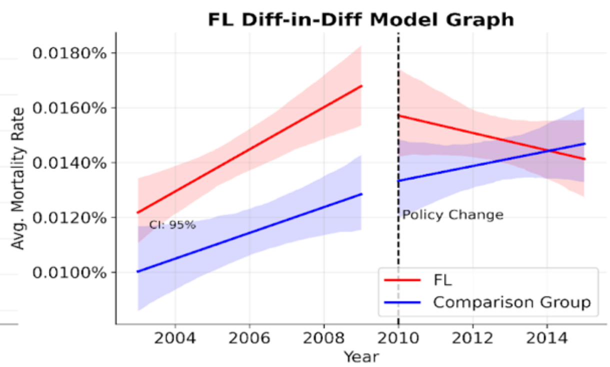




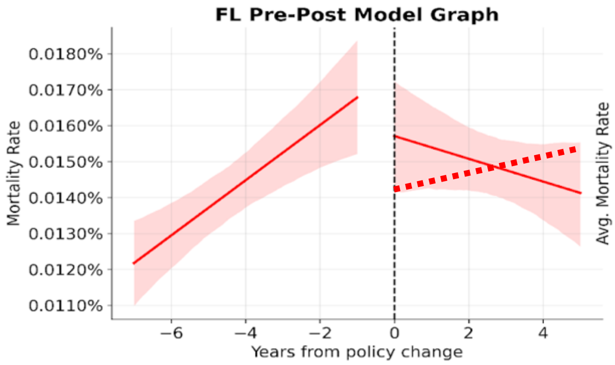
The effects of the policy implementation can be best observed through some plots (see above). The left-hand plot is a pre- and post-policy comparison of the amount of drugs (in a standardized unit MME) per capita for the state of interest, Florida, and the right-hand plot is comparison of both Florida and its comparison states, also known as the difference-in-differences plot. We can observe from the plots that the number of opioids shipped per capita in Florida decreased significantly after the drug control policy was introduced, confirming that the policy implementation is associated with a decrease in opioid shipments. However, causation cannot be concluded without also looking at the comparison states. While the increase in prescription opioids per capita appeared to slow down after 2010, the general opioid per capita trend of Florida's comparison states continued to rise in stark contrast to Florida's decline. This difference in trend change indicates that the policy did cause a reduction in opioid prescriptions per capita in Florida. This can be explained by the fact that the policy enforces stricter rules and monitoring around prescribing opioids so physicians have to be more rigorous and cannot prescribe as many opioids as before.

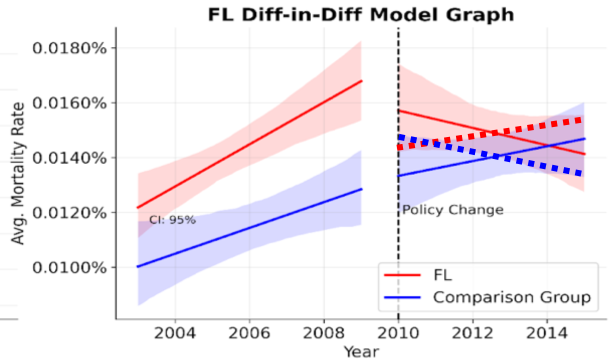
Mortality Data





Similar to the assessment of the plots for the Florida shipments data, we need not only a decreasing trend for mortality rates in Florida, but also a contrasting trend in its comparison states to show that the policy caused a decrease in mortality rates in Florida. If we look at the red and blue lines that represent the trends (it is the best fit line if we had to minimize the total distance of all our data points to one straight line), we want to conclude that the drug policy in Florida caused a decrease in mortality rates. However, we also need to consider the shaded area around the lines, which is our 95% confidence interval. To interpret this interval, we can say that we are 95% confident that the true trend of mortality rates lies within the shaded region, so intuitively speaking the smaller the shaded region, the more we are confident that our best fit line is accurate.



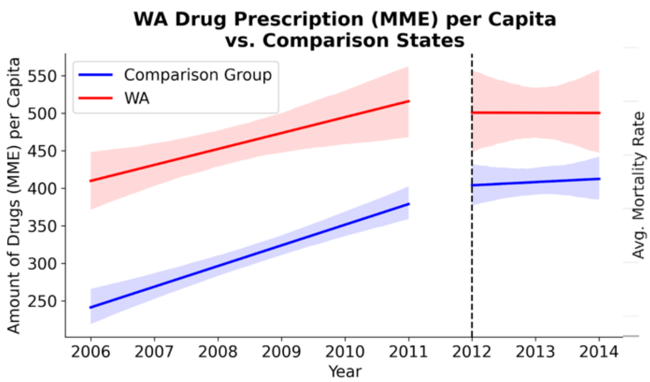


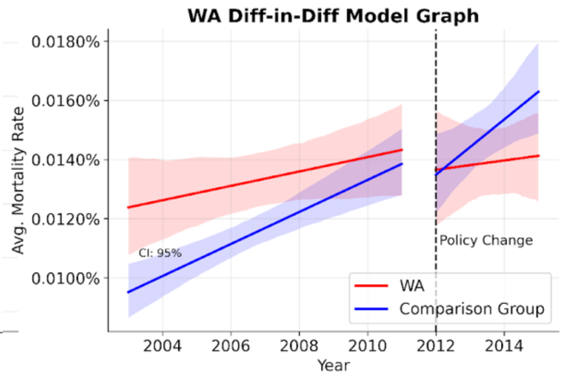
In our case, because the shaded region is so wide, the actual trend of mortality rates in Florida could still be increasing while the trend in the comparison states decreases within our 95% confidence (shown by the dashed trend lines above). As a result, we are unable to conclude that the policy was effective.

Washington

Shipments & Mortality Data

Given we cannot draw conclusions on causation looking only at any changes in trends in the state of interest, we will examine only the difference-in-differences plots going forward. The two plots below represent the difference-in-difference plots of opioid prescriptions per capita (on the right) and mortality rates (on the left).



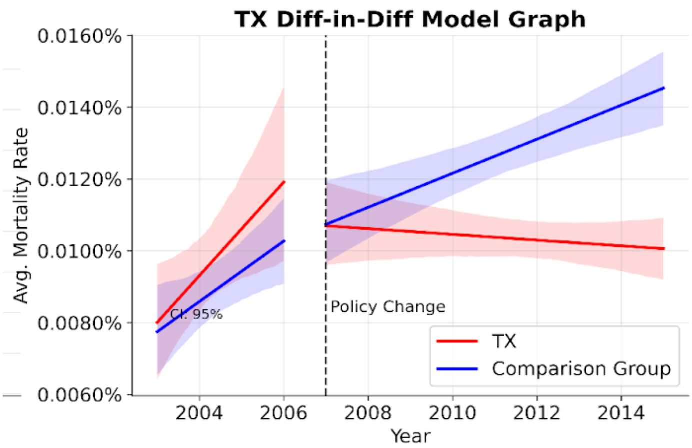


From the first plot, we can observe that opioid prescriptions for both Washington and its comparison states have stagnated after Washington implemented drug-related policies in 2012. However, similar to Florida's mortality rate analysis, we observe a wide enough confidence interval that the actual trend of opioid prescriptions in both Washington and its comparison states can either increase or decreasing. Therefore, we cannot draw any definitive conclusions on whether or not Washington's policies had an effect on prescription drug shipments. This inconclusion also holds true for the changes in mortality rates, as while we observe a definite upward trend of mortality rate in Washington's comparison states, the actual trend in Washington remains inconclusive, thus the effects of the policy on mortality rate are also inconclusive.

It is worth noting, however, that given our plots, even if we were confident in our best fit lines, the lack of difference between the pre- and post-policy trends of Washington and its comparison states would lead us to conclude that the enactment of Washington's drug policy did not cause a decline in neither prescribed opioids nor drug-related death rates. Instead, perhaps other factors (one that also affected the comparison states) influenced shipped opioids per capita and mortality rate. Also worth noting is that the inability for us to draw conclusions may very well be due to the fact that we only have two years of data post Washington's opioid policies. Given a few more years of data, the direction of the best fit lines may change and we may be able to draw a conclusion on the efficacy of the policy.

Texas

Mortality Data



Looking at the plot above, we observe that the mortality rate dropped when the policy was implemented in Texas, with the trend of drug-related death rate shifting from a substantial increase to a minor decrease after 2007. While the minor decrease in mortality rate combined with the shaded red 95% confidence area could point to a slight increase *or* decrease in the actual trend, the significantly increasing trend of the comparison states allow us to conclude that the policy caused a decrease in drug-related mortality in Texas.

Conclusion & Limitations

Overall, we can show that drug control measures only reduced drug-related mortality in Texas if the comparator states are adequate probabilistic reasoning for the states under investigation. While the general trend indicates that Florida has a successful policy, the confidence intervals around our trend lines preclude us from reaching a clear judgment. Finally, statistics reveal that the policy had no impact on Washington's drug-related mortality rate.

The plots of opioids prescribed and drug related mortality show that before any drug policies were introduced both rates were steadily rising in all states as well as comparison states. After drug control policies have been introduced, we see that the amount of opioids prescribed in Florida drastically reduces. The same does not hold true for Washington. The drug-related mortality seems to drop in Florida and Texas, while again we cannot observe any effect in Washington. To answer the question whether the policy caused a reduction in these rates, we have to compare the trends to the corresponding comparison states. Doing so indicates that for Florida our estimates too uncertain to conclude that the policy caused a change. For Texas, however, we are 95% certain that the policy caused a reduction in drug related mortality. Finally, for Washington, our estimates are too uncertain to conclude that the policy was effective in reducing drug-related mortality. This might be caused by the low number of data points we have after the policy was introduced. Besides having two little data to provide confident estimates, this study is subject to serval other limitations. The most important one is the choice of comparison states. Our causal conclusions are only valid assuming that the comparison states we chose accurately represent the versions of our states had they not introduced drug control policies. This, however, cannot be validated, although they seem to have similar pre-policy trends. Moreover, a large portion of the data was missing, as counties do not report very low number of deaths. We have tried different strategies to remedy this issue, all of which have significantly biased our results. Therefore, we decided to only model the data we have, which might affect the generalizability of our conclusions.

The selection of acceptable alternative representations is crucial in the difference-in-differences approach. We made every effort to come up with a solid method for identifying comparative states. We discovered that employing comparison states as trustworthy alternative proxies is not always practicable. Furthermore, while many counties did not release data for all death codes because certain absolute counts per category are fewer than 10, this study only looks at the counties that did. Therefore, our findings might only reflect this subset and not generalize well to the entire United States.